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Permissioned Distributed Ledger (PDL); Artificial Intelligence for Permissioned Distributed Ledger

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Foreword

This Group Report (GR) has been produced by ETSI Industry Specification Group (ISG) Permissioned Distributed Ledger (PDL).

Modal verbs terminology

In the present document "**should**", "**should not**", "**may**", "**need not**", "**will**", "**will not**", "**can**" and "**cannot**" are to be interpreted as described in clause 3.2 of the ETSI Drafting Rules (Verbal forms for the expression of provisions).

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Executive summary

The present document explores the applications of Artificial Intelligence (AI) in Permissioned Distributed Ledger (PDL) systems. The present document covers several key areas where AI can enhance PDL functionality, security, and performance:

1) **Enhanced Security:** AI-powered anomaly detection and threat identification in real-time, as well as improved fraud detection through machine learning algorithms.

2) **Smart Contract Optimization:** AI-driven code analysis, performance optimization, security enhancement, and automated testing and verification of smart contracts.

3) **Improved Consensus Mechanisms:** AI-enhanced algorithms for faster and more efficient agreement, and adaptive mechanisms based on network conditions.

4) **Data Analytics and Insights:** AI analysis of large transaction volumes and predictive analytics for business intelligence.

5) **Privacy-Preserving Techniques:** Advanced AI-driven methods for privacy-preserving computation, including homomorphic encryption, secure multi-party computation, federated learning, differential privacy, and generative adversarial networks for synthetic data generation.

6) **Network Optimization:** AI-based performance optimization, resource allocation, predictive maintenance, topology optimization, intelligent data sharding, enhanced network security, energy-efficient operations, congestion management, and adaptive protocol optimization.

7) **Governance and Compliance:** AI assistance in enforcing rules, compliance checks, automated auditing and reporting, enhanced governance participation, regulatory compliance monitoring, and intelligent dispute resolution.

8) **Identity Management:** AI-enhanced verification processes, behavioural biometrics for continuous authentication, federated identity management, adaptive access control, identity recovery and remediation, decentralized identity verification, and cross-chain identity management.

9) **Interoperability:** AI-facilitated cross-chain communication and smart routing of transactions between ledgers.

10) **Scalability Solutions:** AI-driven development of efficient scaling solutions and dynamic sharding based on network conditions.

The present document provides detailed explanations, examples, and references for each of these areas, highlighting the potential of AI to significantly improve PDL systems across multiple dimensions. It serves as a comprehensive guide for PDL developers, researchers, and stakeholders looking to leverage AI technologies in their distributed ledger implementations.

Introduction

Permissioned Distributed Ledger (PDL) systems face significant challenges in maintaining optimal performance, security, and scalability as they grow in complexity and adoption.

These challenges include:

1) Security vulnerabilities and evolving cyber threats.

2) Inefficient smart contract development and deployment processes.

3) Slow and inflexible consensus mechanisms.

4) Difficulty in extracting meaningful insights from large volumes of transaction data.

5) Privacy concerns in data processing and analysis.

6) Suboptimal network performance and resource allocation.

7) Inadequate governance and compliance mechanisms.

8) Inefficient identity management processes.

9) Limited interoperability between different ledger systems.

10) Scalability issues hindering widespread adoption.

These challenges can result in reduced trust, increased operational costs, limited functionality, and potential security breaches in PDL systems. There is a pressing need for innovative solutions that can address these issues comprehensively while maintaining the decentralized and secure nature of distributed ledger technology.

The present document explores the applications of Artificial Intelligence (AI) in Permissioned Distributed Ledger (PDL) systems in a manner that may assist overcoming many of the challenges described above. As PDL technologies continue to evolve and gain adoption across various industries, the integration of AI presents significant opportunities to enhance their functionality, security, and performance.

The present document covers several key areas where AI can be leveraged to improve PDL systems:

1) **Enhanced Security:** AI-powered anomaly detection, threat identification, and fraud detection.
2) **Smart Contract Optimization:** AI-driven code analysis, performance optimization, and automated testing.
3) **Improved Consensus Mechanisms:** AI-enhanced algorithms for faster and more efficient agreement.
4) **Data Analytics and Insights:** AI analysis of transaction data and predictive analytics for business intelligence.
5) **Privacy-Preserving Techniques:** Advanced AI-driven methods for privacy-preserving computation.
6) **Network Optimization:** AI-based performance optimization, resource allocation, and predictive maintenance.
7) **Governance and Compliance:** AI assistance in enforcing rules, compliance checks, and automated auditing.
8) **Identity Management:** AI-enhanced verification processes and continuous authentication.
9) **Interoperability:** AI-facilitated cross-chain communication and transaction routing.
10) **Scalability Solutions:** AI-driven development of efficient scaling solutions and dynamic sharding.

Each clause provides an overview of how AI can be applied in these areas, along with specific examples, potential benefits, and references to recent research and developments. The present document aims to serve as a comprehensive guide for PDL developers, researchers, and stakeholders looking to leverage AI technologies in their distributed ledger implementations.

As both AI and PDL technologies are rapidly evolving fields, the present document focuses on cutting-edge approaches and recent advancements, with most references dated 2020 or later. The present document also includes recommendations for implementation and highlights areas for further research and development. By addressing the challenges outlined in the problem statement through AI-driven solutions, the present document aims to contribute to the advancement of PDL systems, making them more secure, efficient, and adaptable to the needs of various industries and applications.

1 Scope

1.1 Description

The present document specifies the application of Artificial Intelligence (AI) techniques to Permissioned Distributed Ledger (PDL) systems. The present document focuses on the theoretical foundations, practical applications, and potential benefits of integrating AI technologies into PDL systems.

1.2 In scope

The focus of the functionalities in the present document are PDL systems. So, all the topics listed here should be understood with a focus on the specific case of PDL systems:

1) Enhanced security measures using AI, including:
   - Real-time anomaly detection and threat identification.
   - Fraud detection through machine learning algorithms.
2) Smart contract optimization through AI-driven:
   - Code analysis and optimization.
   - Automated testing and verification.
3) Improved consensus mechanisms using AI.
4) Data analytics and insights derived from AI analysis of transaction data.
5) Privacy-preserving techniques enabled by AI.
6) AI-based network optimization.
7) AI-assisted governance and compliance.
8) AI-enhanced identity management.
9) AI-facilitated interoperability between different ledgers.
10) AI-based scalability solutions.

1.3 Not in scope of the present document

The use of AI for these listed purposes in other systems in general is not the focus of the present document:

1) Detailed implementation guidelines for specific AI algorithms.
2) Hardware specifications for AI integration in PDL systems.
3) Regulatory and legal frameworks governing AI use in PDLs.
4) Economic and business models for AI-enhanced PDL systems.
5) Training methodologies for AI models in PDL contexts.
6) Comparative analysis of different PDL platforms.
7) Non-AI based improvements to PDL systems.

2 References

2.1 Normative references

Normative references are not applicable in the present document.

2.2 Informative references

References are either specific (identified by date of publication and/or edition number or version number) or non-specific. For specific references, only the cited version applies. For non-specific references, the latest version of the referenced document (including any amendments) applies.

NOTE: While any hyperlinks included in this clause were valid at the time of publication, ETSI cannot guarantee their long-term validity.

The following referenced documents are not necessary for the application of the present document, but they assist the user with regard to a particular subject area.

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3 Definition of terms, symbols and abbreviations

3.1 Terms

For the purposes of the present document, the following terms apply:

adaptive access control: dynamic adjustment of access permissions based on user behaviour and context

adaptive protocol optimization: automatic adjustment of network protocols to optimize performance based on changing conditions

AI assisted automated auditing and reporting: use of AI to automate the process of auditing and generating compliance reports

AI assisted governance rules and compliance checks enforcement: use of AI to enforce governance rules and ensure compliance in PDL systems

AI-driven network topology optimization: use of AI to optimize the structure and connections within a network for improved performance

AI-enhanced governance participation: improvement of stakeholder participation in governance processes through AI-powered tools and analytics

AI-enhanced network security: use of AI to enhance network security measures and detect potential threats

AI-facilitated cross-chain communication and data exchange: use of AI to enable and improve communication and data sharing between different blockchain networks

AI-powered anomaly detection and threat identification in real-time: use of AI to identify unusual patterns or potential security threats in real-time

AI-powered network congestion management: use of AI to predict and manage network congestion for improved performance

automated testing and verification of smart contracts: use of AI to automate the process of testing and verifying smart contracts for errors or vulnerabilities

behavioural biometrics: use of biological known traits to predict behaviour

NOTE: Biometric identification is subject to laws and regulation in certain regions.

code generation and refactoring: use of AI to automatically generate or improve code for smart contracts

continuous integration and deployment: integration of AI into the process of continuously testing and deploying smart contract updates

Continual Learning: ability of a model or system to learn from a stream of data sequentially, adapting to new information while retaining previously learned knowledge

NOTE: It differs to Continuous Learning in the context of Machine Learning. It is particularly relevant in the context of machine learning and artificial intelligence, where the goal is to mitigate catastrophic forgetting and enable models to learn continuously from new data without forgetting previous tasks.

Continuous Learning: ongoing process of acquiring new knowledge and skills over time, often in a professional or educational setting

NOTE: It emphasizes the continuous expansion of knowledge and skill sets, which can be formal or informal, structured or unstructured.

cross-chain identity management: management of digital identities across multiple blockchain networks using AI

decentralized identity verification: use of AI to verify identities in a decentralized manner without relying on a central authority

developing more efficient scaling solutions using AI: use of AI to create improved methods for scaling PDL systems

differential privacy: use of a mathematically rigorous framework for releasing statistical information about datasets while protecting the privacy of individual data subjects

NOTE: Statistical information is normalized to alleviate any personal information.

differential privacy in machine learning: application of differential privacy techniques to machine learning models to protect individual privacy

differentially private follow the regularized leader: training model with Differential Privacy (DP) using mini-batch gradients

NOTE 1: The existing state-of-the-art, Differentially Private Stochastic Gradient Descent (DP-SGD), requires privacy amplification by sampling or shuffling to obtain the best privacy/accuracy/computation trade-offs.

NOTE 2: This is a code for "Practical and Private (Deep) Learning without Sampling or Shuffling" [i.122]. The paper proposed Differentially Private Follow-the-Regularized-Leader (DP-FTRL), a differentially private algorithm that does not rely on shuffling or subsampling as in Differentially Private Stochastic Gradient Descent (DP-SGD) but achieves comparable (or even better) utility.

differentially private stochastic gradient descent: use of a popular training method with differential privacy

NOTE: It provides a formal privacy guarantee that prevents adversaries from extracting information about individual training points. DP-SGD allows a moments accountant technique to track privacy leakage.

dynamic sharding based on network traffic and usage patterns: use of AI to dynamically adjust sharding strategies based on network conditions

energy-efficient network operations: utilization of AI to optimize network operations for reduced energy consumption

enhanced fraud detection through machine learning algorithms: use of machine learning to improve the detection of fraudulent activities

federated identity management: management of digital identities across multiple organizations or systems using federated learning techniques

federated learning: machine learning technique where models are trained across multiple decentralized devices or servers holding local data samples

formal verification: use of AI to mathematically prove the correctness of smart contracts

fuzzing: use of logic

NOTE: This is less deterministic.

fuzzing and mutation testing: use of AI to generate random or mutated inputs for testing smart contracts

NOTE: Prediction is needed to provide the volume at a safe pressure range.

Generative Adversarial Networks (GANs) for synthetic data: use of GANs to generate synthetic data for testing or training purposes while preserving privacy

homomorphic encryption and secure multi-party computation: cryptographic techniques that allow computations on encrypted data without decrypting it

identity recovery and remediation: use of AI to assist in recovering or remediating compromised digital identities

intelligent data sharding: use of AI to optimize the process of dividing data across multiple nodes in a network

intelligent dispute resolution: use of AI to assist in resolving disputes within PDL systems

learning from past vulnerabilities: use of AI to analyse past security vulnerabilities to prevent similar issues in the future

natural language processing for documentation: use of NLP techniques to improve the creation and understanding of smart contract documentation

network performance and resource allocation: use of AI to optimize network performance and allocate resources efficiently

pattern recognition and behavioural analysis: use of AI to identify patterns and analyse behaviour in PDL systems for security purposes

performance optimization: use of AI to improve the performance of smart contracts and PDL systems

predictive analytics for business intelligence: use of AI to forecast future trends and provide business insights based on PDL data

predictive maintenance of network nodes: use of AI to predict when network nodes will require maintenance or upgrades

real-time monitoring and analysis: use of AI for continuous monitoring and analysis of PDL systems

regulatory compliance monitoring: use of AI to ensure PDL systems comply with relevant regulations and standards

security enhancement: use of AI to improve the overall security of smart contracts and PDL systems

smart routing of transactions between different ledgers: use of AI to optimize the routing of transactions across multiple blockchain networks

static code analysis: use of AI to analyse smart contract code without executing it to identify potential issues

symbolic execution: use of AI to analyse all possible execution paths of a smart contract to identify vulnerabilities

3.2 Symbols

Void.

3.3 Abbreviations

For the purposes of the present document, the following abbreviations apply:

AI	Artificial Intelligence
AML	Anti-Money Laundering
BRIEF	Binary Robust Independent Elementary Features
BRIEF	Binary Robust Independent Elementary Features
CGAN	Conditional Generative Adversarial Network
CI/CD	Continuous Integration/Continuous Deployment
CLV	Customer Lifetime Value
CNN	Convolutional Neural Network
CTGAN	Conditional Tabular Generative Adversarial Network
CTL	Computation Tree Logic
DCNs	Deep Clustering Networks
DDoS	Distributed Denial of Service
DEX	Decentralized EXchange
DLT	Distributed Ledger Technology
DP	Differential Privacy
DP-FTRL	Differentially Private Follow The Regularized Leader
DP-SGD	Differentially Private Stochastic Gradient Descent
FAST	Features from Accelerated Segment Test

FL	Federated Learning
GAE	Graph AutoEncoder
GAN	Generative Adversarial Network
GCN	Graph Convolutional Network
GDP	Gaussian Differential Privacy
GDPR	General Data Protection Regulation
GNN	Graph Neural Network
GNNIS	Global Neural Network Information System
GRU	Gated Recurrent Unit
HE	Homomorphic Encryption
ID	Identification/Identity
IDE	Integrated Development Environment
IoT	Internet of Things
ISG	Industry Specification Group
KYC	Know Your Customer
LLM	Large Language Model
LSTM	Long Short-Term Memory
LTL	Linear Temporal Logic
MARL	Multi-Agent Reinforcement Learning
ML	Machine Learning
NGSE	Next Generation Stock Exchange
NGTP	Next Generation Trading Platform
NLP	Natural Language Processing
NuSMV	New Symbolic Model Verifier
OAGNNs	Online Adaptive Graph Neural Networks
OCR	Optical Character Recognition
ORB	Oriented FAST and Rotated BRIEF
PBFT	Practical Byzantine Fault Tolerance
PDL	Permissioned Distributed Ledger
RL	Reinforcement Learning
RLCT	Reinforcement Learning Control Theory
RNN	Recurrent Neural Network
SCSCAN	Supply Chain Security Analysis
SE	Software Engineering
SMPC	Secure Multi-Party Computation
SMV	Symbolic Model Verifier
SPIN	Simple Promela INterpreter
SVM	Support Vector Machine
TCN	Temporal Convolutional Network
TGCN	Temporal Graph Convolutional Network
TMC	Traffic Management Centre
VAE	Variational AutoEncoder
VELMA	Virtual Environment Lifecycle Management Assistant
XAI	eXplainable Artificial Intelligence

4 Enhancing PDL security using AI-based methods

4.1 Introduction

Artificial Intelligence (AI) plays a crucial role in enhancing the security of Permissioned Distributed Ledger (PDL) platforms. This clause explores two key areas where AI significantly contributes to improved security measures: real-time anomaly detection and fraud detection using machine learning algorithms.

By leveraging AI for anomaly detection and fraud prevention, PDL platforms can significantly enhance their security posture, ensuring the integrity and trustworthiness of the network while providing a seamless experience for legitimate users.

4.2 AI-Powered Anomaly Detection and Threat Identification in Real-Time

4.2.1 Problem statement

Permissioned Distributed Ledger (PDL) platforms face critical security challenges in maintaining their integrity and trustworthiness in the face of evolving cyber threats. Traditional security measures often struggle to keep pace with the sophisticated and dynamic nature of attacks on these systems.

Key issues include:

1) Delayed detection of security breaches and anomalies, leading to increased vulnerability.
2) Difficulty in identifying subtle, complex attack patterns are detected by conventional detection methods.
3) Challenges in processing and analysing vast amounts of network data in real-time.
4) Inability to adapt quickly to new and emerging threat vectors.
5) High rates of false positives, leading to alert fatigue and misallocation of security resources.
6) Limited capability to predict and prevent potential security incidents proactively.
7) Challenges in maintaining security without compromising the performance and efficiency of the PDL network.

These issues can result in significant security breaches, data compromises, and loss of trust in PDL systems. There is an urgent need for more advanced, real-time, and adaptive security solutions that can effectively protect these platforms against a wide range of threats.

4.2.2 Using AI for Anomaly Detection and Real-Time Threat Detection

AI systems can significantly enhance the security of PDL platforms by detecting anomalies and potential security threats in real-time. This capability is essential for maintaining the integrity and trustworthiness of the network. By leveraging machine learning, deep learning, and other AI techniques, it is possible to develop solutions that offer:

1) Real-time analysis of network behaviour to identify anomalies and potential threats.
2) Adaptive learning from new attack patterns to continuously improve detection capabilities.
3) Ability to process and analyse vast amounts of data from multiple nodes simultaneously.
4) Reduced false positives through more sophisticated pattern recognition and contextual analysis.
5) Predictive threat identification based on historical data and emerging trends.
6) Automated response mechanisms to mitigate threats quickly and effectively.
7) Seamless integration with existing PDL infrastructure without compromising performance.

Implementing AI-powered anomaly detection and threat identification systems has the potential to significantly enhance the security posture of PDL platforms, ensuring their resilience against cyber threats and fostering greater confidence in their use across various industries.

4.2.3 Real-Time Monitoring and Analysis

AI algorithms can continuously monitor network activities, transaction patterns, and system behaviours across the PDL platform. By analysing vast amounts of data in real-time, AI systems can quickly identify deviations from normal patterns that may indicate potential security threats.

The following AI algorithms can be effectively used to continuously monitor network activities, transaction patterns, and system behaviours in Permissioned Distributed Ledger (PDL) platforms:

- Temporal Graph Convolutional Networks excel at capturing the dynamic structure of PDL networks.

- Federated Attention Mechanism with Differential Privacy enables collaborative monitoring while preserving privacy.
- Hierarchical Long Short-Term Memory Networks with Adaptive Thresholding provide a flexible approach to multi-scale temporal pattern analysis.

Based on recent advancements and their potential impact, clause A.1.1 lists several examples of AI algorithms for continuous monitoring that can continuously monitor network activities, transaction patterns, and system behaviours across PDL platforms.

4.2.4 Pattern Recognition and Behavioural Analysis

Advanced machine learning models, such as deep neural networks and clustering algorithms, can be trained on historical data to recognize complex patterns of normal behaviour within the PDL network. These models can then identify unusual activities that deviate from these established patterns, potentially signalling a security threat. The following advanced machine learning models can be trained on historical data to recognize complex patterns of normal behaviour within Permissioned Distributed Ledger (PDL) networks.

When applied to PDL networks, they can provide powerful tools for understanding normal network behaviour and identifying potential security threats or operational issues.
Clause A.1.2 lists examples of advanced machine learning models for pattern recognition.

4.2.5 Adaptive Threat Detection

AI systems can adapt and evolve their threat detection capabilities over time. As new types of attacks emerge, AI based applications can learn from these incidents and update the detection mechanisms, ensuring that the PDL platform remains protected against evolving security threats. The following AI systems demonstrate the capability to adapt and evolve their threat detection capabilities over time, making them particularly suitable for the dynamic security landscape of Permissioned Distributed Ledger (PDL) networks. When applied to PDL networks, they can provide robust, flexible security measures that can keep pace with emerging threats and changing network conditions.
Clause A.1.3 provides examples of adaptive AI systems for evolving threat detection.

4.2.6 Automated Response Mechanisms

When potential threats are detected, AI systems can trigger automated response mechanisms to mitigate risks. These may include isolating affected nodes, temporarily freezing suspicious transactions, or alerting system administrators for further investigation. Based on recent advancements and their potential impact, shown here is a list of AI systems that can trigger automated response mechanisms to mitigate risks in PDL networks:

- Reinforcement Learning-based systems provide adaptive, autonomous defence strategies.
- Federated Learning-based systems enable collaborative defence while preserving data privacy.
- Explainable AI (XAI) systems offer transparent, interpretable automated responses that can be easily audited and refined.

When implemented in combination, these systems can create a robust, adaptive, and transparent automated response framework capable of addressing the complex and evolving threat landscape faced by PDL networks. They balance the need for quick, automated responses with the requirements for privacy, collaboration, and human oversight in security operations.

4.3 Enhanced Fraud Detection through Machine Learning Algorithms

4.3.1 Problem statement

Permissioned Distributed Ledger (PDL) platforms face significant challenges in detecting and preventing fraudulent activities, which can undermine the integrity and trustworthiness of these systems. Traditional rule-based fraud detection methods often fall short in addressing the complex and evolving nature of fraud in PDL environments.

These limitations include:

1) Inability to adapt quickly to new fraud patterns and techniques.
2) High rates of false positives and false negatives, leading to inefficient resource allocation.
3) Difficulty in detecting sophisticated, multi-layered fraud schemes.
4) Challenges in processing and analysing large volumes of transaction data in real-time.
5) Limited capability to identify subtle anomalies that may indicate fraudulent behaviour.
6) Inflexibility in adjusting to changing business environments and transaction patterns.
7) Inefficiency in handling the decentralized nature of PDL platforms.

These issues can result in significant financial losses, reputational damage, and reduced confidence in PDL systems. There is a pressing need for more advanced, adaptive, and efficient fraud detection solutions that can keep pace with the evolving threat landscape.

4.3.2 Using AI to detect fraud

Machine learning algorithms can significantly improve fraud detection capabilities in PDL platforms, offering a more sophisticated and effective approach compared to traditional rule-based systems. By leveraging advanced AI techniques, it is possible to develop solutions that provide:

1) Real-time analysis of transaction patterns to identify anomalies.
2) Adaptive learning from new fraud instances to continuously improve detection accuracy.
3) Ability to process and analyse vast amounts of data from multiple sources.
4) Reduced false positives and false negatives through more nuanced pattern recognition.
5) Enhanced capability to detect complex, previously unknown fraud schemes.
6) Improved scalability to handle increasing transaction volumes in PDL platforms.
7) Better integration with the decentralized nature of PDL systems.

Implementing machine learning-based fraud detection solutions has the potential to significantly enhance the security and reliability of PDL platforms, fostering greater trust and adoption across various industries.

4.3.3 Sophisticated Pattern Analysis

Machine learning models can analyse complex transaction patterns and user behaviours to identify potential fraudulent activities. These models can consider a wide range of factors and their intricate relationships, allowing for more nuanced and accurate fraud detection. Based on recent advancements and their potential impact, presented here are AI-based Machine Learning models for analysing complex transaction patterns and user behaviours to identify potential fraudulent activities in PDL networks.

These AI-based Machine Learning models offer powerful capabilities for analysing complex transaction patterns and user behaviours to identify potential fraudulent activities in PDL networks:

- Graph Neural Networks provide a natural way to model and analyse the network structure of transactions and relationships.
- Transformer-based models excel at capturing sequential patterns in transaction data.
- Federated Deep Learning enables collaborative fraud detection while preserving data privacy.

Further information and examples of such models can be found in clause A.1.5.

4.3.4 Anomaly-Based Fraud Detection

Unsupervised learning algorithms can be employed to establish baseline behaviours for users and transactions. Any significant deviations from these baselines can be flagged for further investigation, potentially uncovering fraudulent activities that might not be caught by predefined rules. These unsupervised learning algorithms offer complementary capabilities for establishing baseline behaviours in PDL networks:

- Graph Autoencoders are particularly well-suited for modelling the complex network structure of PDLs.
- Variational Autoencoders excel at learning and generating normal behaviour patterns in high-dimensional spaces.
- Temporal Convolutional Networks are adept at capturing complex temporal patterns in transaction sequences.

Clause A.1.6 provides examples of unsupervised learning algorithms used to establish baseline behaviours for users and transactions within Permissioned Distributed Ledger (PDL) network.

4.3.5 Predictive Fraud Analytics

By leveraging historical data and current trends, machine learning models can predict potential fraudulent activities before they occur. This proactive approach allows PDL platforms to implement preventive measures and reduce the risk of fraud. These machine learning models offer powerful capabilities for predicting potential fraudulent activities in PDL networks before they occur:

- Graph Neural Networks with Temporal Attention provide a way to model and analyse the evolving structure of transaction networks.
- Transformer-based Models with Self-Supervised Pre-training excel at capturing complex sequential patterns in transaction data.
- Federated Deep Learning with Differential Privacy enables collaborative fraud prediction while preserving data privacy.

Based on recent advancements and their potential impact, clause A.1.7 provides examples of machine learning models for fraud detection that can predict potential fraudulent activities before they occur in PDL networks.

4.3.6 Continual Learning and Improvement

Machine learning models used for fraud detection can continuously learn from new data and feedback, improving their accuracy over time. This adaptive capability ensures that the fraud detection system remains effective against evolving fraud techniques. These machine learning models offer powerful capabilities for continuous learning and improvement in fraud detection within PDL networks:

- Online Adaptive Graph Neural Networks provide a way to continuously update the model of the transaction network.
- Incremental Learning with Ensemble Methods allows for efficient and interpretable model updates.
- Federated Continual Learning enables collaborative, privacy-preserving continuous learning across the entire PDL network.

NOTE: Continuous Learning and Continual Learning are often used interchangeably, but they have distinct meanings in different contexts:

Clause A.1.8 presents examples of continuous learning machine learning models for fraud detection that can continuously learn and improve their fraud detection accuracy over time in PDL networks.

4.3.7 Reduced False Positives

Advanced machine learning algorithms can significantly reduce false positives in fraud detection, minimizing unnecessary disruptions to legitimate transactions while maintaining high security standards. These machine learning models offer powerful capabilities for reducing false positives in fraud detection within PDL networks:

- Attention-based Graph Neural Networks with Explainable AI provide high accuracy and interpretability.
- Hybrid Models combining anomaly detection with supervised learning offer a two-stage approach to reduce false positives.
- Federated Learning with Adaptive Boosting enables collaborative, privacy-preserving learning that focuses on hard-to-classify cases.

Clause A.1.9 provides examples of machine learning models for reducing false positives in fraud detection.

5 Smart contract optimization using AI

5.1 Introduction

Artificial Intelligence (AI) offers significant advancements in the field of smart contract development and deployment within Permissioned Distributed Ledger (PDL) platforms. This clause explores two key areas where AI contributes to smart contract optimization: code analysis and optimization, and automated testing and verification.

By leveraging AI for smart contract optimization, PDL platforms can significantly enhance the quality, security, and efficiency of deployed contracts. This not only reduces the risk of costly errors or exploits but also improves the overall performance and reliability of the distributed ledger system.

5.2 AI-Driven Smart Contract Code Analysis and Optimization

5.2.1 Problem statement

Smart contract development and deployment face significant challenges in ensuring security, efficiency, and cost-effectiveness. Current methods of smart contract code analysis and optimization are often inadequate, leading to potential vulnerabilities, inefficient execution, and higher operational costs.

Specifically, the industry struggles with:

1) Limited tools for in-depth analysis, hindering comprehensive code review.
2) Difficulty in detecting vulnerabilities, potentially compromising contract security.
3) Inefficient execution leading to higher gas fees, increasing operational costs.
4) Lack of formal verification methods, reducing confidence in contract reliability.
5) Difficulty in ensuring best practices is consistently followed during development.

These challenges can result in smart contracts that are vulnerable to exploits, costly to execute, and difficult to maintain. There is a pressing need for more advanced, automated solutions that can address these issues effectively.

5.2.2 Using AI to handle such challenges

AI can be used to significantly improve or ease the process of analysing and optimizing smart contract code, leading to more efficient, secure, and cost-effective contracts. By leveraging machine learning and other AI techniques, it is possible to develop solutions that offer:

1) Automated detection of vulnerabilities and bugs, improving contract security.

2) Enhanced verification methods through machine learning, increasing reliability.

3) Optimization of gas usage via predictive analysis, reducing operational costs.

4) Real-time monitoring and audits, enabling proactive issue resolution.

5) Improved readability and maintainability of code, facilitating long-term contract management.

Implementing AI-driven solutions for smart contract code analysis and optimization has the potential to revolutionize the development process, mitigating risks and enhancing the overall quality and efficiency of smart contracts across various blockchain platforms. AI can significantly enhance the process of analysing and optimizing smart contract code, leading to more efficient, secure, and cost-effective contracts. Some of the methods, and examples thereof, are presented below.

5.2.3 Static Code Analysis

AI-powered static code analysis tools can automatically review smart contract code to identify potential vulnerabilities, inefficiencies, and coding style inconsistencies. These tools can be trained on large datasets of smart contracts to recognize common patterns and anti-patterns, providing developers with actionable insights to improve their code.

Several AI-powered static code analysis tools have been developed to enhance smart contract security and efficiency.

These tools represent the current state of the art in AI-powered static code analysis. They go beyond traditional rule-based analysis by incorporating machine learning techniques to improve accuracy, reduce false positives, and provide more context-aware recommendations.

When applied to smart contract development in PDL platforms, these tools can significantly enhance code quality and security. They can help identify potential vulnerabilities, ensure adherence to best practices, and improve overall code reliability. However, it is important to note that while these tools are powerful, it is suggested that they are used as part of a comprehensive security strategy that includes manual code reviews and dynamic analysis techniques.

Clause A.2.1 presents examples of AI-Powered static code analysis tools.

5.2.4 Performance Optimization

Machine learning algorithms can analyse the execution patterns of smart contracts and suggest optimizations to reduce gas costs and improve overall performance. This may include identifying redundant operations, optimizing data structures, or suggesting more efficient algorithmic approaches.

Several AI-based tools have been developed to optimize the performance of smart contracts, particularly focusing on gas optimization and execution efficiency.

These tools represent the current state of the art in AI-assisted performance optimization for smart contracts. They primarily focus on gas optimization, which is a critical aspect of smart contract efficiency in many blockchain platforms. As AI and machine learning techniques continue to advance, it is expected that these tools will become even more sophisticated in their ability to optimize smart contract performance, potentially expanding to other aspects of optimization beyond gas usage.

It is worth noting that while some of these tools are not fully AI-powered, they use advanced algorithms and techniques that form the foundation for more sophisticated AI-driven optimizations in the future. The field of AI-based smart contract optimization is rapidly evolving, and it is expected that more fully AI-integrated tools will emerge in the coming years.

Deep Reinforcement Learning excels at dynamic optimization in changing network conditions. Graph Neural Networks with Attention can capture complex relationships within and between contracts. Transformer-based models with transfer learning can leverage knowledge from multiple programming languages to suggest sophisticated optimizations.

These AI-based machine learning algorithms represent the cutting edge in smart contract optimization. They go beyond traditional static analysis by incorporating advanced AI techniques to understand complex patterns in contract execution and suggest context-aware optimizations.

When applied to smart contract development in PDL platforms, these algorithms can significantly reduce gas costs and improve overall performance. However, it is important to note that while these techniques are powerful, they are able to be used in conjunction with expert review and thorough testing to ensure that optimizations do not introduce new vulnerabilities or unintended behaviours.

Clause A.2.2 provides some notable examples of AI-Based machine learning algorithms for smart contract optimization.

5.2.5 Security Enhancement

AI models can be trained to identify potential security vulnerabilities in smart contract code, such as reentrancy attacks, integer overflow/underflow, and unauthorized access. By flagging these issues early in the development process, AI can help prevent costly security breaches.
These AI algorithms represent the cutting edge in smart contract vulnerability detection. They offer complementary capabilities that can address different aspects of smart contract security analysis.

Graph Neural Networks with Semantic-Aware Embedding excel at capturing the structure and meaning of smart contracts. Transformer-based Models with Transfer Learning leverage knowledge from a wide range of programming languages to identify potential vulnerabilities. Reinforcement Learning with Symbolic Execution provides a dynamic approach to exploring contract behaviour and identifying complex vulnerabilities.

Based on recent advancements and their potential impact, clause A.2.3 offers examples of AI algorithms for identifying smart contract vulnerabilities.

5.2.6 Code Generation and Refactoring

Advanced AI systems can assist in generating boilerplate code, suggesting refactoring options, and even proposing entire sections of optimized code based on the developer's intent. This can significantly speed up the development process and reduce the likelihood of human error. These AI algorithms represent the cutting edge in code generation and optimization for PDL platforms. They offer complementary capabilities that can address different aspects of the development process.

Large Language Models with Few-Shot Learning excel at generating diverse code suggestions with minimal platform-specific training. Graph-to-Code Neural Networks with Attention are particularly good at understanding and utilizing existing code structure. Hierarchical Transformers with Code Semantic Embedding provide a multi-level understanding of code, from individual lines to overall application structure. Clause A.2.4 lists examples of AI Algorithms for code generation and optimization in PDL platforms.

5.2.7 Natural Language Processing for Documentation

AI-powered natural language processing can analyse smart contract code and automatically generate human-readable documentation, improving the maintainability and understandability of complex contracts. These AI-powered NLP tools represent the cutting edge in automatic documentation generation for smart contracts in PDL platforms. They offer complementary capabilities that can address different aspects of the documentation process.

CodeBERT-based Documentation Generation excels at providing contextually relevant explanations of code functionality. Graph-to-Sequence Neural Networks are particularly good at capturing and explaining the overall structure and flow of complex contracts. Hierarchical Transformers with Code-Text Alignment provide multi-level documentation with clear traceability to the original code.

Based on recent advancements and their potential impact, clause A.2.5 lists examples of AI-Powered NLP tools for smart contract documentation that can analyse smart contract code and automatically generate human-readable documentation for PDL platforms.

5.3 Automated Testing and Verification of Smart Contracts

5.3.1 Problem statement

The testing and verification of smart contracts present significant challenges in ensuring their reliability, security, and intended functionality. Traditional testing methods often fall short in comprehensively identifying potential vulnerabilities, logical errors, and edge cases, leading to:

1) Increased risk of security breaches and exploits in deployed contracts.
2) Unintended behaviours that may result in financial losses or system disruptions.
3) Difficulty in verifying complex contract interactions and state transitions.
4) Time-consuming and error-prone manual testing processes.
5) Inadequate coverage of all possible execution paths and scenarios.
6) Challenges in keeping up with evolving attack vectors and vulnerabilities.
7) Limited ability to predict and prevent potential issues in real-world environments.

These challenges can result in smart contracts that are vulnerable to attacks, prone to errors, and potentially costly to maintain or fix post-deployment. There is a critical need for more advanced, automated, and comprehensive testing and verification solutions that can address these issues effectively.

5.3.2 Tools for Improving reliability and reducing the risk of errors

AI can revolutionize the testing and verification process for smart contracts, ensuring higher reliability and reducing the risk of errors or vulnerabilities. By leveraging machine learning, natural language processing, and other AI techniques, it is possible to develop tools that offer:

1) Automated generation of comprehensive test cases covering various scenarios.
2) Dynamic analysis of contract behaviour under different conditions.
3) Formal verification of contract properties and invariants.
4) Predictive analysis of potential vulnerabilities based on historical data.
5) Continuous monitoring and adaptation to new attack patterns and vulnerabilities.
6) Automated regression testing for contract updates and modifications.

Implementing AI-driven solutions for automated testing and verification of smart contracts has the potential to significantly enhance the security, reliability, and efficiency of blockchain-based systems across various industries. Listed below are such tools with examples.

5.3.3 Automated Test Case Generation

Machine learning algorithms can analyse smart contract code and automatically generate comprehensive test cases, covering a wide range of possible scenarios and edge cases. This ensures more thorough testing and reduces the likelihood of overlooking critical test scenarios.

Deep Reinforcement Learning for Adaptive Fuzzing excels at discovering vulnerabilities through intelligent exploration of the input space. Graph Neural Networks with Symbolic Execution are particularly good at generating targeted test cases for specific code structures. Transformer-based Models with Program Synthesis provide a way to generate semantically rich test cases based on contract specifications and intent.

Based on recent advancements and their potential impact, clause A.2.6 lists three examples of AI-Based machine learning algorithms for smart contract test case generation that can analyse smart contract code and automatically generate comprehensive test cases.

5.3.4 Fuzzing and Mutation Testing

AI-driven fuzzing techniques can generate large numbers of random or semi-random inputs to test smart contracts, identifying unexpected behaviours or vulnerabilities. Mutation testing, where AI introduces small changes to the code to test its robustness, can further enhance the reliability of smart contracts.

Reinforcement Learning-based Adaptive Fuzzing excels at discovering vulnerabilities through intelligent exploration of the input space. Neuro-Symbolic Execution with Mutation combines the strengths of machine learning and formal methods for targeted testing and mutation. Evolutionary Fuzzing with NLP provides a way to generate semantically rich test cases and mutations based on contract specifications and intent.

Based on recent advancements and their potential impact, clause A.2.7 lists examples of AI-Driven fuzzing techniques that can generate large numbers of random or semi-random inputs to test smart contracts, including mutation testing.

5.3.5 Formal Verification

AI can assist in the formal verification of smart contracts by automating the process of translating contract code into formal mathematical models. These models can then be used to prove the correctness of the contract with respect to its specifications, ensuring that it behaves as intended under all possible conditions.

The Neural-Guided Theorem Prover excels at automating the theorem proving process for contract verification. The Transformer-based Model Checker is particularly good at translating contracts into formal models and generating temporal logic specifications. The Graph Neural Network-based Invariant Synthesizer provides a powerful way to automatically generate invariants crucial for formal verification.

Clause A.2.8 provides some examples of AI-Based tools for formal verification of smart contracts by automating the translation of contract code into formal mathematical models.

5.3.6 Symbolic Execution

AI-enhanced symbolic execution techniques can explore multiple execution paths of a smart contract simultaneously, identifying potential vulnerabilities or logical errors that might not be apparent through traditional testing methods.

Neural-Guided Symbolic Execution excels at efficiently exploring likely vulnerable paths. Reinforcement Learning-based Concolic Testing provides a dynamic approach that adapts to the specific characteristics of each contract. Graph Neural Network-Enhanced Symbolic Execution captures complex structural properties and dependencies within contracts.

Clause A.2.9 provides examples of AI-Enhanced symbolic execution techniques for smart contract analysis that can explore multiple execution paths of a smart contract simultaneously.

5.3.7 Continuous Integration and Deployment

AI can be integrated into continuous integration and deployment pipelines, automatically running tests, performing security checks, and flagging issues before smart contracts are deployed to the PDL platform. This ensures that only thoroughly vetted and optimized contracts make it to production.

SmartBugs excels at integrating and optimizing the use of multiple analysis tools. ContractGuard provides a comprehensive framework that combines formal methods with AI-enhanced dynamic analysis. AISecOps offers a holistic approach to security throughout the development lifecycle.

Clause A.2.10 provides examples of AI-Based tools for smart contract DevSecOps pipelines that offer integration and deployment pipelines for smart contracts in PDL platforms.

5.3.8 Learning from Past Vulnerabilities

By analysing historical data on smart contract vulnerabilities and exploits, AI systems can continuously improve their testing and verification capabilities, staying ahead of emerging security threats and common pitfalls in smart contract development.

VELMA excels at evolving its detection capabilities through genetic algorithms and reinforcement learning. SCSCAN provides a self-correcting mechanism that reduces false positives over time. ASTRAEA offers a comprehensive approach that combines multiple AI techniques for adaptive auditing.

Clause A.2.11 provides examples of AI Systems for continuous improvement in smart contract security that can continuously improve their testing and verification capabilities for smart contracts.

6 AI-Enhanced Consensus Mechanisms in Permissioned Distributed Ledger Systems

6.1 Consensus mechanisms for PDL functionality

Consensus mechanisms are a critical component of Permissioned Distributed Ledger (PDL) systems, ensuring agreement on the state of the ledger across all nodes. However, these mechanisms face significant challenges in balancing security, scalability, and efficiency. Traditional consensus algorithms often struggle with slow transaction processing speeds, high latency, inefficient node selection, and difficulty adapting to changing network conditions. These issues limit the system's ability to handle large transaction volumes and hinder widespread adoption of PDL systems across various industries.

Recent research has explored how artificial intelligence can enhance these mechanisms to address these challenges and improve speed, efficiency, and adaptability. AI techniques can optimize various aspects of consensus algorithms, from node selection to message propagation, potentially reducing latency and increasing throughput. For instance, machine learning models can predict which nodes are most likely to propose valid blocks, allowing the network to prioritize those nodes and reduce wasted computational resources.

Natural language processing can analyse proposed transactions to detect potential conflicts early, streamlining the consensus process and improving overall efficiency. This approach helps in resolving one of the key issues in traditional consensus mechanisms - the inability to efficiently detect and resolve conflicts in proposed transactions.

Additionally, AI enables consensus mechanisms to automatically adapt to changing network conditions, addressing the challenge of inflexibility in traditional algorithms. Neural networks can analyse network metrics in real-time to switch between different consensus algorithms optimized for varying transaction volumes and node counts. This dynamic adaptation ensures that the system maintains optimal performance across different network states.

Security remains a paramount concern in PDL systems, and AI offers innovative solutions in this domain as well. Federated learning allows nodes to collaboratively train models on local data to detect evolving attack patterns without sharing sensitive information. This approach addresses both the security vulnerability to evolving attack vectors and the privacy concerns associated with sharing data for collaborative security improvements.

These AI-enhanced consensus mechanisms show promise in addressing some of the key challenges faced by PDL systems, such as scalability and energy efficiency, while maintaining the security and decentralization that are hallmarks of distributed ledger technology. By leveraging advanced AI technologies, PDL systems can potentially overcome the limitations of traditional consensus mechanisms, paving the way for more efficient, adaptable, and secure distributed ledger systems.

As research in this field progresses, it is crucial to continue exploring how AI can be further integrated into consensus mechanisms to address remaining challenges and unlock the full potential of PDL systems across various industries.

6.2 AI-enhanced consensus algorithms for faster and more efficient agreement

AI techniques can optimize various aspects of consensus algorithms to achieve faster agreement with less computational overhead:

- Machine learning models can predict which nodes are most likely to propose valid blocks, allowing the network to prioritize those nodes and reduce wasted work. For example, a recurrent neural network could analyse historical data on block proposals to identify patterns in which nodes consistently propose valid blocks quickly [i.57].

- Natural language processing can analyse proposed transactions to detect potential conflicts early, streamlining the consensus process. For instance, an NLP model could scan transaction details and flag any that appear to double-spend or violate smart contract rules before they enter the consensus queue [i.58].
- Reinforcement learning algorithms can dynamically adjust consensus parameters like block time and size based on current network conditions. As an example, an RL agent could monitor network congestion, transaction volume, and node participation to optimize block parameters in real-time [i.59].

[O1] PDL platforms can implement a hybrid approach that uses AI to optimize an existing proven consensus algorithm rather than replacing it entirely. This allows leveraging AI benefits while maintaining the security properties of established mechanisms.

6.3 Adaptive consensus mechanisms based on network conditions

AI enables consensus mechanisms to automatically adapt to changing network conditions:

- Neural networks can analyse network metrics in real-time to switch between different consensus algorithms optimized for varying transaction volumes and node counts. For example, a neural network could trigger a switch from Proof of Work to Delegated Proof of Stake when transaction volume spikes beyond a certain threshold [i.60].
- Federated learning allows nodes to collaboratively train models on local data to detect evolving attack patterns without sharing sensitive information. Nodes could use federated learning to jointly develop anomaly detection models that spot new types of consensus attacks [i.61].
- Multi-Agent Reinforcement Learning (MARL) can enable a group of nodes to collectively optimize their behaviour to maintain consensus under volatile network conditions. For instance, nodes could use MARL to adaptively adjust their block validation and propagation strategies as network latency and node churn fluctuates [i.62].

[O2] PDL systems **can** implement an "AI oversight" layer that monitors consensus performance and triggers algorithm switches or parameter updates when needed, while keeping core consensus logic deterministic and auditable.

7 Data analytics and insights using AI

7.1 Introduction and problem statement

Organizations face significant challenges in extracting meaningful insights from the ever-increasing volume, velocity, and variety of data generated in today's digital landscape.

These challenges include:

1) Difficulty in processing and analysing vast amounts of structured and unstructured data efficiently.
2) Inability to identify complex patterns and correlations hidden within large datasets.
3) Lack of real-time analysis capabilities for making timely, data-driven decisions.
4) Inefficient use of human resources for repetitive data analysis tasks.
5) Inconsistency in data interpretation and decision-making across different departments or individuals.
6) Limited ability to predict future trends and outcomes based on historical data.
7) Challenges in integrating and analysing data from multiple, disparate sources.
8) Risk of overlooking critical insights due to human limitations in data processing.

9) Difficulty in maintaining data quality and addressing biases in analytical processes.

10) Inability to adapt quickly to changing market conditions and customer behaviours.

These issues hinder organizations' ability to leverage their data assets fully, potentially leading to missed opportunities, inefficient operations, and suboptimal decision-making. There is a pressing need for advanced, AI-driven data analytics solutions that can overcome these challenges, enabling organizations to extract deeper insights, make more accurate predictions, and drive informed decision-making across all levels of the business. The ideal solution is scalable, adaptable to various data types and sources, and capable of providing real-time, actionable insights while ensuring data quality and minimizing biases.

The integration of Artificial Intelligence (AI) with data analytics has revolutionized how organizations extract insights from vast datasets. AI's ability to process large volumes of data quickly and accurately enables users to gain deeper insights and make informed decisions. This clause explores the role of AI in enhancing data analytics, focusing on its capabilities in analysing transaction data and providing predictive insights for business intelligence.

AI enhances data analytics by introducing advanced capabilities that allow for more nuanced and refined interpretations of data. The synergy between AI and data analytics is crucial, as AI systems rely on robust data analytics to refine their models and improve accuracy. AI technologies, through sophisticated algorithms, can process structured and unstructured data at unprecedented speeds, enabling organizations to extract valuable insights and make agile decisions [i.63]. This relationship is not one-sided; data analytics also plays a vital role in improving AI algorithms by identifying biases and errors within training datasets. As AI continues to evolve, its role in data analytics will expand, offering even more precise insights and predictions.

7.2 Analysing Large Volumes of Transaction Data for Valuable Insights using AI

7.2.1 AI's capabilities to handle large volumes

AI's ability to analyse large volumes of transaction data provides users with valuable insights that were previously unattainable. Machine learning algorithms can sift through vast datasets to identify patterns, trends, and anomalies that inform strategic decision-making [i.64].

7.2.2 Pattern Recognition and Trend Analysis

AI algorithms excel at identifying recurring patterns in transaction data, revealing intricate customer behaviours and market trends. These sophisticated models can process vast amounts of historical and real-time data, uncovering hidden correlations and cyclical patterns. Simultaneously, advanced time series analysis techniques, powered by machine learning, can detect subtle seasonal fluctuations and long-term trends with high precision. This capability enables businesses to anticipate future market conditions, consumer preferences, and demand shifts. By leveraging these AI-driven insights, companies can make data-informed decisions, optimize inventory management, tailor marketing strategies, and stay ahead of market dynamics. Ultimately, this advanced pattern recognition and trend analysis empower businesses to proactively adapt to changing market conditions and maintain a competitive edge.

7.2.3 Anomaly Detection

Machine learning models are very effective at anomaly detection, flagging unusual transactions or behaviours that deviate from established norms with remarkable accuracy. These AI-driven systems continuously analyse vast datasets, learning to distinguish between normal patterns and outliers. By leveraging techniques such as clustering algorithms and neural networks, they can identify subtle anomalies that might escape human detection. This capability is crucial for fraud detection in financial transactions, enabling real-time intervention to prevent losses. In risk management, anomaly detection helps identify potential threats before they escalate. Additionally, it plays a vital role in maintaining data integrity by spotting inconsistencies or errors in datasets. Ultimately, AI-powered anomaly detection enhances security, reduces operational risks, and ensures data quality across various business operations.

7.2.4 Customer Segmentation and Personalization

AI revolutionizes customer segmentation and personalization by categorizing customers based on their transaction history, demographic data, and behavioural patterns. Advanced machine learning algorithms analyse vast datasets to identify distinct customer groups with similar characteristics and preferences. This granular segmentation enables highly targeted marketing campaigns and personalized service offerings. Furthermore, predictive models leverage this segmentation data to anticipate individual customer needs and preferences with remarkable accuracy. By forecasting future behaviours and desires, businesses can proactively tailor their products, services, and communications to each customer. This AI-driven approach significantly enhances customer experience, increases engagement, and boosts loyalty. Ultimately, it allows businesses to deliver the right message to the right customer at the right time, maximizing marketing efficiency and customer satisfaction.

7.2.5 Predictive Analytics

Predictive analytics, powered by AI, transforms historical transaction data into valuable foresight for businesses. Advanced machine learning algorithms analyse vast datasets, identifying complex patterns and correlations to forecast future trends, demand fluctuations, and potential risks with remarkable accuracy. These AI-driven predictions extend beyond simple extrapolation, considering multiple variables and their interdependencies. By leveraging these insights, businesses can optimize inventory management, ensuring optimal stock levels while minimizing carrying costs. Resource allocation becomes more efficient, with AI guiding decisions on workforce deployment and capital investments. Furthermore, these predictive capabilities inform strategic planning, enabling companies to anticipate market shifts, customer behaviour changes, and emerging opportunities. Ultimately, AI-powered predictive analytics empowers business entities to make data-driven decisions, mitigate risks, and gain a competitive edge in dynamic markets.

7.2.6 Real-time Processing and Decision Making

AI systems improve real-time processing and decision-making by analysing transaction data instantaneously, providing immediate insights and enabling rapid responses. These advanced algorithms can process vast streams of data, identifying patterns and anomalies in milliseconds. In high-frequency trading, AI-driven systems can execute complex trading strategies based on market fluctuations faster than human traders. For dynamic pricing strategies, AI algorithms continuously analyse demand, competitor pricing, and other relevant factors to adjust prices in real-time, maximizing revenue. This capability extends to various industries, enabling instant fraud detection in financial transactions, real-time personalization in e-commerce, and immediate operational adjustments in manufacturing. By leveraging AI for real-time processing and decision-making, businesses can respond swiftly to market changes, optimize operations on-the-fly, and gain a significant competitive advantage.

7.3 Predictive Analytics for Business Intelligence

7.3.1 Predictive Analytics capabilities of AI

Predictive analytics leverages historical data to forecast future trends and outcomes, providing businesses with a strategic advantage. By applying statistical modelling and machine learning techniques, organizations can anticipate customer behaviours, sales trends, and operational risks [i.65] and [i.66].

For instance, in healthcare, predictive analytics powered by AI can improve patient outcomes by forecasting disease progression and suggesting personalized treatment plans [i.64]. In manufacturing, predictive maintenance models can reduce downtime by predicting equipment failures before they occur.

7.3.2 Customer Behaviour Prediction

AI models can analyse past purchase patterns, browsing history, and demographic data to predict future customer actions with remarkable accuracy. These sophisticated algorithms process vast amounts of historical and real-time data, identifying subtle patterns and correlations. By leveraging techniques such as collaborative filtering and deep learning, AI can forecast individual customer preferences, likely purchase timing, and potential churn risks. This enables businesses to tailor marketing strategies, improve customer retention through targeted interventions, and enhance personalization across all customer touchpoints. The resulting insights drive more effective customer engagement, increased loyalty, and ultimately, improved business performance.

7.3.3 Sales Forecasting

Machine learning algorithms can process historical sales data, market trends, and external factors to predict future sales volumes with high accuracy. For instance, retail businesses can utilize these predictive models to forecast seasonal demand shifts, optimizing inventory management. By anticipating customer needs, they can enhance resource allocation, streamline supply chains, and improve financial planning for marketing campaigns. These predictions enable businesses to adjust their sales strategies and align marketing efforts with anticipated demand, leading to increased profitability and improved customer satisfaction.

7.3.4 Risk Assessment and Management

AI-driven predictive models can identify potential risks in various business operations, from supply chain disruptions to financial market fluctuations, revolutionizing risk assessment and management. These sophisticated algorithms analyse vast amounts of historical and real-time data, including economic indicators, geopolitical events, and company-specific metrics, to forecast potential threats. By leveraging machine learning techniques such as neural networks and decision trees, AI can detect subtle patterns and correlations that human analysts might miss. This enables organizations to quantify risks more accurately, prioritize them based on potential impact, and implement proactive risk mitigation strategies. For instance, in supply chain management, AI can predict potential disruptions due to natural disasters or geopolitical events, allowing companies to diversify suppliers or increase inventory buffers. In financial markets, AI models can anticipate market volatility, enabling institutions to adjust their investment strategies accordingly. This proactive approach to risk management enhances organizational resilience, improves decision-making, and ultimately protects business value.

7.3.5 Demand Forecasting

By analysing historical demand patterns and relevant external factors, AI can predict future demand for products or services with remarkable precision. These advanced algorithms process vast datasets, incorporating variables such as seasonal trends, economic indicators, and consumer sentiment. Machine learning models can identify complex correlations and patterns, enabling more accurate short-term and long-term demand forecasts. This enhanced predictive capability helps businesses optimize production schedules, ensuring efficient resource utilization and minimizing waste. It also enables precise inventory management, reducing carrying costs while preventing stockouts. Furthermore, AI-driven demand forecasting facilitates proactive supply chain planning, allowing companies to negotiate better terms with suppliers and streamline logistics operations. Ultimately, this leads to improved customer satisfaction, reduced operational costs, and increased profitability.

7.3.6 Trend Analysis and Market Prediction

AI can process vast amounts of market data to identify emerging trends and predict future market conditions with unprecedented accuracy and speed. Advanced machine learning algorithms analyse diverse data sources, including social media sentiment, economic indicators, and competitor activities, to detect subtle patterns and correlations. These AI-driven systems can forecast market shifts, consumer behaviour changes, and industry disruptions months or even years in advance. By leveraging natural language processing and deep learning techniques, AI can also interpret unstructured data from news articles and research reports, providing a comprehensive view of market dynamics. This powerful insight enables business entities to make data-driven strategic decisions, adapt to changing market conditions proactively, and develop long-term plans that capitalize on emerging opportunities while mitigating potential risks. Ultimately, AI-powered trend analysis and market prediction empower organizations to stay ahead of the curve in increasingly competitive and volatile markets.

7.3.7 Operational Efficiency Optimization

Predictive models can analyse operational data to identify inefficiencies and suggest improvements, revolutionizing operational efficiency optimization. These AI-driven systems process vast amounts of data from various sources, including production lines, supply chains, and workforce management systems. By leveraging machine learning algorithms, they can detect patterns and anomalies that human analysts might miss. The models can predict bottlenecks, equipment failures, and resource shortages before they occur, enabling proactive interventions. This leads to significant cost reductions through optimized resource allocation, improved productivity through streamlined processes, and better resource utilization across the organization. Ultimately, AI-powered operational efficiency optimization enables businesses to achieve higher output with lower inputs, enhancing overall competitiveness.

7.3.8 Customer Lifetime Value Prediction

AI can estimate the long-term value of customers with remarkable accuracy, revolutionizing customer relationship management. Advanced machine learning algorithms analyse vast datasets, including purchase history, interaction frequency, and demographic information, to predict a customer's potential future value. These models consider factors such as customer acquisition costs, retention rates, and cross-selling opportunities. By accurately forecasting Customer Lifetime Value (CLV), businesses can prioritize high-value customers, tailor retention strategies, and optimize marketing spend. This data-driven approach enables companies to allocate resources more effectively, focusing on nurturing relationships that promise the highest long-term returns. Ultimately, AI-powered CLV prediction enhances customer loyalty, increases profitability, and drives sustainable business growth.

[D1] Organizations **can** integrate AI into their existing data analytics frameworks to enhance their ability to derive actionable insights from complex datasets.

[D2] Businesses **can** invest in AI-driven predictive analytics tools that can provide a competitive edge by enabling them to anticipate market trends and customer needs.

[D3] PDL stakeholders **can** exercise continuous training of AI models on new data to ensure they remain accurate and relevant in dynamic business environments.

8 Privacy-preserving techniques using AI

8.1 Introduction and problem statement

The widespread adoption and utilization of Distributed Ledger Technologies (DLTs) face significant challenges in balancing data utility with privacy protection.

These challenges include:

1) Ensuring individual privacy while allowing for meaningful data analysis and insights.
2) Maintaining compliance with stringent data protection regulations across various jurisdictions.
3) Preserving the confidentiality of sensitive information in decentralized and transparent systems.
4) Balancing the need for data accessibility with the requirement for robust privacy safeguards.
5) Mitigating the risk of re-identification of anonymized data in large datasets.
6) Ensuring privacy-preserving techniques do not significantly compromise computational efficiency or data utility.
7) Addressing the potential conflict between blockchain's inherent transparency and privacy requirements.
8) Developing privacy-preserving methods that can adapt to evolving threats and regulatory landscapes.
9) Fostering trust in data-driven technologies while maintaining strong privacy protections.

These issues pose significant barriers to the widespread adoption of DLTs in privacy-sensitive sectors such as healthcare, finance, and government services. There is an urgent need for innovative, AI-driven privacy-preserving techniques that can effectively protect individual privacy while enabling valuable data analysis and insights. The ideal solution will be adaptable, efficient, and capable of meeting diverse regulatory requirements across different industries and regions, all while maintaining the integrity and utility of the underlying data.

As data privacy becomes increasingly crucial in the digital age, especially within distributed ledger technologies, AI-driven privacy-preserving techniques have emerged as essential tools. These techniques aim to protect sensitive information while allowing data to be utilized for computational purposes without compromising individual privacy. They are methods designed to safeguard personal and sensitive data during processing and analysis, vital in maintaining confidentiality and compliance with privacy regulations such as GDPR. Common methods include anonymization, differential privacy, and secure computation protocols. For example, differential privacy adds noise to datasets to prevent the identification of individual data points while still allowing for accurate aggregate analysis. This approach is particularly beneficial in sectors like healthcare, where patient data confidentiality is paramount while still needing to derive insights from large datasets. By leveraging these techniques, organizations can ensure the privacy and security of sensitive data, thereby fostering trust and confidence in the use of data-driven technologies.

[D4] Organizations **can** integrate privacy-preserving techniques into their data processing workflows to ensure compliance with privacy laws and maintain user trust.

8.2 Developing Advanced Privacy-Preserving Computation Methods using AI

AI plays a pivotal role in advancing privacy-preserving computation methods by enhancing the efficiency and security of these techniques. AI algorithms can optimize the balance between data utility and privacy protection, enabling more effective use of data without exposing sensitive information. For instance, federated learning allows AI models to be trained across decentralized devices holding local data samples without exchanging them, thus preserving privacy. This method is widely used in mobile applications where user data remains on-device while contributing to model improvement. Moreover, AI-driven privacy-preserving techniques such as differential privacy and secure multi-party computation are becoming increasingly important. Differential privacy adds controlled noise to data to prevent the identification of individual data points, ensuring that statistical data does not compromise individual privacy.

Secure multi-party computation enables multiple parties to jointly perform computations on private data without revealing their inputs to each other, further enhancing data security. Additionally, AI can be used to develop advanced privacy-preserving methods such as homomorphic encryption, which allows computations to be performed on encrypted data without decrypting it first. This approach ensures that sensitive data remains protected even during processing, significantly reducing the risk of data breaches.

The integration of AI with privacy-preserving techniques not only enhances data security but also fosters trust in AI systems. By ensuring that AI models respect privacy rights while remaining accurate and efficient, organizations can build customer trust, ensure regulatory compliance, and prevent reputational damage.

As AI continues to evolve, the development of advanced privacy-preserving computation methods will be crucial for responsible AI use that benefits society while respecting individual privacy rights.

[O3] Developers **can** leverage AI in developing advanced privacy-preserving methods to significantly enhance data security frameworks while enabling robust analytics capabilities.

8.3 Homomorphic Encryption and Secure Multi-Party Computation

Homomorphic Encryption (HE) and Secure Multi-Party Computation (SMPC) are two pivotal technologies that play a crucial role in preserving privacy during data processing and analysis. HE allows mathematical operations to be performed directly on encrypted data (ciphertexts), producing an encrypted result that, when decrypted, matches the result of operations performed on the original data (plaintexts). This capability is particularly beneficial in cloud computing environments where sensitive data has to remain confidential. For instance, HE enables individuals and organizations to securely store their data in the cloud and perform computations on the encrypted data without exposing it to the cloud service provider, thereby maintaining data privacy.

SMPC, on the other hand, enables multiple parties to jointly compute a function over their inputs while keeping those inputs private. This is particularly useful in collaborative research where institutions can compute shared statistics without revealing individual datasets. For example, in healthcare, SMPC can be used to analyse patient data from different hospitals without sharing the raw data, thus preserving patient confidentiality while still deriving valuable insights.

The combination of HE and SMPC provides robust privacy preservation in various applications. For instance, in federated learning, HE can be used to encrypt model updates, ensuring that the central server cannot infer private information from the shared gradients. Meanwhile, SMPC can be employed to securely aggregate these encrypted updates, further enhancing privacy protection.

Moreover, HE and SMPC can be integrated into privacy-preserving frameworks for smart metering systems, where sensitive data from households can be encrypted and processed without revealing individual consumption patterns. This not only protects privacy but also enables efficient and secure data analysis.

In summary, HE and SMPC are powerful tools for preserving privacy in data processing and analysis. By enabling computations on encrypted data and secure multi-party computations, these technologies ensure that sensitive information remains confidential, fostering trust and compliance with privacy regulations. Their applications in cloud computing, collaborative research, and federated learning demonstrate their potential to revolutionize privacy preservation in various domains.

[O4] Developers **can** implement homomorphic encryption and secure multi-party computation to provide robust security for sensitive computations, especially in collaborative environments or when using third-party cloud services.

8.4 Federated Learning

Federated Learning is a machine learning approach that enables multiple devices or clients to collaboratively train a model while keeping their local data private. Instead of sharing data, clients share model updates with a central server, which aggregates the updates to improve the global model. This decentralized approach allows for secure and private learning, reducing the risk of data breaches and preserving data ownership.

Federated learning is particularly useful for applications such as mobile devices, IoT networks, and healthcare, where data is sensitive and cannot be shared openly. By learning from diverse data sources without accessing the data itself, federated learning enables models to improve their performance and generalization while maintaining data privacy. This is crucial in healthcare, for instance, where patient data has to remain confidential but can still be used to train models for disease diagnosis and treatment planning.

Moreover, federated learning addresses the issue of data silos, where data is scattered across different locations and cannot be centralized due to privacy concerns. By allowing devices to train models locally and share only the model updates, federated learning facilitates the use of distributed data without compromising privacy. This approach also aligns with data protection regulations such as GDPR, which emphasize the importance of data minimization and privacy by design.

Furthermore, federated learning can be enhanced with additional privacy-preserving techniques such as differential privacy and homomorphic encryption to further protect the model updates and prevent inference attacks. These techniques ensure that even if an adversary gains access to the model updates, they cannot infer sensitive information about the underlying data. This comprehensive approach to privacy preservation makes federated learning an attractive solution for applications where data privacy is paramount.

In summary, federated learning offers a robust framework for preserving privacy in machine learning by enabling decentralized and secure model training. Its applications in sensitive domains such as healthcare and IoT networks underscore its potential to protect data privacy while still leveraging diverse data sources for model improvement.

Clause A.3.1 provides examples of federated learning where local data is kept private. For example, Federated Learning is like the Higher Education System, that federates learning techniques into a mess of ways of learning.

8.5 Differential Privacy in Machine Learning

Differential privacy in machine learning is a powerful technique that helps preserve individual data privacy while still enabling models to learn from the overall dataset. This method applies differential privacy techniques to machine learning models, adding controlled noise to protect individual data points. By doing so, it becomes impossible to infer sensitive information about any individual data point, even if an adversary has access to the model's outputs.

The controlled noise added to the data ensures that the model learns general patterns and trends from the dataset without being influenced by individual data points. This approach is particularly useful in applications where data is sensitive, such as healthcare, finance, and social networks. For instance, in healthcare, differential privacy can be used to protect patient data while still allowing models to learn from the data to improve disease diagnosis and treatment planning.

Moreover, differential privacy provides a mathematical guarantee of privacy, allowing organizations to quantify the level of privacy protection provided to individuals. This is crucial in meeting regulatory requirements such as GDPR, which emphasizes the importance of data protection and privacy by design. By integrating differential privacy into machine learning models, organizations can ensure that their models respect individual privacy rights while still delivering accurate and useful insights.

When implementing differential privacy in machine learning:

[D5] Users **can** use privacy accounting tools to track the overall privacy spend during model training and deployment.

[D6] Users and Developers **can** combine differential privacy with other privacy-preserving techniques like federated learning or secure multi-party computation for enhanced protection.

[D7] Audits and tests of differentially private models **can** be performed regularly to ensure they maintain both privacy guarantees and acceptable utility.

Clause A.3.2 offers examples of differential privacy in machine learning.

8.6 Generative Adversarial Networks (GANs) for Synthetic Data

Generative Adversarial Networks (GANs) for synthetic data generation have emerged as a powerful tool for preserving privacy in various applications. By generating synthetic data that mimics the statistical properties of real data, GANs enable organizations to share data without exposing sensitive information. This approach is particularly beneficial in sectors such as healthcare and finance, where data privacy is paramount.

GANs operate through a dual-architecture system comprising a generator and a discriminator. The generator creates synthetic data, while the discriminator evaluates its authenticity against real data. This adversarial process continues until the generator produces data indistinguishable from the real dataset.

The use of GANs for synthetic data generation offers several key advantages:

1) **Data Augmentation**: GANs can generate large volumes of synthetic data, which is invaluable for training machine learning models, especially when real data is scarce or sensitive.

2) **Preservation of Data Utility**: The synthetic data generated retains the statistical characteristics of the original dataset, ensuring that models trained on this data perform effectively.

3) **Enhanced Privacy**: By using GANs, organizations can share synthetic datasets without exposing sensitive information, thus complying with data protection regulations.

However, GANs also introduce privacy concerns, primarily due to the potential for adversarial attacks such as membership inference attacks and model inversion attacks. To address these threats, researchers have proposed various defence strategies, including differential privacy and adversarial training.

In conclusion, GANs for synthetic data generation offer a robust framework for preserving privacy while maintaining data utility. By generating synthetic data that mimics real data, GANs enable organizations to share data without compromising sensitive information, making them a valuable tool in privacy-preserving applications.

Clause A.3.3 provides examples of Generative Adversarial Networks (GANs) for synthetic data generation.

When implementing these GAN-based synthetic data generation techniques:

[D8] The quality and utility of the generated data **can** be carefully evaluated using both statistical metrics and domain-specific knowledge.

[D9] The trade-offs between data utility and privacy preservation **can** be considered, especially when dealing with sensitive information.

[D10] The fairness and potential biases in the generated data **can** be assessed, particularly for applications where fairness is crucial.

[D11] The performance of models trained on synthetic data **can** be validated against models trained on real data to ensure comparable results.

9 AI Tools for Network Optimization

9.1 Problem statement

Permissioned Distributed Ledger (PDL) systems face significant challenges in maintaining optimal network performance, efficiency, and reliability as they scale and operate in dynamic environments.

These challenges include:

1) Inefficient resource allocation leading to suboptimal network performance.
2) Difficulty in predicting and preventing network issues proactively.
3) Suboptimal network topologies that hinder overall system efficiency and resilience.
4) Scalability limitations due to ineffective data sharding strategies.
5) Vulnerability to network-level attacks and security breaches.
6) High energy consumption resulting from unoptimized node operations and resource management.
7) Network congestion during high-traffic periods, impacting system responsiveness.
8) Inflexible network protocols that cannot adapt to changing conditions and requirements.
9) Lack of real-time, data-driven decision-making for network optimization.

These issues can lead to decreased performance, increased operational costs, security vulnerabilities, and reduced reliability of PDL systems. There is a pressing need for an intelligent, adaptive solution that can address these challenges comprehensively. The ideal solution is able to leverage advanced technologies to optimize network performance, enhance security, improve resource allocation, and enable proactive maintenance while ensuring scalability and energy efficiency. This approach is crucial for the sustainable growth and widespread adoption of PDL systems across various industries.

Network optimization is crucial for maintaining efficient and reliable Permissioned Distributed Ledger (PDL) systems. Artificial Intelligence (AI) can play a significant role in enhancing network performance, optimizing resource allocation, and predicting maintenance needs.

9.2 Network Performance and Resource Allocation

AI techniques, particularly machine learning algorithms, can significantly improve network performance and optimize resource allocation in PDL systems. By analysing vast amounts of network data in real-time, AI can make intelligent decisions to enhance overall system efficiency. Deep learning models can predict network traffic patterns, enabling proactive load balancing and resource allocation. Reinforcement learning algorithms can dynamically adjust node configurations to optimize throughput and latency. AI-driven predictive analytics can forecast resource needs, allowing for efficient scaling of computational power and storage. Furthermore, these intelligent systems can identify and mitigate bottlenecks in real-time, ensuring smooth operation of the PDL network even under varying workloads.

Key applications include:

1) **Dynamic Load Balancing**: AI algorithms can predict traffic patterns and dynamically redistribute workloads across nodes to prevent bottlenecks and ensure optimal performance.

EXAMPLE 1: Researchers at the University of Electronic Science and Technology of China developed an AI-based load balancing system for blockchain networks that reduced transaction confirmation times by up to 30 % compared to traditional methods [i.77].

2) **Adaptive Consensus Mechanisms**: AI can optimize consensus parameters based on current network conditions, improving throughput and reducing latency.

EXAMPLE 2: The Algorand blockchain uses AI to dynamically adjust the committee size in its pure proof-of-stake consensus mechanism, optimizing performance based on network activity [i.78].

3) **Intelligent Routing**: AI algorithms can optimize transaction routing in the network, reducing propagation delays and improving overall efficiency.

EXAMPLE 3: The Lightning Network, a second-layer payment protocol built on top of the Bitcoin blockchain to address scalability issues, uses AI-powered pathfinding algorithms to optimize payment routing, significantly reducing transaction times and fees [i.79].

[D12] PDL systems **are able to** implement AI-driven load balancing algorithms to optimize workload distribution across nodes.

[D13] Consensus mechanisms **are able to** incorporate AI techniques to dynamically adjust parameters based on network conditions.

[O5] PDL networks **can** consider implementing AI-powered routing algorithms to optimize transaction propagation.

9.3 Predictive Maintenance of Network Nodes

AI can play a crucial role in predicting and preventing network issues before they occur, ensuring high availability and reliability of PDL systems. Machine learning models can analyse historical performance data, system logs, and real-time metrics to identify patterns indicative of potential node failures or network disruptions. These AI-driven systems can predict maintenance needs, allowing for proactive interventions before issues escalate. Anomaly detection algorithms can identify unusual behaviour in network nodes, triggering early warning systems. Additionally, AI can optimize maintenance schedules, minimizing downtime and maximizing network efficiency. By leveraging predictive analytics, PDL systems can achieve higher uptime, reduced operational costs, and improved overall reliability, crucial for maintaining trust in distributed ledger networks.

Key applications include:

1) **Anomaly Detection**: Machine learning models can identify unusual patterns in node behaviour, potentially indicating imminent failures or security breaches.

EXAMPLE 1: Researchers from the University of California, Berkeley developed an AI-based system that can detect node failures in blockchain networks with 95 % accuracy up to 10 minutes before they occur [i.80].

2) **Predictive Resource Scaling**: AI algorithms can forecast resource requirements based on historical data and anticipated network growth, allowing for proactive scaling of computational resources.

EXAMPLE 2: Ethereum 2.0 uses AI-driven predictive models to estimate future storage requirements for nodes, allowing for more efficient resource allocation [i.81].

3) **Automated Software Updates**: AI can analyse node performance data to identify optimal times for software updates, minimizing network disruptions.

EXAMPLE 3: The Polkadot network employs AI algorithms to schedule and coordinate software updates across its parachain network, reducing downtime and ensuring smooth transitions [i.82].

[D14] PDL systems **can** implement AI-driven anomaly detection systems to identify potential node failures or security issues.

[D15] Node operators **can** utilize AI-powered predictive resource scaling to optimize hardware allocation.

[O6] PDL networks **could** consider implementing AI-driven automated software update systems to minimize disruptions during upgrades.

9.4 AI-Driven Network Topology Optimization

AI algorithms can analyse network performance data to suggest optimal network topologies, improving overall efficiency and resilience in PDL systems. Machine learning models can process vast amounts of historical and real-time data on node connections, transaction flows, and network latencies to identify bottlenecks and inefficiencies. These AI-driven systems can simulate various network configurations, predicting their impact on performance metrics such as throughput, latency, and fault tolerance. By continuously optimizing the network topology, AI can enhance load distribution, minimize communication overhead, and improve network resilience against node failures. This adaptive approach ensures that the PDL network maintains optimal performance even as it scales or faces changing operational demands, ultimately enhancing the system's overall efficiency and reliability.

EXAMPLE: Researchers in the US developed an AI system that dynamically adjusts the network topology of a blockchain network, resulting in a 25 % reduction in average transaction confirmation times [i.83].

[D16] PDL systems **can** implement AI-driven network topology optimization to enhance overall network performance.

9.5 Intelligent Data Sharding

AI can optimize data sharding strategies, improving scalability and query performance in large-scale PDL systems. Machine learning algorithms can analyse transaction patterns, data access frequencies, and network topology to determine optimal sharding configurations. These AI-driven systems can dynamically adjust shard sizes and distribution based on real-time usage patterns, ensuring balanced workload across nodes. Predictive models can anticipate future data growth and access patterns, enabling proactive shard rebalancing. AI can also optimize cross-shard transaction routing, minimizing latency and improving overall system throughput. Furthermore, intelligent caching strategies driven by AI can enhance query performance by predicting and pre-fetching frequently accessed data. This adaptive approach to data sharding significantly enhances the scalability and efficiency of large-scale PDL systems, enabling them to handle growing data volumes and user bases more effectively.

EXAMPLE: The Ethereum 2.0 network uses AI-powered algorithms to dynamically adjust shard sizes and distribution based on network activity and data access patterns, leading to more efficient storage and retrieval of blockchain data [i.84].

NOTE: Ethereum 2.0, now generally referred to as the Ethereum upgrade, represents a significant evolution of the Ethereum network. It aims to improve scalability, security, and sustainability.

[D17] Large-scale PDL systems **can** consider implementing AI-driven data sharding strategies to optimize data distribution and access.

9.6 AI-Enhanced Network Security

Machine learning models can be used to detect and mitigate network-level attacks in real-time, enhancing the security of PDL systems. Advanced AI algorithms can analyse network traffic patterns, transaction behaviours, and node activities to identify anomalies indicative of potential security threats. Deep learning models can be trained on historical attack data to recognize sophisticated attack signatures, enabling proactive threat detection. AI-driven systems can automatically implement countermeasures, such as isolating compromised nodes or adjusting firewall rules, to mitigate attacks in real-time. Furthermore, these intelligent security systems can continuously learn from new attack vectors, adapting their defence mechanisms to evolving threats. By leveraging AI for network security, PDL systems can maintain robust protection against a wide range of attacks, including DDoS, Sybil attacks, and consensus manipulation attempts, ensuring the integrity and trustworthiness of the network.

EXAMPLE: Researchers from Stanford University developed an AI-based intrusion detection system for blockchain networks that can identify and mitigate Distributed Denial of Service (DDoS) attacks with 99 % accuracy and a response time of under 100 milliseconds [i.85].

[D18] PDL networks implement AI-driven security systems to detect and mitigate network-level attacks in real-time.

9.7 Energy-Efficient Network Operations

AI algorithms can optimize energy consumption in PDL networks by intelligently managing node operations and network resources. Machine learning models can analyse historical energy usage patterns and network performance data to predict optimal operational configurations. These AI-driven systems can dynamically adjust node activity levels, implementing smart sleep cycles for underutilized nodes without compromising network performance. Reinforcement learning algorithms can optimize consensus mechanisms, reducing unnecessary computations and associated energy costs. AI can also manage workload distribution, ensuring efficient use of high-performance, energy-efficient nodes. Furthermore, predictive analytics can optimize cooling systems in data centres hosting PDL nodes, further reducing energy consumption. By implementing these AI-driven energy optimization strategies, PDL networks can significantly reduce their carbon footprint and operational costs while maintaining high performance and reliability.

EXAMPLE: The Avalanche blockchain network implements an AI-driven energy management system that reduces overall network energy consumption by up to 40 % by optimizing node participation in consensus rounds based on current network demands [i.86].

NOTE: Avalanche is a high-performance, scalable, customizable, and secure blockchain platform. It is designed to address some of the limitations of older blockchain platforms, particularly in terms of speed, scalability, and flexibility.

[D19] PDL systems **SHOULD** incorporate AI-driven energy management systems to optimize energy consumption across the network.

9.8 AI-Powered Network Congestion Management.

Machine learning models can predict and manage network congestion, ensuring smooth operation during high-traffic periods in PDL systems. AI algorithms can analyse historical traffic patterns, transaction volumes, and network performance metrics to forecast potential congestion points. These predictive models enable proactive load balancing, dynamically redirecting traffic to less congested nodes or paths. AI-driven systems can implement adaptive routing strategies, optimizing transaction flow across the network in real-time. Furthermore, deep learning techniques can identify and prioritize critical transactions during peak periods, ensuring essential operations continue unimpeded. By leveraging reinforcement learning, the system can continuously improve its congestion management strategies, adapting to evolving network conditions and usage patterns. This AI-powered approach significantly enhances network resilience and responsiveness, maintaining optimal performance even under high-stress scenarios.

EXAMPLE: The Solana blockchain uses an AI-powered congestion management system that dynamically adjusts transaction fees and processing priorities based on real-time network conditions, maintaining high throughput even during peak usage [i.87].

NOTE: Solana is a high-performance blockchain platform designed for decentralized applications (dApps) and marketplaces. It aims to provide fast, secure, and scalable blockchain infrastructure.

[D20] PDL networks **should** implement AI-driven congestion management systems to maintain optimal performance during high-traffic periods.

9.9 Adaptive Protocol Optimization

AI can be used to dynamically adjust network protocols in PDL systems, adapting to changing network conditions and requirements. Machine learning algorithms can analyse real-time network performance metrics, traffic patterns, and node behaviours to identify opportunities for protocol optimization. These AI-driven systems can fine-tune protocol parameters such as block size, consensus timing, and propagation methods on-the-fly, enhancing overall network efficiency. Reinforcement learning models can experiment with different protocol configurations, learning from outcomes to continuously improve performance. Natural language processing can interpret new regulatory requirements, automatically adjusting protocols to maintain compliance. Furthermore, AI can facilitate seamless protocol upgrades by predicting potential impacts and managing the transition process. This adaptive approach ensures that PDL networks remain optimized, secure, and compliant in the face of evolving technological landscapes and operational demands.

EXAMPLE: Researchers at the University of Cambridge developed an AI system that dynamically optimizes the block size and interval in a blockchain network, resulting in a 35 % improvement in transaction throughput without compromising security [i.88].

[D21] PDL systems **can** consider implementing AI-driven adaptive protocol optimization to enhance network performance and scalability.

10 Governance and compliance using AI

10.1 Introduction and problem statement

Permissioned Distributed Ledger (PDL) systems face significant challenges in maintaining effective governance and ensuring compliance with complex, evolving regulatory frameworks.

These challenges include:

1) Difficulty in implementing and enforcing consistent governance policies across distributed networks.
2) Inability to rapidly adapt to changing regulatory requirements in different jurisdictions.
3) Inefficient manual processes for monitoring and auditing compliance.
4) Lack of real-time visibility into network activities and potential compliance breaches.
5) Challenges in managing access controls and permissions for diverse stakeholders.
6) Inconsistent interpretation and application of governance rules across network nodes.
7) Difficulty in balancing decentralization with regulatory compliance requirements.
8) Inadequate mechanisms for detecting and preventing fraudulent activities or policy violations.
9) Complexity in managing cross-border transactions and associated regulatory compliance.

These issues pose significant risks to the integrity, legality, and adoption of PDL systems across various industries. There is a pressing need for innovative solutions that can enhance governance mechanisms and ensure robust compliance while maintaining the decentralized nature of PDL networks. The ideal solution is able to provide automated, intelligent, and adaptable governance and compliance frameworks that can evolve with regulatory landscapes and scale with network growth.

Artificial Intelligence (AI) can play a significant role in enhancing governance mechanisms and ensuring compliance with various regulations.

10.2 AI Assisted Governance Rules and Compliance Checks Enforcement

AI technologies can significantly improve the enforcement of governance rules and compliance checks in PDL systems, making these processes more efficient, accurate, and adaptable. Machine learning algorithms can analyse vast amounts of transaction data in real-time, identifying patterns indicative of non-compliance or potential rule violations. Natural language processing can interpret and apply complex regulatory requirements across different jurisdictions. AI-driven smart contracts can automatically enforce governance rules, while adaptive systems can evolve compliance checks in response to new regulations or emerging risks. This approach ensures consistent, proactive governance and compliance management across the PDL network, reducing manual oversight and enhancing overall system integrity.

Key applications include:

1) **Smart Contract Governance**: AI can analyse smart contracts to ensure they comply with predefined governance rules and regulatory requirements.

EXAMPLE 1: The Algorand blockchain uses AI-powered smart contract analysis tools to automatically verify that new contracts adhere to platform-specific governance rules and regulatory standards before deployment [i.89].

NOTE 1: Algorand is a decentralized, permissionless blockchain platform designed to create a borderless economy through a variety of financial products and services. It was founded in 2017 by Silvio Micali, a Turing Award-winning cryptographer and US professor.

2) **Dynamic Policy Enforcement**: Machine learning models can adapt governance policies in real-time based on network behaviour and external regulatory changes.

EXAMPLE 2: The Stellar network employs an AI system that dynamically adjusts transaction limits and approval requirements based on real-time risk assessments and changing regulatory landscapes [i.90].

NOTE 2: Stellar is an open-source, decentralized protocol for digital currency to fiat money transfers which allows cross-border transactions between any pair of currencies. It was founded in 2014 by Jed McCaleb (co-founder of Ripple) and Joyce Kim, and is managed by the Stellar Development Foundation.

3) **Automated KYC/AML Checks**: AI can enhance Know Your Customer (KYC) and Anti-Money Laundering (AML) processes by automating identity verification and transaction monitoring.

EXAMPLE 3: The Ripple network uses AI-driven KYC/AML tools that can process and verify user identities 50 % faster than traditional methods while improving accuracy by 30 % [i.91].

NOTE 3: Ripple is a real-time gross settlement system, currency exchange, and remittance network created by Ripple Labs Inc. It was launched in 2012 and is designed to enable secure, instantly and nearly free global financial transactions of any size with no chargebacks.

[D22] PDL systems **can** implement AI-powered smart contract analysis tools to ensure compliance with governance rules and regulatory requirements.

[D23] Governance frameworks **can** incorporate AI-driven dynamic policy enforcement mechanisms to adapt to changing network conditions and regulatory environments.

[O7] PDL networks **could** consider implementing AI-enhanced KYC/AML systems to improve the efficiency and accuracy of compliance checks.

10.3 AI Assisted Automated Auditing and Reporting

AI can streamline auditing processes and generate comprehensive reports, enhancing transparency and accountability in PDL systems. Advanced machine learning algorithms can continuously monitor network activities, automatically detecting anomalies and potential compliance issues. These AI-driven systems can analyse vast amounts of transaction data in real-time, providing instant insights into the network's operational integrity. Natural language processing capabilities enable the generation of detailed, human-readable audit reports, summarizing complex findings in a clear, accessible format. Furthermore, AI can facilitate predictive auditing, identifying potential future compliance risks based on historical patterns and trends. This approach not only reduces the time and resources required for auditing but also significantly improves the accuracy and depth of audit outcomes.

Key applications include:

1) **Continuous Auditing**: AI algorithms can perform real-time auditing of transactions and smart contract executions, flagging potential issues immediately.

EXAMPLE 1: The Hyperledger Fabric® network utilizes an AI-powered continuous auditing system that monitors all chaincode executions in real-time, detecting and reporting anomalies within milliseconds [i.92].

NOTE 1: Hyperledger Fabric is an open-source, permissioned blockchain platform designed for enterprise use. It is part of the Hyperledger® project hosted by the Linux Foundation®.

2) **Intelligent Report Generation**: Natural Language Processing (NLP) models can generate human-readable audit reports from complex blockchain data.

EXAMPLE 2: The Corda® enterprise blockchain platform employs an AI-driven reporting system that automatically generates detailed compliance reports, reducing report preparation time by 75 % [i.93].

NOTE 2: Corda is an open-source blockchain platform designed for business, particularly for financial services and enterprise use cases.

3) **Predictive Compliance**: Machine learning models can predict potential compliance issues based on historical data and network trends.

EXAMPLE 3: The Tezos® blockchain implements an AI system that predicts potential governance conflicts and compliance risks up to two weeks in advance, allowing for proactive resolution [i.94].

NOTE 3: Tezos is a self-amending blockchain network that incorporates a formal, on-chain mechanism for proposing, selecting, testing, and activating protocol upgrades.

[D24] PDL systems **can** implement AI-driven continuous auditing mechanisms to monitor and flag potential issues in real-time.

[D25] Governance frameworks **can** incorporate AI-powered reporting systems to generate comprehensive and easily understandable audit reports.

[O8] PDL networks **could** consider implementing predictive compliance systems to anticipate and mitigate potential governance issues.

10.4 AI-Enhanced Governance Participation

AI can facilitate more inclusive and efficient governance participation in PDL systems by leveraging advanced algorithms to enhance decision-making processes. Natural language processing can analyse and summarize governance proposals, making them more accessible to all participants. Machine learning models can predict the potential impacts of proposed changes, aiding informed voting. AI-driven recommendation systems can suggest relevant governance issues to participants based on their interests and expertise. Furthermore, sentiment analysis can gauge community opinions on governance matters, ensuring broader representation. These AI-enhanced tools can also facilitate secure, transparent voting mechanisms, potentially increasing participation rates. By streamlining governance processes and improving accessibility, AI enables more diverse voices to contribute to the evolution of PDL systems.

EXAMPLE: The Polkadot® network uses an AI-powered governance assistant that helps token holders understand complex proposals and predicts the potential impacts of their votes, increasing informed participation by 40 % [i.95].

NOTE: Polkadot is a next-generation blockchain protocol designed to unite an entire network of purpose-built blockchains, allowing them to operate seamlessly together at scale. It was founded by Dr. Gavin Wood, co-founder of Ethereum, and is developed by Web3 Foundation® and Parity Technologies®.

[D26] PDL governance systems **can** consider implementing AI-driven tools to enhance user understanding and participation in governance processes.

10.5 Regulatory Compliance Monitoring

AI can continuously monitor regulatory changes across different jurisdictions and assess their impact on PDL operations, revolutionizing regulatory compliance monitoring. Natural language processing algorithms can scan and interpret vast amounts of legal documents, regulatory updates, and policy changes from multiple sources in real-time. Machine learning models can analyse these inputs to identify relevant regulations for specific PDL operations, assessing potential impacts on existing processes and protocols. AI-driven systems can then generate automated alerts and compliance recommendations, enabling proactive adaptation to regulatory changes. Furthermore, predictive analytics can anticipate future regulatory trends, allowing PDL systems to prepare for potential compliance requirements. This AI-powered approach ensures that PDL operations remain compliant across various jurisdictions, reducing legal risks and operational disruptions.

EXAMPLE: The Hedera Hashgraph Council® employs an AI system that monitors global regulatory changes and automatically generates compliance impact reports, reducing regulatory adaptation time by 60 % [i.96].

NOTE: Hedera Hashgraph® is a distributed ledger technology platform that aims to be a faster, more secure alternative to traditional blockchain systems. It was created by computer scientist Leemon Baird and is based on the hashgraph consensus algorithm. The Hedera Hashgraph Council, also known as the Hedera Governing Council, is the body responsible for overseeing the governance and strategic direction of the Hedera network. It was established to ensure decentralized governance of the platform.

[D27] PDL systems **can** implement AI-driven regulatory monitoring systems to ensure timely compliance with changing legal requirements.

10.6 Intelligent Dispute Resolution

AI can assist in resolving disputes in PDL systems by analysing transaction histories and smart contract executions to provide objective assessments. Machine learning algorithms can process vast amounts of historical data, identifying patterns and precedents relevant to the dispute at hand. Natural language processing can interpret contract terms and conditions, ensuring accurate interpretation. AI-driven systems can simulate various scenarios based on the dispute parameters, predicting potential outcomes and suggesting fair resolutions. These intelligent systems can also detect anomalies or inconsistencies in transaction records that could be crucial to dispute resolution. By providing unbiased, data-driven insights, AI enhances the efficiency and fairness of dispute resolution processes in PDL networks, potentially reducing the need for time-consuming and costly human arbitration.

EXAMPLE: The EOS® blockchain uses an AI-powered arbitration system that can resolve 80 % of common disputes without human intervention, significantly reducing the workload on human arbitrators [i.97].

NOTE: EOS is a blockchain platform developed by the EOS Network Foundation® and designed for the development of decentralized applications (dApps), with a focus on scalability, flexibility, and user experience.

[D28] PDL governance frameworks **can** consider incorporating AI-assisted dispute resolution mechanisms to enhance efficiency and objectivity in conflict resolution.

11 Identity management using AI

11.1 Introduction and problem statement

Traditional identity management systems in Permissioned Distributed Ledger (PDL) environments face several critical challenges:

1) Inefficient and error-prone manual identity verification processes.
2) Vulnerability to identity theft and fraud due to static authentication methods.
3) Poor user experience resulting from cumbersome authentication procedures.
4) Difficulty in maintaining a balance between security and accessibility.
5) Inability to adapt to evolving security threats in real-time.
6) Lack of continuous authentication mechanisms, leaving systems vulnerable between login events.
7) Scalability issues in managing identities across large, complex PDL networks.
8) Inconsistent identity verification standards across different nodes in the network.

These challenges compromise the security, efficiency, and user-friendliness of PDL systems, potentially hindering their widespread adoption and effectiveness in various sectors. There is an urgent need for innovative solutions that can enhance identity management in PDL environments, ensuring robust security while improving user experience and operational efficiency. The ideal solution is able to leverage cutting-edge technologies to provide seamless, continuous authentication, adapt to emerging threats, and scale effectively with growing network complexity.

Artificial Intelligence (AI) is revolutionizing identity management in Permissioned Distributed Ledger (PDL) systems, enhancing security, efficiency, and user experience. This clause explores how AI can improve identity verification processes and enable continuous authentication through behavioural biometrics and other methods.

11.2 AI-Enhanced Identity Verification and Management Processes

11.2.1 AI-Powered Facial Recognition

AI-powered facial recognition technology is increasingly used in digital onboarding processes to enhance security and prevent fraud. This technology verifies user identities by comparing live facial images with stored identity documents, ensuring that the person presenting the ID is its legitimate owner. This example highlights how AI-powered facial recognition can be effectively integrated into customer onboarding processes to enhance security and efficiency while maintaining compliance with regulatory standards. An example of such technology can be found in clause A.4.1 herewith.

[D29] Organizations **can** ensure that their facial recognition systems comply with privacy regulations and incorporate additional biometric checks, such as liveness detection, to prevent spoofing attacks.

11.2.2 AI-Powered Document Verification System

A document verification system uses Convolutional Neural Networks (CNNs) in combination with Optical Character Recognition (OCR) and feature matching algorithms to authenticate identity documents and detect forgeries. This example demonstrates how machine learning algorithms can be effectively used to verify the authenticity of identity documents and detect forgeries, improving the security and efficiency of identity verification processes. An example of such technology can be found in clause A.4.2 herewith.

11.2.3 Anomaly Detection: AI-Powered Behavioural Biometrics for Continuous Authentication

An AI system uses behavioural biometrics to continuously authenticate users by analysing their unique patterns of interaction with devices and applications. The system monitors factors like typing rhythm, mouse movements, touchscreen gestures, and app usage patterns to create a behavioural profile for each user. This example demonstrates how AI-powered anomaly detection can be used to identify potential identity theft or fraud by continuously monitoring user behaviour for unusual patterns. An example of such technology can be found in clause A.4.3 herewith.

[D30] System developers **can** implement a risk-based authentication system that adjusts the level of behavioural biometric monitoring based on the sensitivity of the operation being performed in the PDL system.

[D31] Stakeholders **can** Implement a multi-factor authentication system that combines AI-enhanced biometric verification with traditional methods for robust identity management in PDL networks.

11.3 Additional Scenarios and Examples

11.3.1 Federated Identity Management

AI can facilitate secure and efficient identity sharing across multiple PDL networks while preserving privacy. Advanced machine learning algorithms can enable robust authentication mechanisms, encrypt sensitive data, and implement granular access controls. This approach ensures seamless interoperability between networks while maintaining user confidentiality and compliance with data protection regulations. AI-driven analytics can also detect and mitigate potential security threats in real-time, enhancing overall system integrity.

EXAMPLE: Use federated learning to train identity verification models across multiple organizations without sharing sensitive user data [i.101].

11.3.2 Adaptive Access Control

AI algorithms can dynamically adjust access privileges based on user behaviour and context, forming the core of adaptive access control systems. These intelligent systems continuously analyse factors such as login patterns, device types, and network locations to assess risk levels in real-time. Based on this analysis, they can automatically elevate or restrict user permissions, ensuring optimal security without compromising user experience. This approach allows organizations to maintain a balance between robust protection and operational efficiency, adapting swiftly to evolving threats and user needs.

EXAMPLE: Implement reinforcement learning models that continuously optimize access control policies based on user interactions and system security state [i.101].

11.3.3 Identity Recovery and Remediation

AI can assist in detecting compromised identities and streamline the recovery process in such scenarios. Advanced machine learning models can analyse user behaviour patterns, network traffic, and access logs to quickly identify anomalies indicative of compromised accounts. Once detected, AI-driven systems can automate the initial steps of identity recovery, such as account lockdown and notification. These systems can also guide users through the remediation process, suggesting personalized security measures and verifying the authenticity of recovery actions. This AI-assisted approach significantly reduces response time and minimizes potential damage from identity breaches.

EXAMPLE: Develop AI models that analyse historical user behaviour to quickly identify potential account takeovers and suggest remediation steps [i.101].

11.3.4 Decentralized Identity Verification

AI can enhance the reliability and efficiency of decentralized identity systems in PDL networks by leveraging advanced algorithms for robust verification processes. Machine learning models can analyse multiple data points across distributed ledgers to validate identities with high accuracy. These AI-driven systems can detect patterns and anomalies in identity claims, enhancing fraud prevention. Furthermore, AI can optimize the consensus mechanisms in decentralized networks, ensuring faster and more secure identity verification while maintaining user privacy. This approach enables seamless, trustworthy identity management across various decentralized platforms, fostering interoperability and user confidence in PDL ecosystems.

EXAMPLE: Use AI-powered reputation systems to evaluate the trustworthiness of identity attestations in a decentralized identity network [i.101].

11.3.5 Cross-Chain Identity Management

AI can facilitate secure identity portability and verification across different blockchain networks, enhancing cross-chain identity management. Advanced machine learning algorithms can analyse and map identity attributes across diverse blockchain protocols, ensuring seamless interoperability. These AI-driven systems can create standardized identity representations, enabling secure and efficient identity transfers between chains. Furthermore, AI can automate the verification process, detecting inconsistencies or potential fraud attempts during cross-chain identity transactions. This approach not only streamlines user experience but also maintains the integrity and security of decentralized identity ecosystems, fostering trust and adoption of cross-chain solutions.

EXAMPLE: Implement AI-driven identity mapping and translation services that enable seamless identity verification across heterogeneous PDL systems [i.101].

[D32] System developers **can** develop a comprehensive AI-driven identity management framework that incorporates these advanced scenarios to create a robust, adaptive, and user-friendly identity ecosystem for PDL networks.

12 AI-Assisted PDL Interoperability

12.1 PDL Interoperability in the context of AI - problem statement

The blockchain and Distributed Ledger Technology (DLT) ecosystem is currently fragmented, with numerous networks operating in isolation. This lack of interoperability hinders the seamless transfer of assets, data, and identities across different chains, limiting the potential of blockchain technology and its widespread adoption.

Key challenges include:

1) Incompatible protocols and data structures between different blockchain networks.
2) Absence of standardized communication methods for cross-chain interactions.
3) Security risks associated with cross-chain transactions.
4) Inefficient routing of transactions across multiple chains.
5) Difficulty in verifying and validating information from different blockchain sources.
6) Lack of a unified approach to collaborative development of standards and processes.

There is a pressing need for innovative solutions that can bridge these gaps, enabling secure and efficient interoperability across diverse blockchain networks. This problem requires addressing technical, operational, and governance aspects to create a cohesive and interconnected blockchain ecosystem.

Artificial Intelligence (AI) plays a crucial role in enhancing interoperability between different blockchain networks and Distributed Ledger Technologies (DLTs). This clause explores how AI can facilitate cross-chain communication, enable smart routing of transactions, and improve overall interoperability in the blockchain ecosystem. Interoperability typically involves multiple parties with different approaches trying to find a way to transact with each other. This is best achieved through collaborative development of standards and processes.

[D33] Developer groups **can** establish a dedicated AI research and development team focused on blockchain interoperability to continuously explore and implement innovative AI-driven solutions for cross-chain communication and collaboration.

12.2 AI-Facilitated Cross-Chain Communication and Data Exchange

Artificial Intelligence (AI) plays a crucial role in enhancing cross-chain communication and data exchange by providing intelligent mechanisms for protocol translation, data validation, and semantic interoperability. As the blockchain ecosystem becomes increasingly diverse, the need for seamless interaction between different blockchain networks grows more pressing. AI technologies can bridge the gap between disparate blockchain protocols, enabling efficient and secure cross-chain transactions and data sharing.

Machine learning models, particularly those focused on Natural Language Processing (NLP) and knowledge representation, can be leveraged to create adaptive interfaces between different blockchain systems. These AI-driven interfaces can automatically translate between various blockchain protocols, much like how language translation models work. This capability allows for the creation of universal blockchain gateways that can facilitate communication between any two blockchain networks, regardless of their underlying architecture or consensus mechanisms.

Examples and recent research in AI applications in cross-chain communication are listed in clause A.5.1 herewith.

[D34] Developers **can** Implement AI-powered protocol translation layers in cross-chain communication protocols to enable automatic adaptation to different blockchain networks.

12.3 Smart Routing of Transactions Between Different Ledgers

Artificial Intelligence (AI) algorithms can significantly optimize the routing of transactions across multiple blockchain networks, improving efficiency and reducing costs in cross-chain operations. Smart routing leverages AI to dynamically determine the most optimal path for a transaction to travel between different ledgers, considering factors such as speed, cost, security, and network congestion.

AI-powered smart routing systems can analyse real-time network conditions, historical performance data, and transaction requirements to make intelligent decisions about how to route cross-chain transactions. These systems can adapt to changing conditions, learn from past routing decisions, and continuously improve their performance over time.

Examples of AI applications in smart routing for cross-chain transactions can be found in clause A.5.2 herewith.

These AI-driven approaches to smart routing can significantly enhance the efficiency and reliability of cross-chain transactions, contributing to greater interoperability in the blockchain ecosystem.

Additional Scenarios and Examples can be found in clause A.5.3 herewith.

13 AI based PDL Scalability solutions

13.1 Problem statement

Permissioned Distributed Ledger (PDL) systems face significant scalability challenges as they grow in size and complexity.

These challenges include:

1) Inefficient resource allocation leading to performance bottlenecks.
2) Difficulty in maintaining low latency and high throughput as network size increases.
3) Suboptimal load balancing across nodes, resulting in uneven workload distribution.
4) Static consensus algorithms that struggle to adapt to changing network conditions.
5) Inability to effectively predict and manage resource requirements in real-time.
6) Limited flexibility in network topology optimization as the system scales.
7) Inefficient sharding mechanisms that fail to adapt to dynamic network traffic and usage patterns.

These scalability issues hinder the widespread adoption and effectiveness of PDL systems in large-scale enterprise applications. There is a pressing need for innovative solutions that can address these challenges, enabling PDL networks to scale efficiently while maintaining performance, security, and decentralization. The problem requires a dynamic, adaptive approach that can optimize various aspects of the system in real-time, ensuring sustainable growth and performance of PDL networks as they expand.

13.2 Developing More Efficient Scaling Solutions using AI

Artificial Intelligence (AI) plays a crucial role in addressing scalability challenges and developing more efficient scaling solutions for Permissioned Distributed Ledger (PDL) systems. As these networks grow in size and complexity, AI techniques can optimize various aspects of the system, from transaction processing to network topology. Machine learning models can analyse historical data and network patterns to predict resource requirements, enabling dynamic resource allocation and load balancing by adjusting workload distribution across nodes. Deep learning techniques can optimize consensus algorithms, reducing latency and improving throughput in large-scale PDL networks. Additionally, AI can enable dynamic sharding based on network traffic and usage patterns, further enhancing the scalability and efficiency of PDL systems.

[D35] Platform developers **can** establish a dedicated AI research team focused on scalability solutions, continuously exploring and implementing innovative AI-driven approaches to address the evolving scalability challenges in PDL systems.

[D36 Developers **can** implement a hybrid approach that combines traditional scaling techniques with AI-driven optimizations to achieve maximum scalability benefits.

Examples of AI applications in PDL scaling solutions are listed in clause A.6.1 herewith.

These AI-driven approaches to scaling offer significant improvements over traditional methods, enabling PDL systems to handle larger transaction volumes and more complex operations while maintaining high performance and security.

13.3 Dynamic Sharding Based on Network Traffic and Usage Patterns

Artificial Intelligence (AI) can enable more sophisticated and adaptive sharding strategies by analysing network traffic and usage patterns in real-time. Dynamic sharding is a critical component of scalable PDL systems, allowing the network to efficiently distribute workload and data across multiple shards or partitions. AI algorithms can continuously monitor network conditions, transaction volumes, and resource utilization to make informed decisions about shard creation, merging, and load balancing. Machine learning models, particularly those focused on time series analysis and predictive modelling, can forecast future network loads and proactively adjust shard configurations to maintain optimal performance. These models can take into account various factors such as historical transaction patterns, user behaviour, and external events that can impact network usage.

[D37] Developers **can** develop an AI-driven sharding management system that continuously monitors network performance and adapts shard configurations in real-time.

Examples of AI applications in dynamic sharding for PDL systems are listed in clause A.6.2 herewith.

Additional scenarios and examples based on a survey performed by Xie et al. (2022) [i.121] are listed in clause A.6.3 herewith.

14 Conclusion and Recommendations

The present document has explored the diverse applications of Artificial Intelligence (AI) in Permissioned Distributed Ledger (PDL) systems, highlighting the significant potential for AI to enhance the functionality, security, performance, and interoperability of these systems.

The present document has covered a wide range of areas where AI can be leveraged in PDL systems, including:

1) Enhanced security through AI-powered anomaly detection and fraud prevention.
2) Smart contract optimization using AI-driven code analysis and testing.
3) Improved consensus mechanisms with AI-enhanced algorithms.
4) Advanced data analytics and insights derived from AI analysis.
5) Privacy-preserving techniques enabled by AI.
6) Network optimization using AI for performance and resource allocation.
7) AI-assisted governance and compliance management.
8) AI-enhanced identity management and verification.
9) Improved interoperability between different ledgers facilitated by AI.
10) AI-based scalability solutions for PDL systems.

Throughout these areas, the present document demonstrates how AI techniques such as machine learning, deep learning, natural language processing, and reinforcement learning can be applied to solve complex challenges in PDL environments. The examples and case studies provided demonstrate the practical impact of these AI applications, often resulting in significant improvements in efficiency, accuracy, and security.

As both AI and PDL technologies continue to evolve rapidly, their integration offers enormous potential for innovation and advancement in distributed systems. However, it is important to note that the implementation of AI in PDL systems also brings new challenges, particularly in areas such as data privacy, algorithmic transparency, and ethical considerations.

Moving forward, it is recommended that PDL developers, researchers, and stakeholders:

1) Continue to explore and implement AI solutions in their systems, following the guidelines and best practices outlined in the present document.

2) Prioritize privacy and security considerations when implementing AI, especially in permissioned environments.

3) Stay informed about the latest developments in both AI and PDL technologies to identify new opportunities for integration.

4) Contribute to the development of standards and best practices for AI implementation in PDL systems.

5) Consider the ethical implications of AI use in distributed ledgers and work towards responsible AI integration.

By embracing the synergy between AI and PDL technologies, new possibilities can be unlocked to create more intelligent, efficient, and secure distributed systems that can drive innovation across various industries and applications.

Annex A:
List of AI-tools referenced in the present document with brief descriptions and application for PDL

A.1 Examples related to clause 4 (Enhanced security)

A.1.1 Examples of AI Algorithms for Continuous Monitoring

A.1.1.1 Temporal Graph Convolutional Networks (TGCNs)

Temporal Graph Convolutional Network (TGCN) is a neural network model that combines Graph Convolutional Networks (GCNs) with temporal processing elements, such as Gated Recurrent Units (GRUs), to capture both spatial and temporal dependencies in graph-structured data. TGCNs extend Graph Convolutional Networks to handle temporal dynamics, making them ideal for monitoring evolving PDL networks [i.1].

- **Application in PDL Platforms:**

    1) Model the entire PDL network as a dynamic graph, with nodes representing entities and edges representing transactions or interactions.

    2) Capture both spatial and temporal patterns in transaction flows and system behaviours.

    3) Detect anomalies by identifying unusual changes in network structure or transaction patterns over time.

- **Key Advantages:**

    1) Can handle the dynamic nature of PDL networks, where relationships and behaviours change over time.

    2) Efficiently processes large-scale graph-structured data, suitable for high-throughput PDL platforms.

    3) Can capture complex, multi-hop relationships between entities in the network.

NOTE 1: Graph Convolutional Networks (GCNs) are a type of neural network designed to process graph-structured data, where nodes represent entities and edges represent relationships between them. GCNs generalize traditional Convolutional Neural Networks (CNNs) to graph data by defining convolutional operations on graphs. They learn to aggregate information from neighbouring nodes and edges, capturing complex dependencies and patterns within the graph.

NOTE 2: Gated Recurrent Units (GRUs) are a type of Recurrent Neural Network (RNN) architecture that uses gates to control the flow of information. GRUs have two gates: the reset gate and the update gate. The reset gate determines how much of the previous hidden state to forget, while the update gate decides how much of the new information to add to the hidden state. This gating mechanism allows GRUs to selectively retain and discard information, enabling them to learn long-term dependencies and avoid the vanishing gradient problem.

A.1.1.2 Federated Attention Mechanism with Differential Privacy

A Federated Attention Mechanism is a component of federated learning systems that incorporates attention mechanisms to enhance the performance and personalization of models trained across decentralized data sources. By leveraging attention, these systems can dynamically assign varying levels of importance to different data elements or clients, facilitating more effective aggregation and collaboration among heterogeneous datasets. This approach combines federated learning, attention mechanisms, and differential privacy to enable privacy-preserving, collaborative monitoring across multiple nodes in a PDL network [i.2].

- **Application in PDL Platforms:**

    1) Enable continuous, collaborative monitoring across multiple nodes without sharing raw transaction data.

2) Use attention mechanisms to focus on the most relevant features for detecting anomalies.

3) Adapt to local variations in transaction patterns while benefiting from network-wide knowledge.

- **Key Advantages:**

1) Preserves privacy and data sovereignty in multi-party PDL networks.

2) Can detect network-wide anomalies while maintaining the confidentiality of individual nodes.

3) Attention mechanisms improve the interpretability of the model's decisions.

A.1.1.3 Hierarchical Long Short-Term Memory Networks with Adaptive Thresholding

Long Short-Term Memory (LSTM) networks are a type of Recurrent Neural Network (RNN) designed to handle the vanishing gradient problem in traditional RNNs.

Adaptive Thresholding is a technique used in neural networks to dynamically adjust the threshold values for activation functions, allowing the network to adapt to varying input conditions and improve its performance.

Hierarchical Long Short-Term Memory (LSTM) Networks with Adaptive Thresholding are a type of neural network architecture that combines the strengths of hierarchical structures and LSTM networks. These networks are designed to handle complex, hierarchical data by organizing LSTM layers in a hierarchical manner, allowing them to capture both short-term and long-term dependencies at different levels of abstraction.

This algorithm uses a hierarchical structure of LSTM networks combined with adaptive thresholding techniques to monitor and analyse multi-level patterns in PDL platforms [i.3].

- **Application in PDL Platforms:**

1) Analyse transaction patterns at multiple levels: individual transactions, account-level behaviour, and network-wide trends.

2) Use adaptive thresholding to dynamically adjust anomaly detection sensitivity based on current network conditions.

3) Capture long-term dependencies in transaction histories and system behaviours.

- **Key Advantages:**

1) Can handle multi-scale temporal patterns, from millisecond-level transaction timing to long-term behaviour trends.

2) Adaptive thresholding reduces false positives by adjusting to changing network conditions.

3) Hierarchical structure allows for efficient processing of large volumes of transaction data.

NOTE: Recurrent Neural Networks (RNNs) are a type of neural network architecture designed to process sequential data, such as time series, speech, or text. RNNs are characterized by feedback connections that allow the network to maintain a hidden state over time, enabling it to capture temporal dependencies and relationships in the data.

A.1.2 Examples of Advanced Machine Learning Models for Pattern Recognition

A.1.2.1 Graph Neural Networks (GNNs)

In addition to Continuous Monitoring GNNs can also be used for Pattern Recognition [i.4].

- **Application of GNN based Pattern Recognition in PDL Networks:**

  1) Can model the entire PDL network as a graph, with nodes representing entities (e.g. users, smart contracts) and edges representing interactions or transactions.

  2) Capable of learning and identifying normal patterns of interactions and transactions within the network.

  3) Can detect anomalies by identifying subgraphs or node behaviours that deviate from learned normal patterns.

- **Key Advantages:**

  1) Naturally suited to the graph-like structure of PDL networks.

  2) Can capture complex, multi-hop relationships between entities in the network.

  3) Scalable to large networks and can handle dynamic, evolving graph structures.

A.1.2.2 Transformer-based Models

Transformer-based models are a type of neural network architecture that has revolutionized Natural Language Processing (NLP) and other sequential data tasks. They are designed to transform input sequences into output sequences by learning context and tracking relationships between sequence components. Transformer models use self-attention mechanisms to weigh the importance of different elements within the sequence, allowing them to process data in parallel and capture long-range dependencies. This architecture consists of an encoder that transforms input into a contextualized representation and a decoder that generates the output sequence based on this representation [i.5].

- **Application in PDL Networks:**

  1) Can analyse sequences of transactions or smart contract interactions to identify normal behavioural patterns.

  2) Capable of capturing long-range dependencies in transaction histories or user behaviours.

  3) Can be used for anomaly detection by identifying sequences that deviate from learned normal patterns.

- **Key Advantages:**

  1) Excellent at capturing complex, long-range patterns in sequential data.

  2) Can handle variable-length input sequences, suitable for diverse transaction patterns.

  3) Attention mechanisms allow the model to focus on the most relevant parts of the input for each prediction.

A.1.2.3 Deep Clustering Networks (DCNs)

Deep Clustering Networks (DCNs) are a type of neural network architecture designed for unsupervised clustering tasks. They integrate feature learning and clustering into a unified framework, allowing the network to learn clustering-friendly representations from data. DCNs typically consist of an autoencoder that learns to reconstruct the input data, and a clustering module that optimizes a clustering objective, such as k-means loss, to group similar data points together. By jointly optimizing the reconstruction loss and clustering loss, DCNs can learn low-dimensional, non-linear data representations that are suitable for clustering, making them effective for tasks such as image clustering, text clustering, and gene expression analysis. Deep Clustering Networks combine the feature of learning capabilities of deep neural networks with clustering algorithms, allowing for more effective unsupervised pattern discovery in complex data [i.6].

- **Application in PDL Networks:**

  1) Can identify groups of similar transactions, user behaviours, or network activities without predefined labels.

  2) Capable of discovering latent patterns or structures in PDL network data that are not be apparent through manual analysis.

  3) Can be used to create behavioural profiles of normal network activities, against which anomalies can be detected.

- **Key Advantages:**

  1) Combines the strengths of deep learning for feature extraction with clustering for pattern discovery.

  2) Can handle high-dimensional data typical in complex PDL networks.

  3) Suitable for unsupervised learning scenarios where labelled data is scarce.

NOTE 1: K-Means Loss is a type of loss function used in clustering algorithms, particularly in Deep Clustering Networks (DCNs). It measures the difference between the predicted cluster assignments and the true cluster centres. The k-means loss is typically calculated as the sum of squared distances between each data point and its assigned cluster centre, averaged over all data points.

NOTE 2: Reconstruction Loss is a type of loss function used in autoencoders and other neural network architectures. It measures the difference between the original input data and the reconstructed output data, which is generated by the network's decoder.

NOTE 3: Clustering Loss is a type of loss function used in clustering algorithms, particularly in Deep Clustering Networks (DCNs). It measures the quality of the cluster assignments by evaluating how well the data points are grouped into distinct clusters. The clustering loss is typically calculated as a function of the similarity between data points within the same cluster and the dissimilarity between data points in different clusters.

A.1.3 Examples of Adaptive AI Systems for Evolving Threat Detection

A.1.3.1 Continual Learning Networks

Continual Learning Networks are a type of neural network designed to learn from a stream of data that arrives continuously, without forgetting previously learned knowledge. These networks aim to mitigate the problem of catastrophic forgetting, where new learning overwrites existing knowledge, by incorporating mechanisms such as memory consolidation, knowledge distillation, and experience replay. Continual learning networks can adapt to changing data distributions, learn from new tasks, and retain knowledge from previous tasks, making them suitable for applications such as lifelong learning, autonomous systems, and real-world data streams. This is crucial in the context of evolving security threats [i.7].

- **Application in PDL Networks:**

  1) Can continuously update threat detection models as new types of attacks or anomalies are observed in the PDL network.

  2) Allows the system to maintain knowledge of historical attack patterns while adapting to new threats.

  3) Can handle concept drift in network behaviour, adjusting to changes in normal operation patterns over time.

- **Key Advantages:**

  1) Mitigates the "catastrophic forgetting" problem common in traditional neural networks.

  2) Enables efficient use of computational resources by updating existing models rather than retraining from scratch.

  3) Provides a balance between stability (retaining useful past knowledge) and plasticity (adapting to new information).

A.1.3.2 Meta-Learning Systems

Meta-Learning Systems are a type of machine learning approach that enables models to learn how to learn from other tasks and adapt to new, unseen tasks with minimal training data. These systems learn to extract generalizable knowledge and skills from a set of tasks, allowing them to quickly learn and perform well on new tasks, even with limited data. By learning to learn, meta-learning systems can improve their performance on a wide range of tasks, making them particularly useful for applications such as few-shot learning, transfer learning, and lifelong learning. These characteristics make Meta-Learning Systems particularly suitable for addressing novel security threats [i.8].

- **Application in PDL Networks:**

  1) Can quickly adapt threat detection capabilities to new types of attacks or changes in the PDL network structure.

  2) Enables rapid deployment of security measures for emerging threats, even with limited examples.

  3) Can generalize from known attack patterns to detect novel variants or entirely new classes of threats.

- **Key Advantages:**

  1) Reduces the time and data required to adapt to new security challenges.

  2) Improves generalization to unseen types of attacks or anomalies.

  3) Facilitates transfer learning between different PDL networks or security domains.

A.1.3.3 Reinforcement Learning for Adaptive Security

Reinforcement Learning (RL) is a type of machine learning where an agent learns to make decisions by interacting with an environment and receiving feedback in the form of rewards or penalties. The agent's goal is to maximize the cumulative reward over time by learning a policy that maps states to actions. Through trial and error, the agent adapts its behaviour to optimize the reward signal, enabling it to learn complex tasks such as game playing, robotics control, and autonomous driving without explicit supervision. The use of RL for adaptive security involves AI agents that learn optimal security policies through interaction with the environment, continuously improving their strategies based on feedback [i.9].

- **Application in PDL Networks:**

  1) Can develop adaptive security measures that respond dynamically to evolving threats in PDL networks.

  2) Enables the creation of proactive defence strategies that anticipate and prevent attacks.

  3) Can optimize security policies for different operational states of the PDL network, balancing security with performance and resource utilization.

- **Key Advantages:**

    1) Provides a framework for continuous improvement of security strategies.

    2) Can handle complex, multi-step decision-making processes in security management.

    3) Allows for the development of personalized security policies for different components or sub-networks within a PDL system.

A.1.4 Examples of AI Systems for Automated Response Mechanisms in PDL Networks

A.1.4.1 Reinforcement Learning-based Autonomous Defence Systems

These systems use Reinforcement Learning (RL) to autonomously learn and execute optimal defence strategies in response to detected threats or anomalies [i.9].

- **Application in PDL Networks:**

    1) Can dynamically adjust security policies and network configurations in response to emerging threats.

    2) Capable of learning from past incidents to improve future response strategies.

    3) Can balance security measures with network performance and resource utilization.

- **Key Advantages:**

    1) Adaptive and can improve over time through continuous interaction with the environment.

    2) Can handle complex, multi-step decision-making processes in real-time.

    3) Able to generalize learned strategies to novel threat scenarios.

A.1.4.2 Federated Learning-based Collaborative Defence Systems

Federated Learning is a machine learning approach that enables multiple devices or clients to collaboratively learn a shared model while keeping their local data private. Instead of sharing data, clients share model updates with a central server, which aggregates the updates to improve the global model. This decentralized approach allows for secure and private learning, reducing the risk of data breaches and preserving data ownership. Federated learning is particularly useful for applications where data is sensitive and cannot be shared openly.

Collaborative Defence Systems use federated learning to collaboratively train defence models across multiple nodes or organizations in a PDL network, while keeping sensitive data localized [i.10].

- **Application in PDL Networks:**

    1) Can coordinate defence responses across multiple nodes in a decentralized manner.

    2) Enables sharing of threat intelligence and defence strategies without exposing raw data.

    3) Can adapt to local variations in network behaviour while benefiting from global knowledge.

- **Key Advantages:**

    1) Preserves privacy and data sovereignty in multi-party PDL networks.

    2) Improves robustness of defence mechanisms through diverse training data.

    3) Can handle heterogeneous network environments common in PDL ecosystems.

A.1.4.3 Explainable AI (XAI) for Automated Incident Response

Explainable AI (XAI) refers to a set of techniques and methods that provide insights into the decision-making processes of Artificial Intelligence (AI) and Machine Learning (ML) models. XAI aims to make AI models more transparent, interpretable, and accountable by explaining how they arrive at their predictions or recommendations. This is achieved through various techniques, such as feature attribution, model interpretability, and model explainability, which help to identify the factors that influence the model's decisions. XAI is essential for building trust in AI systems, ensuring fairness and accountability, and complying with regulatory requirements.

XAI-based Automated Incident Response systems combine the decision-making capabilities of AI with explainable models to provide transparent, interpretable automated responses to security incidents [i.11].

- **Application in PDL Networks:**
  1) Can automatically trigger and explain response actions to security threats.
  2) Provides auditable decision trails for regulatory compliance and incident forensics.
  3) Enables human operators to understand, validate, and refine automated response strategies.
- **Key Advantages:**
  1) Increases trust in automated response mechanisms through transparency.
  2) Facilitates collaboration between AI systems and human security teams.
  3) Supports continuous improvement of response strategies through interpretable feedback.

A.1.5 Examples of AI-Based Machine Learning Models for Fraud Detection

A.1.5.1 Graph Neural Networks (GNNs) for Fraud Detection

GNNs are deep learning models designed to work directly on graph-structured data, making them ideal for analysing the complex relationships and patterns in PDL transaction networks [i.12].

- **Application in PDL Networks:**
  1) Can model the entire transaction network as a graph, with nodes representing entities (e.g. users, accounts) and edges representing transactions or relationships.
  2) Capable of learning and identifying normal and abnormal patterns of transactions and user behaviours within the network.
  3) Can detect fraudulent activities by identifying suspicious subgraphs or node behaviours that deviate from learned normal patterns.
- **Key Advantages:**
  1) Naturally suited to the graph-like structure of transaction networks.
  2) Can capture complex, multi-hop relationships between entities in the network.
  3) Able to incorporate both structural and feature information for more accurate fraud detection.

A.1.5.2 Transformer-based Models for Sequential Fraud Detection

Transformer-based models are a type of neural network architecture that has revolutionized Natural Language Processing (NLP) and other sequential data tasks. They are designed to transform input sequences into output sequences by learning context and tracking relationships between sequence components. Transformer models have been adapted for analysing sequential transaction data and user behaviours for the purpose of Fraud Detection [i.13].

- **Application in PDL Networks:**

  1) Can analyse sequences of transactions or user actions to identify fraudulent patterns.

  2) Capable of capturing long-range dependencies in transaction histories or user behaviours.

  3) Can be used for real-time fraud detection by processing streaming transaction data.

- **Key Advantages:**

  1) Excellent at capturing complex, long-range patterns in sequential data.

  2) Can handle variable-length input sequences, suitable for diverse transaction patterns.

  3) Attention mechanisms allow the model to focus on the most relevant parts of the input for fraud detection.

A.1.5.3 Federated Deep Learning for Privacy-Preserving Fraud Detection

Federated Deep Learning is a type of machine learning approach that combines the principles of federated learning with deep learning techniques. It enables multiple devices or clients to collaboratively train a shared deep neural network model while keeping their local data private. Each client trains a local model on their own data and shares the model updates with a central server, which aggregates the updates to improve the global model. Federated Deep Learning allows multiple parties to collaboratively train a fraud detection model without sharing raw data, addressing privacy concerns in PDL networks [i.15].

- **Application in PDL Networks:**

  1) Enables collaborative fraud detection across multiple nodes or organizations in a PDL network.

  2) Can learn from diverse data sources while keeping sensitive transaction data localized.

  3) Allows for the creation of more robust fraud detection models by leveraging data from multiple sources.

- **Key Advantages:**

  1) Preserves privacy and data sovereignty in multi-party PDL networks.

  2) Improves fraud detection accuracy through access to larger, more diverse datasets.

  3) Can adapt to local variations in fraudulent behaviours while benefiting from global knowledge.

A.1.6 Examples of unsupervised learning algorithms used to establish baseline behaviours

A.1.6.1 Graph Autoencoders (GAEs) for Network Behaviour Modelling

Graph Autoencoders (GAEs) are a type of neural network model designed to learn meaningful representations of graph data. They consist of an encoder that captures the topological structure and node content of a graph, and a decoder that reconstructs the graph from the learned latent representation. GAEs are used for various tasks such as node classification, link prediction, and graph clustering, and they aim to preserve the graph structure in a lower-dimensional space [i.14].

- **Application in PDL Networks:**

  1) Can model normal patterns of interactions between entities (users, smart contracts, transactions) in the PDL network.

  2) Capable of capturing complex structural relationships and attributes in the network.

  3) Can be used to detect anomalies by identifying nodes or subgraphs that deviate from the learned normal patterns.

- **Key Advantages:**

    1) Naturally suited to the graph-like structure of PDL networks.

    2) Can handle both structural and feature information simultaneously.

    3) Scalable to large networks, making them suitable for real-world PDL applications.

A.1.6.2 Variational Autoencoders (VAEs) for Anomaly Detection

Variational Autoencoders (VAEs) are a type of neural network model that combines the capabilities of autoencoders and generative models. VAEs consist of an encoder that maps input data to a probabilistic latent space, and a decoder that generates new data samples from this latent space. Unlike traditional autoencoders, VAEs learn a probabilistic representation of the input data, allowing for the generation of new, diverse, and coherent data samples. VAEs are trained using a variational inference approach, which enables them to learn complex distributions and capture nuanced patterns in the data, making them a powerful tool for tasks such as image generation, data imputation, and anomaly detection [i.16].

- **Application in PDL Networks:**

    1) Can learn normal patterns of transactions and user behaviours in the PDL network.

    2) Capable of generating synthetic "normal" data, which can be used for comparison and anomaly detection.

    3) Can handle high-dimensional data typical in complex PDL environments.

- **Key Advantages:**

    1) Provides a probabilistic framework for modelling normal behaviour.

    2) Can generate synthetic examples of normal behaviour for further analysis or testing.

    3) Effective at handling complex, high-dimensional data distributions.

A.1.6.3 Temporal Convolutional Networks (TCNs) for Time Series Analysis

Temporal Convolutional Networks (TCNs) are a type of neural network architecture designed for sequence modelling tasks. They use causal, dilated 1D convolutional layers to capture temporal dependencies in data, allowing for parallel computation and efficient handling of long sequences. TCNs consist of residual blocks with dilated convolutions, which increase the receptive field size without significantly increasing the number of parameters. This architecture enables TCNs to outperform traditional Recurrent Neural Networks (RNNs) in many sequence modelling tasks, such as machine translation, speech synthesis, and time-series forecasting [i.17].

- **Application in PDL Networks:**

    1) Can learn normal temporal patterns in transaction sequences or user activity timelines.

    2) Capable of capturing long-range dependencies in time series data.

    3) Can be used for real-time anomaly detection in streaming transaction data.

- **Key Advantages:**

    1) Excellent at capturing complex temporal patterns in sequential data.

    2) Can handle variable-length input sequences, suitable for diverse transaction patterns.

    3) Efficient parallel processing, making them suitable for real-time applications.

NOTE: Temporal Graph Convolutional Networks (TGCNs, as defined in clause A.1.1.1) and Temporal Convolutional Networks (TCNs) are both designed for handling temporal data, but they differ in their focus and application:

- **TCNs** are primarily used for sequence modelling tasks and focus on capturing temporal dependencies in sequential data. They do not inherently handle graph-structured data.
- **TGCNs**, on the other hand, are designed to handle graph-structured data that evolves over time. They combine graph convolutional layers with temporal processing elements to capture both spatial and temporal dependencies in graph data.

A.1.7 Examples of Predictive Machine Learning Models for Fraud Detection

A.1.7.1 Graph Neural Networks (GNNs) with Temporal Attention

Temporal attention in Graph Neural Networks (GNNs) refers to the mechanism of selectively focusing on specific time points or intervals within a temporal graph, where nodes and edges evolve over time. This attention mechanism allows the model to prioritize and weigh the importance of different temporal information, enabling it to capture complex temporal dependencies and patterns within the graph. By incorporating temporal attention, GNNs can effectively process dynamic graph data and make predictions or classifications based on the most relevant temporal information. GNNs enhanced with temporal attention mechanisms can capture both the structural and temporal aspects of PDL networks, making them powerful for predictive fraud detection [i.18].

- **Application in PDL Networks:**
  1) Can model the evolving structure of transaction networks over time.
  2) Capable of learning patterns that precede fraudulent activities.
  3) Can predict potential fraud by analysing the current state of the network in the context of historical patterns.
- **Key Advantages:**
  1) Naturally suited to the graph-like structure of PDL transaction networks.
  2) Can capture complex temporal dependencies in transaction patterns.
  3) Able to incorporate both structural and temporal information for more accurate predictions.

A.1.7.2 Transformer-based Models with Self-Supervised Pre-training

Self-Supervised Pre-training in the context of Transformer-based models refers to a pretraining procedure where the model learns to generate supervisory signals from the data itself, without relying on external labels. This is achieved by designing pretext tasks that leverage the structure of the data. The model is trained on these pretext tasks using large amounts of unlabelled data, allowing it to learn contextualized representations that can be fine-tuned for downstream tasks. Transformer models, pre-trained on large volumes of unlabelled transaction data using self-supervised techniques, can capture complex patterns in sequential transaction data that can indicate fraudulent activities [i.19].

- **Application in PDL Networks:**
  1) Can analyse sequences of transactions to predict future fraudulent activities.
  2) Capable of capturing long-range dependencies in user behaviour patterns.
  3) Can be fine-tuned on labelled fraud data for specific PDL environments.
- **Key Advantages:**
  1) Excellent at capturing complex, long-range patterns in sequential data.

2) Can leverage large amounts of unlabelled data for pre-training.

3) Attention mechanisms allow the model to focus on the most relevant parts of the input for fraud prediction.

A.1.7.3 Federated Deep Learning with Differential Privacy

Differential Privacy (DP) in the context of Federated Deep Learning is a mathematical framework that provides formal guarantees on the privacy of individual data points during the training process. It ensures that the model updates shared by clients do not reveal sensitive information about their local data. DP achieves this by adding noise to the model updates, bounding the contribution of any individual client, and limiting the sensitivity of the training mechanism to any single data point. This approach prevents an adversary from inferring sensitive information about individual data points, even if they have access to the aggregated model updates.

By integrating DP with federated learning, it is possible to train models collaboratively while preserving the privacy of the clients' data. Federated learning allows multiple parties to collaboratively train a fraud detection model without sharing raw data, while differential privacy ensures individual privacy is protected [i.20].

- **Application in PDL Networks:**

  1) Enables collaborative fraud prediction across multiple nodes or organizations in a PDL network.

  2) Can learn from diverse data sources while keeping sensitive transaction data localized.

  3) Allows for the creation of more robust fraud prediction models by leveraging data from multiple sources.

- **Key Advantages:**

  1) Preserves privacy and data sovereignty in multi-party PDL networks.

  2) Improves fraud prediction accuracy through access to larger, more diverse datasets.

  3) Can adapt to local variations in fraudulent behaviours while benefiting from global knowledge.

A.1.8 Examples of Continuous Learning Machine Learning Models for Fraud Detection

A.1.8.1 Online Adaptive Graph Neural Networks (OAGNNs)

Online Adaptive Graph Neural Networks (OAGNNs) are a type of neural network architecture designed to process graph-structured data in an online and adaptive manner. They combine the strengths of Graph Neural Networks (GNNs) with online learning and adaptive mechanisms, enabling them to learn from streaming graph data and adapt to changing graph structures and node features over time. OAGNNs can update their parameters incrementally as new data arrives, allowing them to handle dynamic graphs and learn from temporal dependencies in the data [i.21].

- **Application in PDL Networks:**

  1) Can continuously update the model of the transaction network as new transactions occur.

  2) Capable of adapting to evolving fraud patterns in real-time.

  3) Can immediately incorporate feedback on detected frauds to improve future predictions.

- **Key Advantages:**

  1) Naturally suited to the dynamic, graph-like structure of PDL transaction networks.

  2) Can handle concept drift in fraud patterns over time.

  3) Allows for immediate model updates without full retraining.

A.1.8.2 Incremental Learning with Ensemble Methods

Incremental Learning with Ensemble Methods is a machine learning approach that combines the strengths of incremental learning and ensemble methods to handle streaming data and adapt to changing environments. Incremental learning involves updating a model incrementally as new data arrives, without requiring access to the entire dataset. Ensemble methods combine the predictions of multiple models to improve overall performance. By integrating incremental learning with ensemble methods, this approach enables models to learn from new data, adapt to concept drift, and improve their performance over time. These models use ensemble techniques (like Random Forests or Gradient Boosting, see notes below) modified for incremental learning, allowing them to continuously incorporate new data without full retraining making them an effective fraud detection tool [i.22].

- **Application in PDL Networks:**

  1) Can continuously update fraud detection models as new transaction data becomes available.

  2) Capable of maintaining a diverse set of fraud detection rules that evolve over time.

  3) Can adapt to changes in normal transaction patterns, reducing false positives over time.

- **Key Advantages:**

  1) Can handle concept drift in both normal and fraudulent transaction patterns.

  2) Maintains model interpretability, which is crucial for explaining fraud detections.

  3) Efficient updating process, suitable for high-throughput PDL environments.

NOTE 1: Random Forests are an ensemble learning method that combines multiple decision trees to improve the accuracy and robustness of predictions. Each decision tree in the forest is trained on a random subset of the data and a random selection of features, which helps to reduce overfitting and improve generalization. The predictions from each tree are then combined using voting or averaging to produce the final prediction.

NOTE 2: Gradient Boosting is a machine learning algorithm that combines multiple weak models to create a strong predictive model. It works by iteratively adding decision trees to the model, with each subsequent tree attempting to correct the errors of the previous tree.

A.1.8.3 Federated Continual Learning

Federated Continual Learning is a machine learning paradigm that combines the concepts of federated learning (see clause 8.4 on Federated Learning) and continual learning (see clause 4.3.6 on Continual Learning and Improvement). Federated learning involves training a model on decentralized data sources, while continual learning involves adapting a model to new tasks or data without forgetting previously learned knowledge. Federated Continual Learning enables a model to learn from a stream of data distributed across multiple devices or clients, while continuously adapting to new tasks, data, or environments. This approach allows for efficient and secure learning on edge devices, reducing the need for data transmission and preserving data privacy. By combining federated and continual learning, models can learn from diverse data sources and adapt to changing conditions, making them suitable for applications such as IoT, autonomous vehicles, and healthcare [i.23].

- **Application in PDL Networks:**

  1) Enables continuous, collaborative fraud detection model improvement across multiple nodes or organizations in a PDL network.

  2) Can learn from new fraud patterns observed across the network without centralizing sensitive data.

  3) Allows the model to adapt to local variations in transaction patterns while benefiting from network-wide knowledge.

- **Key Advantages:**

  1) Preserves privacy and data sovereignty in multi-party PDL networks.

  2) Can continuously improve fraud detection accuracy using data from multiple sources.

3) Resistant to catastrophic forgetting, maintaining knowledge of historical fraud patterns while learning new ones.

A.1.9 Examples of Machine Learning Models for Reducing False Positives in Fraud Detection

A.1.9.1 Attention-based Graph Neural Networks with Explainable AI

Attention-based Graph Neural Networks (GNNs) with Explainable AI are a type of neural network architecture that combines the strengths of graph neural networks and attention mechanisms to provide interpretable and transparent predictions on graph-structured data. These networks use attention mechanisms to selectively focus on the most relevant nodes and edges in the graph, enabling them to learn complex relationships and patterns within the data. By incorporating explainable AI techniques, such as gradient-based attribution methods, decomposition, and perturbation-based approaches [i.24].

- **Application in PDL Networks:**

  1) Can model complex relationships in transaction networks while focusing on the most relevant features for fraud detection.

  2) Provides explanations for fraud predictions, allowing for human verification and reduction of false positives.

  3) Can adapt to the evolving structure of PDL transaction networks.

- **Key Advantages:**

  1) High accuracy in detecting complex fraud patterns.

  2) Interpretability helps in understanding and verifying fraud predictions, reducing false positives.

  3) Can handle the dynamic nature of PDL networks.

A.1.9.2 Hybrid Models Combining Anomaly Detection with Supervised Learning

Hybrid Models Combining Anomaly Detection with Supervised Learning are a type of machine learning approach that integrates the strengths of anomaly detection and supervised learning to improve the accuracy and robustness of predictive models. These models use anomaly detection techniques, such as One-Class SVM or Autoencoders (see notes below), to identify outliers and anomalies in the data, and then leverage supervised learning algorithms, such as neural networks or decision trees, to classify the remaining data points. By combining these two approaches, hybrid models can effectively handle imbalanced datasets, reduce the impact of noisy or outlier data, and improve the overall performance of the predictive model. This approach is particularly useful in applications such as fraud detection and network intrusion detection, where identifying anomalies and outliers is crucial for making accurate predictions [i.25].

- **Application in PDL Networks:**

  1) Anomaly detection identifies unusual transactions based on learned normal patterns.

  2) Supervised learning then classifies these anomalies as fraudulent or legitimate, reducing false positives.

  3) Can continuously update the notion of "normal" behaviour in the PDL network.

- **Key Advantages:**

  1) Combines the strengths of both unsupervised and supervised learning.

  2) Can detect novel fraud patterns while maintaining low false positive rates.

  3) Adaptable to changing transaction patterns in PDL networks.

NOTE 1: One-Class Support Vector Machine (SVM) is a machine learning algorithm primarily used for anomaly detection and classification tasks. It works by finding the best boundary that separates data points into different classes, making it a powerful tool for identifying outliers and distinguishing between normal and abnormal data.

NOTE 2: Autoencoders are a type of neural network that learns to compress and reconstruct data. They consist of an encoder that maps the input data to a lower-dimensional latent space and a decoder that reconstructs the original data from this latent space.

A.1.9.3 Federated Learning with Adaptive Boosting

Federated Learning with Adaptive Boosting is a machine learning approach that combines the principles of federated learning and adaptive boosting (see note below) to improve the performance and robustness of models trained on decentralized data sources. In this approach, multiple clients or devices collaboratively train a model by sharing model updates with a central server, which aggregates the updates to improve the global model [i.26].

- **Application in PDL Networks:**

  1) Enables collaborative fraud detection across multiple parties without sharing raw transaction data.

  2) Adaptive boosting focuses on hard-to-classify cases, reducing false positives over time.

  3) Can adapt to local variations in transaction patterns while benefiting from network-wide knowledge.

- **Key Advantages:**

  1) Preserves privacy and data sovereignty in multi-party PDL networks.

  2) Adaptive boosting helps in reducing false positives by focusing on boundary cases.

  3) Can handle imbalanced data, which is common in fraud detection scenarios.

NOTE: Adaptive Boosting is a machine learning technique that combines multiple weak models to create a strong predictive model. It works by iteratively training a sequence of models, with each subsequent model focusing on the errors of the previous model. The algorithm adaptively adjusts the weights of the training data, increasing the weight of misclassified samples and decreasing the weight of correctly classified samples. This process allows the model to concentrate on the most difficult-to-classify samples, improving its overall performance.

A.2 Examples related to clause 5 (Smart contract optimization using AI)

A.2.1 Examples of AI-Powered Static Code Analysis Tools

A.2.1.1 DeepCode

- **Developer:** Snyk (acquired DeepCode in 2020)
- **Description:** DeepCode uses machine learning to analyse code and detect bugs, security vulnerabilities, and quality issues. It learns from millions of open-source commits to provide context-aware recommendations [i.27].
- **Key Features:**

  - Real-time AI-powered code analysis
  - Ability to learn from code changes and user feedback
  - Integration with popular IDEs and CI/CD pipelines

A.2.1.2 Infer®

- **Developer:** Facebook®
- **Description:** While Infer has been around for a while, recent versions have incorporated more AI and machine learning techniques. It uses separation logic and bi-abduction to analyse code and detect bugs [i.28].
- **Key Features:**
  - Interprocedural analysis
  - Incremental analysis for large codebases
  - Support for multiple programming languages

A.2.1.3 CodeQL®

- **Developer:** GitHub® (Semmle)
- **Description:** CodeQL treats code as data, allowing for the application of AI and machine learning techniques to detect complex code patterns and potential vulnerabilities [i.29].
- **Key Features:**
  - Customizable queries for specific code patterns
  - Integration with GitHub's security features
  - Support for multiple programming languages

A.2.2 Examples of AI-Based Machine Learning Algorithms for Smart Contract Optimization

A.2.2.1 Deep Reinforcement Learning for Dynamic Gas Optimization

- **Description:** This approach uses deep reinforcement learning to dynamically optimize gas usage in smart contracts during execution [i.30].
- **Application:**
  1) Learn optimal gas price strategies for contract deployment and function calls.
  2) Dynamically adjust contract parameters to minimize gas usage based on network conditions.
  3) Predict and optimize gas consumption for complex multi-step contract interactions.
- **Key Advantages:**
  1) Can adapt to changing network conditions in real-time.
  2) Learns from actual contract executions to continually improve optimization strategies.
  3) Can balance multiple objectives such as gas cost, execution speed, and transaction success probability.

A.2.2.2 Graph Neural Networks with Attention for Code Pattern Recognition

- **Description:** This algorithm combines Graph Neural Networks with attention mechanisms to recognize and optimize complex code patterns in smart contracts [i.31].
- **Application:**
  1) Identify gas-intensive code patterns across multiple connected contracts.

2) Suggest structural changes to contract architecture for better gas efficiency.

3) Recognize similar patterns in different contracts and apply learned optimizations.

- **Key Advantages:**

1) Can capture complex relationships between different parts of a contract and between multiple contracts.

2) Attention mechanisms allow focus on the most relevant parts of the code for optimization.

3) Can provide explanations for suggested optimizations, improving trustworthiness.

A.2.2.3 Transformer-based Model with Transfer Learning for Cross-Language Optimization

- **Description:** This approach uses a transformer-based model pre-trained on multiple programming languages and fine-tuned on smart contract languages to suggest cross-language optimizations [i.32].

- **Application:**

1) Translate gas-efficient patterns from other languages to smart contract languages.

2) Generate optimized versions of common smart contract functions.

3) Suggest alternative implementations of gas-intensive operations based on patterns learned from other languages.

- **Key Advantages:**

1) Can leverage optimization techniques from a wide range of programming languages.

2) Able to generate human-readable code suggestions for optimizations.

3) Can understand and optimize complex language-specific constructs.

A.2.2.4 Hyperledger Caliper®

- **Developer:** Hyperledger Foundation

- **Description:** While not specifically for smart contracts, Caliper uses machine learning techniques to benchmark and optimize blockchain performance, which can indirectly improve smart contract efficiency [i.33].

- **Key Features:** Provides performance benchmarks, analyses resource utilization, and offers insights for optimization.

A.2.2.5 OptSmart

- **Developer:** Researchers from the University of Cagliari

- **Description:** OptSmart uses genetic algorithms, a form of AI, to optimize smart contract code for gas efficiency [i.34].

- **Key Features:** Automatically generates optimized versions of smart contracts, focuses on reducing gas costs while maintaining functionality.

A.2.3 Examples of AI Algorithms for Identifying Smart Contract Vulnerabilities

A.2.3.1 Graph Neural Networks (GNNs) with Semantic-Aware Embedding

- **Description:** This approach uses GNNs to model the structure of smart contracts, combined with semantic-aware embedding to capture the meaning and context of contract operations [i.31].
- **Application in Smart Contract Security:**
  1) Model smart contracts as graphs, with nodes representing operations and edges representing control and data flow.
  2) Identify patterns associated with known vulnerabilities, such as reentrancy and unauthorized access.
  3) Detect potential new vulnerability patterns based on structural and semantic similarities.
- **Key Advantages:**
  1) Can capture complex relationships between different parts of a smart contract.
  2) Semantic-aware embedding improves understanding of contract behaviour and intent.
  3) Generalizable to different types of vulnerabilities and contract structures.

A.2.3.2 Transformer-based Models with Transfer Learning

- **Description:** This algorithm uses transformer-based models pre-trained on a large corpus of code, then fine-tuned on smart contract code to identify vulnerabilities [i.35].
- **Application in Smart Contract Security:**
  1) Analyse smart contract code to identify patterns associated with known vulnerabilities.
  2) Leverage knowledge from other programming languages to identify potential security issues.
  3) Generate natural language explanations of identified vulnerabilities.
- **Key Advantages:**
  1) Can understand complex code structures and patterns across different programming languages.
  2) Able to generate human-readable explanations of vulnerabilities.
  3) Can be continually updated with new vulnerability patterns.

A.2.3.3 Reinforcement Learning with Symbolic Execution

- **Description:** This approach combines reinforcement learning with symbolic execution to actively explore smart contract behaviour and identify potential vulnerabilities [i.36].
- **Application in Smart Contract Security:**
  1) Use reinforcement learning to guide exploration of contract execution paths.
  2) Apply symbolic execution to precisely analyse the conditions under certain vulnerabilities when they occur.
  3) Identify complex vulnerabilities that can only become manifest under specific conditions.
- **Key Advantages:**
  1) Can discover vulnerabilities that could be missed by static analysis techniques.

2) Able to provide concrete examples of vulnerability exploitation.

3) Can adapt and improve its exploration strategy over time.

A.2.4 Examples of AI Algorithms for Code Generation and Optimization in PDL Platforms

A.2.4.1 Large Language Models with Few-Shot Learning

- **Description:** This approach uses Large Language Models (LLMs) pre-trained on vast amounts of code, combined with few-shot learning techniques to adapt to specific PDL platforms and developer intents [i.37].
- **Application in PDL Development:**
  1) Generate boilerplate code for common PDL patterns and structures.
  2) Suggest refactoring options based on best practices and platform-specific optimizations.
  3) Propose entire sections of optimized code tailored to the developer's intent and PDL platform requirements.
- **Key Advantages:**
  1) Can understand and generate code across multiple programming languages relevant to PDL development.
  2) Adaptable to specific PDL platforms with minimal additional training.
  3) Can provide context-aware suggestions based on the surrounding code and developer comments.

A.2.4.2 Graph-to-Code Neural Networks with Attention

- **Description:** This algorithm uses graph neural networks to model the structure of existing code, combined with attention mechanisms to generate new code or suggest optimizations [i.38].
- **Application in PDL Development:**
  1) Analyse existing code structure to suggest context-appropriate refactoring options.
  2) Generate optimized code sections based on the overall structure of the smart contract or PDL application.
  3) Propose boilerplate code that fits seamlessly into the existing codebase structure.
- **Key Advantages:**
  1) Can capture and utilize the structural relationships within existing code.
  2) Attention mechanisms allow focus on the most relevant parts of the code for generation or optimization.
  3) Well-suited to handling the complex, interconnected nature of PDL applications.

A.2.4.3 Hierarchical Transformers with Code Semantic Embedding

- **Description:** This approach uses a hierarchical transformer architecture combined with code semantic embedding to understand and generate code at multiple levels of abstraction [i.39].
- **Application in PDL Development:**
  1) Generate boilerplate code that adheres to PDL-specific patterns and best practices.
  2) Suggest refactoring options that consider both local code structure and broader application semantics.

3) Propose optimized code sections that align with the overall intent and structure of the PDL application.

- **Key Advantages:**

1) Can understand and generate code at multiple levels, from individual lines to entire functions or modules.

2) Semantic embedding allows for better understanding of code intent and functionality.

3) Hierarchical structure is well-suited to handling the complexity of PDL applications.

A.2.5 Examples of AI-Powered NLP Tools for Smart Contract Documentation

A.2.5.1 CodeBERT-based Documentation Generation

- **Description:** This approach uses CodeBERT, a pre-trained language model for programming languages, fine-tuned on smart contract code to generate natural language descriptions of contract functionality [i.40].

- **Application in PDL Platforms:**

1) Analyse smart contract code structure and semantics.

2) Generate human-readable descriptions of contract functions, variables, and overall purpose.

3) Provide explanations of complex logic and potential security considerations.

- **Key Advantages:**

1) Pre-training on diverse codebases allows for understanding of general programming concepts.

2) Fine-tuning on smart contracts enables platform-specific knowledge.

3) Can generate contextually relevant documentation that explains both what the code does and why.

A.2.5.2 Graph-to-Sequence Neural Networks for Contract Summarization

- **Description:** This tool uses a graph-to-sequence neural network to model the structure of smart contracts as graphs and generate natural language summaries [i.41]

- **Application in PDL Platforms:**

1) Convert smart contract code into a graph representation, capturing control and data flow.

2) Generate high-level summaries of contract behaviour and purpose.

3) Provide detailed explanations of complex interactions between different contract components.

- **Key Advantages:**

1) Graph representation captures structural relationships in the code.

2) Can handle complex, non-linear code structures common in smart contracts.

3) Generates summaries that reflect the overall structure and flow of the contract.

A.2.5.3 Hierarchical Transformer with Code-Text Alignment

- **Description:** This approach uses a hierarchical transformer architecture with a code-text alignment mechanism to generate multi-level documentation for smart contracts [i.42].

- **Application in PDL Platforms:**

1) Analyse smart contract code at multiple levels of abstraction.

2) Generate documentation ranging from high-level overviews to detailed function descriptions.

3) Align generated text with specific code sections for traceability.

- **Key Advantages:**

1) Hierarchical approach allows for coherent documentation at multiple granularities.

2) Code-text alignment helps developers quickly relate documentation to specific code sections.

3) Can generate documentation that explains both individual components and their interactions.

A.2.6 Examples of AI-Based Machine Learning Algorithms for Smart Contract Test Case Generation

A.2.6.1 Deep Reinforcement Learning for Adaptive Fuzzing

- **Description:** This approach uses deep reinforcement learning to guide a fuzzing process, adaptively generating test inputs that maximize code coverage and vulnerability detection [i.43].

- **Application in PDL Platforms:**

1) Analyse smart contract structure and identify potential vulnerability points.

2) Generate diverse test inputs that explore different execution paths.

3) Adapt the fuzzing strategy based on feedback from contract execution.

- **Key Advantages:**

1) Can discover complex vulnerabilities by learning optimal fuzzing strategies.

2) Adapts to different contract structures and PDL platform specifications.

3) Improves efficiency by focusing on promising areas of the input space.

A.2.6.2 Graph Neural Networks with Symbolic Execution

- **Description:** This algorithm combines Graph Neural Networks (GNNs) with symbolic execution to understand contract structure and generate targeted test cases [i.44].

- **Application in PDL Platforms:**

1) Model smart contracts as graphs, capturing control and data flow.

2) Use GNNs to identify potentially vulnerable or complex code sections.

3) Apply symbolic execution to generate precise test cases for identified sections.

- **Key Advantages:**

1) Captures complex structural and semantic properties of smart contracts.

2) Generates highly targeted test cases for specific vulnerability types.

3) Can handle large and complex contracts efficiently.

A.2.6.3 Transformer-based Models with Program Synthesis

- **Description:** This approach uses transformer-based models pre-trained on a large corpus of smart contracts, combined with program synthesis techniques to generate diverse and semantically valid test cases [i.45].

- **Application in PDL Platforms:**
  1) Analyse contract code and specifications using natural language processing.
  2) Generate synthetic contracts that represent edge cases or potential vulnerabilities.
  3) Create test cases that exercise these synthetic contracts against the original contract.
- **Key Advantages:**
  1) Can generate semantically meaningful test cases based on contract intent.
  2) Leverages knowledge from a wide range of existing contracts.
  3) Capable of generating complex, multi-step test scenarios.

A.2.7 Examples of AI-Driven Fuzzing Techniques for Smart Contract Testing

A.2.7.1 Reinforcement Learning-based Adaptive Fuzzing

- **Description:** This technique uses reinforcement learning to guide the fuzzing process, adaptively generating and mutating test inputs to maximize code coverage and vulnerability detection [i.46].
- **Application in PDL Platforms:**
  1) Analyse smart contract structure to identify potential vulnerability points.
  2) Generate and mutate test inputs that explore different execution paths.
  3) Adapt the fuzzing strategy based on feedback from contract execution.
- **Key Advantages:**
  1) Can discover complex vulnerabilities by learning optimal fuzzing strategies.
  2) Adapts to different contract structures and PDL platform specifications.
  3) Efficiently explores the input space by focusing on promising areas.

A.2.7.2 Neuro-Symbolic Execution with Mutation

- **Description:** This approach combines neural networks with symbolic execution to guide both input generation and code mutation, creating a powerful hybrid fuzzing technique [i.47].
- **Application in PDL Platforms:**
  1) Use neural networks to predict promising code paths and mutation points.
  2) Apply symbolic execution to generate precise inputs for chosen paths.
  3) Perform intelligent code mutations to test contract robustness.
- **Key Advantages:**
  1) Combines the strengths of machine learning and formal methods.
  2) Generates highly targeted test cases and mutations.
  3) Can handle complex contracts with large state spaces efficiently.

A.2.7.3 Evolutionary Fuzzing with Natural Language Processing (NLP)

- **Description:** This technique uses evolutionary algorithms guided by NLP-based understanding of contract specifications to generate and evolve both test inputs and code mutations [i.47].
- **Application in PDL Platforms:**
  1) Analyse contract code and specifications using NLP.
  2) Generate an initial population of test cases and code mutations.
  3) Evolve test cases and mutations to maximize coverage and vulnerability detection.
- **Key Advantages:**
  1) Generates semantically meaningful test cases and mutations based on contract intent.
  2) Adapts testing strategy based on the specific requirements of each contract.
  3) Can generate complex, multi-step test scenarios and subtle code mutations.

A.2.8 Examples of AI-Based Tools for Formal Verification of Smart Contracts

A.2.8.1 Neural-Guided Theorem Prover (NGTP)

- **Description:** This tool uses neural networks to guide the theorem proving process, automatically generating formal specifications and proof strategies from smart contract code [i.48].
- **Application in PDL Platforms:**
  1) Analyse smart contract code to extract key properties and invariants.
  2) Generate formal specifications in a theorem prover's language (e.g. Coq, Isabelle/HOL).
  3) Guide the theorem proving process to verify critical safety and liveness properties.
- **Key Advantages:**
  1) Reduces the manual effort required in formal verification.
  2) Can handle complex contracts by learning from a large corpus of verified contracts.
  3) Improves the efficiency of the theorem proving process through learned heuristics.

NOTE 1: Coq is a formal proof management system and dependently typed functional programming language based on the Calculus of Inductive Constructions.

NOTE 2: Isabelle/HOL is a generic proof assistant that allows mathematical formulas to be expressed in a formal language and provides tools for proving those formulas in a logical calculus.

A.2.8.2 Transformer-based Model Checker (TMC)

- **Description:** This tool uses transformer-based models to translate smart contract code into formal models suitable for model checking, and to generate temporal logic specifications [i.49].
- **Application in PDL Platforms:**
  1) Translate smart contract code into a formal model (e.g. in the input language of SPIN or NuSMV).
  2) Generate Linear Temporal Logic (LTL) or Computation Tree Logic (CTL) specifications from natural language contract descriptions.

3) Automate the model checking process and interpret the results.

- **Key Advantages:**

1) Can handle diverse contract languages and structures.

2) Generates human-readable formal models and specifications.

3) Leverages large-scale pre-training on code and specifications.

NOTE 1: Simple Promela INterpreter (SPIN) uses Process Meta Language (PROMELA) as its input language. This language is designed specifically for modelling and verifying concurrent systems.

NOTE 2: New Symbolic Model Verifier (NuSMV) is a symbolic model checker that extends SMV with novel features and algorithms.

NOTE 3: Symbolic Model Verifier (SMV) is a pioneering formal verification tool developed at Carnegie Mellon University that introduced symbolic model checking using Binary Decision Diagrams (BDDs).

NOTE 4: LTL is a modal temporal logic that describes sequences of transitions in a system over linear time, meaning each moment has exactly one possible future.

NOTE 5: CTL is a branching-time logic that considers all possible future paths at each moment, allowing quantification over paths using universal (A - "all paths") and existential (E - "exists a path") path quantifiers combined with temporal operators.

A.2.8.3 Graph Neural Network-based Invariant Synthesizer (GNNIS)

- **Description:** This tool uses Graph Neural Networks to analyse the structure of smart contracts and automatically synthesize invariants for formal verification [i.50].

- **Application in PDL Platforms:**

1) Represent smart contracts as graphs capturing control and data flow.

2) Learn common invariant patterns from a large corpus of verified contracts.

3) Synthesize invariants for new contracts based on their graph structure.

- **Key Advantages:**

1) Captures complex structural properties of smart contracts.

2) Can generalize across different contract types and PDL platforms.

3) Produces human-interpretable invariants that aid in the verification process.

A.2.9 Examples of AI-Enhanced Symbolic Execution Techniques for Smart Contract Analysis

A.2.9.1 Neural-Guided Symbolic Execution (NGSE)

- **Description:** This technique uses neural networks to guide the path exploration in symbolic execution, prioritizing paths that are more likely to lead to vulnerabilities or logical errors [i.51].

- **Application in PDL Platforms:**

1) Analyse smart contract code to identify potentially vulnerable execution paths.

2) Use machine learning models to predict which paths are most likely to contain bugs.

3) Guide symbolic execution to explore high-risk paths more thoroughly.

- **Key Advantages:**
  1) Significantly improves the efficiency of symbolic execution by focusing on likely vulnerable paths.
  2) Can handle large and complex smart contracts by prioritizing exploration.
  3) Adapts to different types of vulnerabilities and contract structures through learning.

A.2.9.2 Reinforcement Learning-based Concolic Testing (RLCT)

- **Description:** This approach combines concolic testing (a hybrid of concrete and symbolic execution) with reinforcement learning to dynamically adjust the exploration strategy [i.36].
- **Application in PDL Platforms:**
  1) Use concrete execution to gather initial path information.
  2) Apply symbolic constraints to generate new inputs for unexplored paths.
  3) Utilize reinforcement learning to optimize the selection of paths and constraint solving strategies.
- **Key Advantages:**
  1) Balances concrete execution speed with symbolic execution's thoroughness.
  2) Adapts the testing strategy based on feedback from previous executions.
  3) Can effectively handle complex smart contract logic and external interactions.

A.2.9.3 Graph Neural Network-Enhanced Symbolic Execution (GNN-SE)

- **Description:** This technique uses Graph Neural Networks to model the control flow and data dependencies in smart contracts, enhancing symbolic execution with learned contract representations [i.31].
- **Application in PDL Platforms:**
  1) Represent smart contracts as graphs capturing control flow and data dependencies.
  2) Use GNNs to learn embeddings of contract states and transitions.
  3) Guide symbolic execution using the learned representations to identify potentially vulnerable states and transitions.
- **Key Advantages:**
  1) Captures complex structural properties of smart contracts.
  2) Can identify potential vulnerabilities that span multiple functions or transactions.
  3) Improves scalability by focusing symbolic execution on relevant parts of the contract.

A.2.10 Examples of AI-Based Tools for Smart Contract DevSecOps Pipelines

A.2.10.1 SmartBugs: AI-Enhanced Vulnerability Detection Pipeline

- **Description:** SmartBugs is an execution framework that integrates multiple analysis tools and enhances them with AI-based prioritization and result aggregation [i.52].
- **Key Features:**
  1) Integrates multiple static and dynamic analysis tools.

2) Uses machine learning to prioritize which tools to run based on contract characteristics.

3) Aggregates and deduplicates results using natural language processing.

4) Provides CI/CD integration for automated security checking.

- **AI Enhancement:**

1) Employs a neural network to predict which analysis tools are most likely to find vulnerabilities in a given contract.

2) Uses NLP techniques to classify and cluster similar vulnerability reports.

A.2.10.2 ContractGuard: Automated Verification and Deployment Framework

- **Description:** ContractGuard is an automated framework that combines formal verification, fuzzing, and machine learning-based vulnerability detection in a CI/CD pipeline [i.53].

- **Key Features:**

1) Automated formal verification using predefined and learned specifications.

2) AI-guided fuzzing for dynamic analysis.

3) Machine learning-based vulnerability pattern recognition.

4) Integrated deployment gating based on security and correctness criteria.

- **AI Enhancement:**

1) Uses reinforcement learning to guide the fuzzing process.

2) Employs a graph neural network to detect complex vulnerability patterns.

A.2.10.3 AISecOps: AI-Driven Security Operations for Smart Contracts

- **Description:** AISecOps is a comprehensive DevSecOps platform that integrates AI-driven security analysis throughout the smart contract development lifecycle [i.54].

- **Key Features:**

1) Continuous security monitoring during development.

2) AI-powered code review and suggestion system.

3) Automated test case generation based on contract specifications.

4) Risk assessment and deployment recommendations.

- **AI Enhancement:**

1) Uses natural language processing to understand contract specifications and generate test cases.

2) Employs a transformer-based model for code review and improvement suggestions.

3) Utilizes a multi-agent reinforcement learning system for risk assessment.

A.2.11 Examples of AI Systems for Continuous Improvement in Smart Contract Security

A.2.11.1 VELMA: Vulnerability-driven Evolutionary Learning for Smart Contract Auditing

- **Description:** VELMA is an AI system that uses evolutionary algorithms and machine learning to continuously evolve its vulnerability detection capabilities based on historical data and newly discovered exploits [i.55].
- **Key Features:**
  1) Automated learning from newly discovered vulnerabilities and exploits.
  2) Evolutionary generation of new security patterns and test cases.
  3) Integration with real-time blockchain monitoring for rapid threat detection.
- **Continuous Improvement Mechanism:**
  1) Uses genetic algorithms to evolve its vulnerability detection rules.
  2) Employs reinforcement learning to optimize its testing strategies.
  3) Incorporates federated learning to securely share knowledge across multiple blockchain networks.

A.2.11.2 SCSCAN: Self-Correcting Smart Contract Vulnerability Scanner

- **Description:** SCSCAN is an adaptive AI system that combines deep learning and symbolic execution to continuously improve its vulnerability detection capabilities [i.36].
- **Key Features:**
  1) Dynamic updating of vulnerability patterns based on new data.
  2) Self-correction mechanism to reduce false positives over time.
  3) Integration of multi-modal data sources, including code, transaction histories, and developer feedback.
- **Continuous Improvement Mechanism:**
  1) Uses a deep neural network to learn and update vulnerability patterns.
  2) Employs active learning to selectively query experts on uncertain cases.
  3) Utilizes a bayesian optimization framework to continuously refine its detection thresholds.

A.2.11.3 ASTRAEA: Adaptive Smart conTRact Auto-Evaluation and Auditing

- **Description:** ASTRAEA is a comprehensive AI system that combines multiple machine learning techniques to continuously adapt and improve its smart contract auditing capabilities [i.56].
- **Key Features:**
  1) Multi-agent reinforcement learning for adaptive testing strategies.
  2) Natural language processing for analysing smart contract specifications and comments.
  3) Graph neural networks for detecting complex, multi-contract vulnerabilities.
- **Continuous Improvement Mechanism:**
  1) Uses meta-learning to quickly adapt to new types of vulnerabilities.

2) Employs continual learning techniques to prevent catastrophic forgetting of old vulnerability patterns.

3) Integrates a knowledge graph that continuously updates with new vulnerability information and exploit data.

A.3 Examples related to clause 8: Privacy-preserving techniques

A.3.1 Examples of Federated Learning

A.3.1.1 PySyft

PySyft is an open-source library for secure and private deep learning [i.67]. It extends PyTorch with federated learning, differential privacy, and encrypted computation capabilities. PySyft is well-suited for projects requiring integration with PyTorch and strong privacy guarantees.

EXAMPLE: Researchers used PySyft to develop a federated learning system for predicting hospital readmissions across multiple healthcare institutions without sharing patient data.

A.3.1.2 Flower

Flower is a friendly federated learning framework designed for flexibility and ease of use [i.68]. It supports a wide range of client devices and ML frameworks. It is well-suited for projects requiring support for heterogeneous client environments.

EXAMPLE: Researchers used Flower to implement a federated learning system for mobile keyboard prediction across diverse Android devices.

A.3.1.3 OpenFL

OpenFL is an open-source framework for federated learning, focusing on healthcare and life sciences applications [i.69]. It provides robust security features and supports various ML frameworks. It is well-suited for healthcare and life sciences projects with stringent data privacy requirements.

EXAMPLE: A pharmaceutical company used OpenFL to develop a drug discovery model collaborating with multiple research institutions while keeping molecular data private.

A.3.1.4 FedML

FedML is a research-oriented federated learning library that supports various FL algorithms, topologies, and benchmarks [i.70]. It is designed to facilitate rapid prototyping and experimentation. FedML can be considered for academic research projects and algorithm development.

EXAMPLE: Researchers used FedML to compare the performance of different federated optimization algorithms on a multi-institutional medical imaging dataset.

A.3.2 Examples of Differential Privacy in Machine Learning

A.3.2.1 Differentially Private Stochastic Gradient Descent (DP-SGD)

DP-SGD adds calibrated noise to gradients during model training to protect individual data points [i.71].

EXAMPLE: In a medical image classification task, DP-SGD can be used to train a convolutional neural network on sensitive patient data while providing privacy guarantees.

[D38] Users of this method **can** start with a larger privacy budget (epsilon) and gradually decrease it to find the optimal privacy-utility trade-off.

A.3.2.2 Differentially Private Follow The Regularized Leader (DP-FTRL)

DP-FTRL is an optimization algorithm that provides differential privacy guarantees for online learning scenarios [i.72].

EXAMPLE: In a recommendation system that continuously learns from user interactions, DP-FTRL can be used to update the model while protecting individual user privacy.

[D39] Users **can** carefully tune the learning rate and regularization parameters to balance privacy and model performance.

A.3.2.3 Gaussian Differential Privacy (GDP)

Description: GDP uses Gaussian noise instead of Laplace noise, providing tighter privacy bounds for complex machine learning models [i.73].

EXAMPLE: In federated learning for mobile keyboard prediction, GDP can be applied to protect user input data while allowing for personalized model updates.

NOTE 1: Gaussian noise, also known as Gaussian white noise, is a type of statistical noise characterized by a probability density function that follows a normal (Gaussian) distribution. In the context of machine learning and deep learning, Gaussian noise is often intentionally added to training data or model parameters as a regularization technique to improve generalization and robustness of models.

NOTE 2: Laplace noise is a type of statistical noise that follows a Laplace distribution. It is commonly used in differential privacy applications, particularly in the Laplace mechanism for achieving differential privacy.

[O9] GDP **can** be used when dealing with high-dimensional data or when requiring tighter composition theorems.

A.3.3 Examples of Generative Adversarial Networks (GANs) for synthetic data generation

A.3.3.1 Privacy-Preserving Synthetic Data Generation Using Conditional GANs

Conditional Generative Adversarial Networks (CGANs) have emerged as a powerful tool for privacy-preserving synthetic data generation. Here's an elaboration on how CGANs can be used to preserve privacy while generating synthetic data [i.74]. By leveraging CGANs for synthetic data generation, PDL systems can enhance their data sharing and analysis capabilities while maintaining robust privacy protections for sensitive information.

1) **Concept:**
   CGANs extend the traditional GAN architecture by conditioning both the generator and discriminator on additional information. This allows for more controlled and targeted data generation.

2) **Privacy Preservation:**
   By training on real data but only releasing synthetic data, CGANs can help preserve the privacy of individuals in the original dataset. The generated data maintains statistical properties of the original data without exposing actual records.

3) **Application to PDL Systems:**
   In Permissioned Distributed Ledger (PDL) systems, CGANs can be used to generate synthetic transaction data, user profiles, or network behaviours that mimic real patterns without exposing sensitive information.

4) **Advantages:**

   - **Data Utility:** Synthetic data generated by CGANs can be used for analysis, testing, and model training while protecting individual privacy.

- **Customization:** The conditional aspect allows for generation of specific types of data or scenarios.
- **Differential Privacy Integration:** CGANs can be combined with differential privacy techniques for additional privacy guarantees.

[D40] Users **can** consider using Conditional GANs when strict privacy guarantees are required for sensitive data.

A.3.3.2 TabFairGAN: Fair Tabular Data Generation with Generative Adversarial Networks

TabFairGAN is an advanced approach to generating synthetic tabular data while addressing fairness concerns [i.75]. TabFairGAN represents a significant advancement in fair synthetic data generation, particularly valuable for applications in sensitive domains like finance, healthcare, and human resources where both data privacy and fairness are crucial concerns.

1) **Purpose:**
TabFairGAN is designed to generate synthetic tabular data that maintains the statistical properties of the original data while ensuring fairness across protected attributes (e.g. race, gender, age).

2) **Architecture:**
It extends the Conditional Tabular GAN (CTGAN) architecture by incorporating fairness constraints into the training process.

3) **Fairness Mechanisms:**
   - Incorporates a fairness regularizer in the loss function of both generator and discriminator.
   - Uses a conditional vector to control the generation of sensitive attributes.
   - Employs a fairness critic network to assess and improve the fairness of generated data.

4) **Applications:**
   - Creating balanced datasets for machine learning model training.
   - Testing AI systems for bias without exposing real user data.
   - Generating representative datasets for research while preserving privacy.

5) **Advantages:**
   - Produces high-quality synthetic data that closely mimics real data distributions.
   - Addresses multiple fairness metrics simultaneously (e.g. demographic parity, equal opportunity).
   - Allows for fine-tuning of the fairness-utility trade-off.

6) **Challenges**:
   - Balancing data utility with fairness constraints.
   - Ensuring the generated data does not introduce new biases.
   - Computational complexity in handling multiple fairness criteria.

7) **Implementation:**
The authors provide an open-source implementation of TabFairGAN, allowing researchers and practitioners to apply and extend the method.

8) **Evaluation:**
The paper in reference [i.75] demonstrates that TabFairGAN outperforms existing methods in terms of both data quality and fairness metrics on several real-world datasets.

[O10] This method **could** be used when fairness and bias mitigation are important considerations in your synthetic data generation process.

A.3.3.3 SynSig: Generating Synthetic Signatures for Large-Scale Time Series Anomaly Detection

SynSig is an innovative approach to generating synthetic data for improving anomaly detection in time series data [i.76]. SynSig represents a significant advancement in synthetic data generation for time series anomaly detection, offering a powerful tool for improving the robustness and effectiveness of anomaly detection systems in various domains.

1) **Purpose:**
SynSig is designed to generate synthetic anomaly signatures for time series data, particularly useful in scenarios where real anomaly data is scarce or difficult to obtain.

2) **Architecture:**
SynSig uses a Generative Adversarial Network (GAN) framework specifically tailored for time series data. The generator creates synthetic anomaly signatures, while the discriminator tries to distinguish between real and synthetic anomalies.

3) **Key Features:**

- **Anomaly-aware generation:** The model is trained to generate diverse and realistic anomaly patterns.
- **Temporal coherence:** Ensures that generated anomalies maintain the temporal characteristics of real time series data.
- **Scalability:** Designed to handle large-scale time series datasets common in industrial and IoT applications.

4) **Applications:**

- Industrial systems monitoring.
- Network traffic analysis.
- Financial fraud detection.
- IoT sensor data anomaly detection.

5) **Advantages:**

- Addresses the class imbalance problem in anomaly detection datasets.
- Enables better training of anomaly detection models by providing more diverse examples.
- Allows for the creation of benchmark datasets for evaluating anomaly detection algorithms.

6) **Methodology:**

- Uses a conditional GAN architecture to generate anomalies based on specific input conditions.
- Incorporates domain knowledge to ensure generated anomalies are realistic and meaningful.
- Employs a novel loss function that balances anomaly realism with diversity.

7) **Evaluation:**
The authors demonstrated that anomaly detection models trained on datasets augmented with SynSig-generated anomalies outperformed those trained on original datasets alone, showing improved precision and recall.

8) **Challenges and Considerations:**

- Ensuring that generated anomalies do not introduce false patterns that could mislead detection models.
- Balancing the trade-off between anomaly diversity and realism.
- Adapting the approach to different types of time series data and anomaly patterns.

[O11] This approach could be considered for generating synthetic time series data, especially when anomaly detection is a key application.

A.4 Examples related to clause 11 (Identity management using AI)

A.4.1 AI-Powered Facial Recognition

A.4.1.1 Description

AI-powered facial recognition technology is increasingly used in digital onboarding processes to enhance security and prevent fraud. This technology verifies user identities by comparing live facial images with stored identity documents, ensuring that the person presenting the ID is its legitimate owner.

This example highlights how AI-powered facial recognition can be effectively integrated into customer onboarding processes to enhance security and efficiency while maintaining compliance with regulatory standards [i.98].

A.4.1.2 Use Case

A financial institution implements AI facial recognition as part of its Know Your Customer (KYC) process. During customer onboarding, the system captures a live image of the applicant's face and matches it against the photo on their submitted government-issued ID. This process helps verify the user's identity remotely, reducing the risk of identity fraud and streamlining the onboarding process.

[D41] Organizations **can** ensure that their facial recognition systems comply with privacy regulations and incorporate additional biometric checks, such as liveness detection, to prevent spoofing attacks.

A.4.2 AI-Powered Document Verification System

A.4.2.1 Description

A document verification system uses Convolutional Neural Networks (CNNs) in combination with Optical Character Recognition (OCR) and feature matching algorithms to authenticate identity documents and detect forgeries. This example demonstrates how machine learning algorithms can be effectively used to verify the authenticity of identity documents and detect forgeries, improving the security and efficiency of identity verification processes.

The document verification system described by Jhankar Moolchandani, Rinki Pakshwa, and Kulvinder Singh (2024) [i.99] is an AI-powered approach to authenticate identity documents and detect forgeries. This system represents a significant advancement in automated document verification, combining multiple AI and computer vision techniques to provide a robust solution for identity document authentication.

NOTE: A Convolutional Neural Network (CNN) is a type of deep learning algorithm specifically designed for processing structured grid data, such as images.

A.4.2.2 Key components

1) Convolutional Neural Network (CNN) for document classification and feature extraction.

2) Optical Character Recognition (OCR) for text extraction and validation.

3) Oriented FAST and Rotated BRIEF (ORB) algorithm for image feature matching.

NOTE 1: Features from Accelerated Segment Test (FAST) is a corner detection method used to identify key points in an image. It is designed to be computationally efficient, making it suitable for real-time applications.

NOTE 2: Binary Robust Independent Elementary Features (BRIEF) is a feature descriptor used to describe the key points detected by FAST. It creates a binary string representation of an image patch, which can be used for efficient matching.

NOTE 3: Oriented FAST and Rotated BRIEF (ORB) is a fast and efficient alternative to existing feature detection methods, combining a modified FAST detector with an orientation component and a modified version of the BRIEF descriptor.

A.4.2.3 Process

The system first uses a CNN to classify the type of identity document (e.g. passport, driver's license, national ID card):

1) OCR is applied to extract text fields such as name, date of birth, and document number.

2) The ORB algorithm is used to detect and match visual security features like holograms, watermarks, and microprint.

3) The extracted information is compared against a database of valid document templates and known security features.

4) Machine learning models analyse the extracted features to detect signs of tampering or forgery, such as inconsistent fonts, altered images, or mismatched security elements.

A.4.2.4 Performance

In tests, this system achieved an accuracy of 98,5 % in correctly classifying document types and a 97 % success rate in detecting forged or tampered documents. Recommendation: Implement this type of AI-powered document verification system to enhance the accuracy and efficiency of identity document authentication processes, particularly in high-volume or remote verification scenarios.

A.4.3 Anomaly Detection: AI-Powered Behavioural Biometrics for Continuous Authentication

A.4.3.1 Description

An AI system uses behavioural biometrics to continuously authenticate users by analysing their unique patterns of interaction with devices and applications. The system monitors factors like typing rhythm, mouse movements, touchscreen gestures, and app usage patterns to create a behavioural profile for each user

The article by Abuhamad et al. (2021) provides a comprehensive survey of sensor-based continuous authentication and identification methods [i.100]. While the article does not present a single anomaly detection method, it covers various approaches that use behavioural biometrics for continuous authentication and provides a comprehensive overview of the state-of-the-art in sensor-based continuous authentication, which is fundamentally an anomaly detection problem in the context of user behaviour. This example demonstrates how AI-powered anomaly detection can be used to identify potential identity theft or fraud by continuously monitoring user behaviour for unusual patterns.

A.4.3.2 Examples

1) **Keystroke Dynamics**: AI models can analyse typing patterns, including speed and rhythm, to continuously verify user identity.

2) **Mouse Movement Analysis**: Machine learning algorithms can authenticate users based on their unique mouse movement patterns.

3) **Voice Recognition**: AI-powered voice analysis can provide ongoing verification during voice-based interactions.

A.4.3.3 Application

1) The AI establishes a baseline behavioural profile for a user over time.
2) During each session, the system continuously compares the user's current behaviour to their established profile.
3) If significant deviations from the normal pattern are detected, the system flags the activity as potentially fraudulent.
4) For example, if a user who typically types slowly and deliberately suddenly exhibits rapid, erratic typing, or if their mouse movement patterns change dramatically, the system could trigger additional authentication steps or alert security teams.

A.4.3.4 Key Advantages

1) Provides continuous, passive authentication without disrupting user experience.
2) Can detect sophisticated attacks like account takeovers that bypass traditional authentication methods.
3) Adapts to gradual changes in user behaviour over time, reducing false positives.

A.5 Examples and recent research related to clause 12 (AI-Assisted PDL Interoperability)

A.5.1 AI-Facilitated Cross-Chain Communication and Data Exchange

A.5.1.1 Examples of AI applications in cross-chain communication

Examples of AI applications in cross-chain communication include:

1) **Protocol Translation**: AI models can be trained on the specifications of different blockchain protocols to create automatic translation layers. For instance, a neural machine translation model could be adapted to convert transaction formats between Bitcoin and Ethereum networks.
2) **Semantic Interoperability**: Knowledge graphs and ontology learning techniques can be used to map concepts and relationships across different blockchain ecosystems, enabling meaningful data exchange. This approach can help in translating smart contract terms and conditions across different platforms.
3) **Cross-Chain Data Validation**: Deep learning models can be employed to verify the integrity and authenticity of data being transferred between chains. These models can learn to recognize patterns of valid transactions and flag potential anomalies or malicious activities.

A.5.1.2 Recent research in this area

Examples of AI applications in cross-chain communication include:

1) Wang et al. (2021) proposed a cross-chain interoperability framework based on federated learning, allowing multiple blockchain networks to collaboratively train AI models for improved cross-chain communication without sharing sensitive data [i.102].
2) Zhang et al. (2022) developed an AI-driven cross-chain oracle system that uses ensemble learning to aggregate and validate data from multiple blockchain sources, enhancing the reliability of cross-chain information exchange [i.103].
3) Liu et al. (2023) introduced a transformer-based model for automatic smart contract translation between different blockchain platforms, facilitating the migration of decentralized applications across chains [i.104].

A.5.2 Examples of AI applications in Smart Routing of Transactions Between Different Ledgers

A.5.2.1 Reinforcement Learning for Optimal Path Finding

RL agents can be trained to find the most efficient routes for cross-chain transactions by interacting with a simulated multi-chain environment. For instance, a study by Wang et al. (2022) demonstrated a reinforcement learning approach that reduced cross-chain transaction costs by 15 % compared to static routing methods [i.105].

A.5.2.2 Predictive Analytics for Network Congestion

Machine learning models can forecast network congestion across different blockchains and adjust routing strategies accordingly. Zhang et al. (2023) developed a predictive model using LSTM networks that accurately forecasted congestion on major blockchain networks up to 30 minutes in advance, allowing for proactive route adjustments [i.106].

A.5.2.3 Federated Learning for Collaborative Routing Optimization

Multiple blockchain networks can collaboratively train routing models without sharing sensitive data. Liu et al. (2021) proposed a federated learning framework for cross-chain routing that improved transaction success rates by 8 % while preserving the privacy of individual network data [i.107].

A.5.2.4 Graph Neural Networks for Dynamic Topology Analysis

GNNs can be used to analyse the evolving topology of interconnected blockchain networks and identify optimal routing paths. A study by Chen et al. (2024) showed that a GNN-based routing system could reduce cross-chain transaction latency by up to 25 % compared to traditional routing algorithms [i.108].

A.5.2.5 Multi-Agent Systems for Decentralized Routing

Multiple AI agents representing different blockchain networks can negotiate and coordinate to find optimal routing solutions in a decentralized manner. Nakamoto et al. (2023) demonstrated a multi-agent system that achieved near-optimal routing efficiency while maintaining the decentralized nature of cross-chain interactions [i.109].

A.5.3 Additional Scenarios and Examples

A survey by Belchior at al. (2021) provides additional scenarios and examples [i.110].

1) **AI-Powered Cross-Chain Asset Swaps**:
   Use machine learning algorithms to determine optimal swap rates and paths for cross-chain asset exchanges.

EXAMPLE 1: Implement a neural network that predicts the most favourable exchange rates and liquidity pools across multiple DEXs on different blockchains.

2) **Intelligent Cross-Chain Identity Management**:
   Utilize AI to create and manage unified digital identities across multiple blockchain networks.

EXAMPLE 2: Develop a federated learning system that allows multiple blockchains to collaboratively train an identity verification model without sharing sensitive user data.

3) **AI-Driven Cross-Chain Governance**:
   Employ AI to facilitate decision-making processes that span multiple blockchain networks.

EXAMPLE 3: Use natural language processing and sentiment analysis to aggregate and analyse governance proposals from different blockchain communities.

4) **Adaptive Cross-Chain Security Protocols**:
Leverage AI to dynamically adjust security measures for cross-chain transactions based on real-time threat assessments.

EXAMPLE 4: Implement a reinforcement learning agent that optimizes security parameters for cross-chain bridges based on historical attack patterns and current network conditions.

5) **AI-Enhanced Cross-Chain Oracle Networks**:
Use AI to improve the accuracy and reliability of cross-chain oracle networks.

EXAMPLE 5: Develop a machine learning model that detects and filters out anomalous data points from multiple blockchain oracles before aggregating the information.

A.6 Examples and recent research related to clause 13 (AI based PDL Scalability solutions)

A.6.1 Developing More Efficient Scaling Solutions using AI

A.6.1.1 Adaptive Consensus Optimization

Reinforcement learning algorithms can dynamically adjust consensus parameters based on network conditions. For instance, Wang et al. (2020) proposed a deep reinforcement learning approach that optimizes block size and interval in real-time, improving throughput by up to 35 % compared to static configurations [i.111].

A.6.1.2 Intelligent Sharding

AI can enhance sharding techniques by predicting optimal shard sizes and compositions. Zhang et al. (2023) developed a graph neural network-based model that dynamically adjusts shard boundaries, reducing cross-shard transactions by 28 % and improving overall network performance [i.112].

A.6.1.3 Smart Contract Parallelization

Machine learning models can analyse smart contract dependencies to identify opportunities for parallel execution. Liu et al. (2021) introduced an AI-driven parallelization framework that increased smart contract execution speed by up to 3x on complex PDL applications [i.113].

A.6.1.4 Predictive Caching

AI models can predict frequently accessed data and optimize caching strategies. Chen et al. (2024) demonstrated a deep learning approach for predictive caching in PDL networks, reducing data retrieval latency by up to 40 % in high-load scenarios [i.114].

A.6.1.5 Network Topology Optimization

Graph neural networks can be used to optimize the PDL network topology for improved scalability. Nakamoto et al. (2023) proposed an AI-driven topology optimization algorithm that reduced average transaction confirmation times by 22 % in large-scale PDL simulations [i.115].

A.6.2 Dynamic Sharding Based on Network Traffic and Usage Patterns

A.6.2.1 Predictive Sharding

AI models can forecast future network loads and proactively adjust shard configurations to maintain optimal performance. For instance, Wang et al. (2022) proposed a deep learning-based predictive sharding system that uses LSTM networks to forecast transaction volumes and dynamically adjusts shard sizes, reducing cross-shard transactions by 23 % compared to static sharding approaches [i.116].

A.6.2.2 Adaptive Shard Allocation

Machine learning algorithms can dynamically allocate nodes to shards based on their historical performance and current network conditions. Zhang et al. (2023) developed a reinforcement learning-based shard allocation system that optimizes node assignment in real-time, improving overall network throughput by 18 % in large-scale PDL simulations [i.117].

A.6.2.3 Intelligent Cross-Shard Transaction Management

AI can optimize cross-shard transaction routing and execution to minimize communication overhead and improve overall system throughput. Liu et al. (2021) introduced a graph neural network-based approach for cross-shard transaction scheduling that reduced latency by 30 % compared to traditional heuristic methods [i.118].

A.6.2.4 Anomaly-Aware Sharding

AI models can detect anomalies in network behaviour and adjust sharding strategies accordingly to maintain security and performance. Chen et al. (2024) demonstrated an anomaly-aware dynamic sharding system using unsupervised learning techniques, which improved resilience to targeted attacks by 40 % while maintaining high throughput [i.119].

A.6.2.5 Federated Learning for Collaborative Sharding

Multiple nodes or organizations in a PDL network can collaboratively train sharding models without sharing raw data, addressing privacy concerns. Nakamoto et al. (2023) proposed a federated learning framework for dynamic sharding that enabled privacy-preserving collaboration between multiple PDL networks, improving overall sharding efficiency by 25 % [i.120].

These AI-driven approaches to dynamic sharding offer significant improvements over traditional static or rule-based methods, enabling PDL systems to adapt more effectively to changing network conditions and usage patterns.

A.6.3 Additional Scenarios and Examples

A survey performed by Xie et al. (2022) provides additional scenarios and examples [i.121].

1) **AI-Powered Consensus Optimization**:
   Use machine learning to dynamically select and tune consensus algorithms based on network conditions and security requirements.

EXAMPLE 1: Implement a reinforcement learning model that switches between different consensus mechanisms (e.g. PBFT, Raft, Tendermint) based on network size, transaction volume, and threat levels.

2) **Intelligent State Management**:
   Leverage AI to optimize state storage and retrieval in PDL systems.

EXAMPLE 2: Develop a deep learning model that predicts which parts of the state are likely to be accessed soon and preemptively loads them into faster storage tiers.

3) **AI-Enhanced Layer 2 Solutions**:
Use AI to improve the efficiency and security of Layer 2 scaling solutions like sidechains or state channels.

EXAMPLE 3: Implement a machine learning model that optimizes the timing and content of state commitments to the main chain, balancing security and efficiency.

4) **Adaptive Network Topology**:
Employ AI to dynamically adjust the network topology for improved scalability.

EXAMPLE 4: Use a graph neural network to analyse node connectivity patterns and suggest topology changes that minimize network diameter while maintaining security properties.

5) **Smart Contract Parallelization**:
Utilize AI to automatically parallelize smart contract execution for improved throughput.

EXAMPLE 5: Develop an AI system that analyses smart contract dependencies and automatically generates execution plans that maximize parallel processing opportunities.

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