

An AI-Based Minimax Optimization Approach for Cryptocurrency Price Prediction and Fraud Detection

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Abstract

This paper explores the integration of AI (artificial intelligence) in predicting the volatility of the crypto-space and detecting fraudulent activities by adopting the quantitative approach to examine fraud detection by using a CNN model and the ability to predict price volatility by using LSTM networks with the help of Google Colab. The findings of this study highlight that artificial intelligence is a critical enabler of long-term stability and trust in the evolving crypto-space. The originality of this study lies in its investigation of the sustainable role of artificial intelligence in predicting future prices and detecting fraudulent activities simultaneously, and integrating efficiency, accuracy, and long-term applicability, which has been explored to a limited extent. Therefore, further research in other related sectors should be explored to understand the influence of artificial intelligence in Crypto-space. This study offers useful insights for regulators, policymakers, and portfolio managers and offers scope for further research. However, the study adopted secondary data for this research, which limits the research and its ability to capture the dynamic nature of cryptocurrency market.

Keywords: Artificial Intelligence, RNN, CNN, Cryptocurrency, Volatility, Price Predictor, Fraud Detection, LSTM, Google Colab, Sustainability.

Introduction

The evolution of Artificial Intelligence and Cryptocurrency has transformed the global technological landscape over the past two decades. These disruptive technologies have significantly influenced the traditional method of practicing fiat currency in the system. This technology, Artificial Intelligence, has introduced new opportunities in the business sector by enhancing day-to-day activities more efficiently. This study explores the integrity of artificial intelligence in the cryptocurrency space, either by monitoring the patterns to detect implicit activities or to predict price fluctuations. There are various methods like ANN, CNN, and Machine Learning (ML) to analyse the market fluctuation or transactions to detect the patterns of illicit activities.

In 1956, John McCarthy introduced the concept of artificial intelligence. Gradual development in the field of computers has made it possible to successfully launch artificial intelligence into business. The adoption of artificial intelligence in business has risen to 88% in 2024 from 20% in 2017¹. In 2008, Satoshi Nakamoto introduced cryptocurrency in a white paper, “Bitcoin: A Peer-to-Peer Electronic Cash System”. After publishing the first white paper on cryptocurrency in 2008, the first digital currency of Bitcoin was launched in 2009 by mining the first block as the “Genesis Block” (Nakamoto, 2008). With the introduction of decentralized transactions, investors can do transactions without being monitored by the central authority (Tierno, 2023). The disruptive transformation of cryptocurrency’s technology has created new opportunities for digital scammers to exploit new investors with limited knowledge, making them vulnerable to digital

¹ https://www.mckinsey.com/featured-insights/week-in-charts/ai-at-work-but-not-at-scale?utm_source

fraudsters (Krishnan et al., 2023). The total illicit crypto value has also increased from 4.3 B in 2019 to 40.9 B in 2024, including scams like phishing, exchange hacks, etc. (Collins, 2022).

To understand the role of artificial intelligence in crypto-space. The researcher tries to address the two research questions.

RQ1: What is the role of artificial intelligence in detecting implicit activities or fraudulent transactions?

RQ2: What is the ability of artificial intelligence to predict price fluctuations?

The researcher used secondary data for this study and analysed it using Google Colab to interpret the output, which concludes the effectiveness of artificial intelligence to forecast the price and to prevent fraudulent activity.

Cryptocurrency has successfully established peer-to-peer system which facilitates the transfer of money from one place to another by keeping traditional financial bodies out of the system (Nakamoto, 2008). With the deployment of blockchain, smart contracts and various algorithms like SHA-256 and SHA-256d, the scope of new business opportunities and challenges is emerging in the real world.

Artificial intelligence has also standardized the effectiveness of business by reducing the cost of operation and analyzing patterns to make investment decisions more convenient. On the other hand, it has also extended its presence into crypto-space to prevent fraudulent activity, protect investors' trust, and predict price volatility to make investment decisions with more precision.

The paper consists of four sections, in which the evolution of artificial intelligence and cryptocurrency is explained in section 1, methodology is explained in section 2, results and implementation in section 3, and in the last section, the limitations and conclusion of the study are explained.

Literature Review

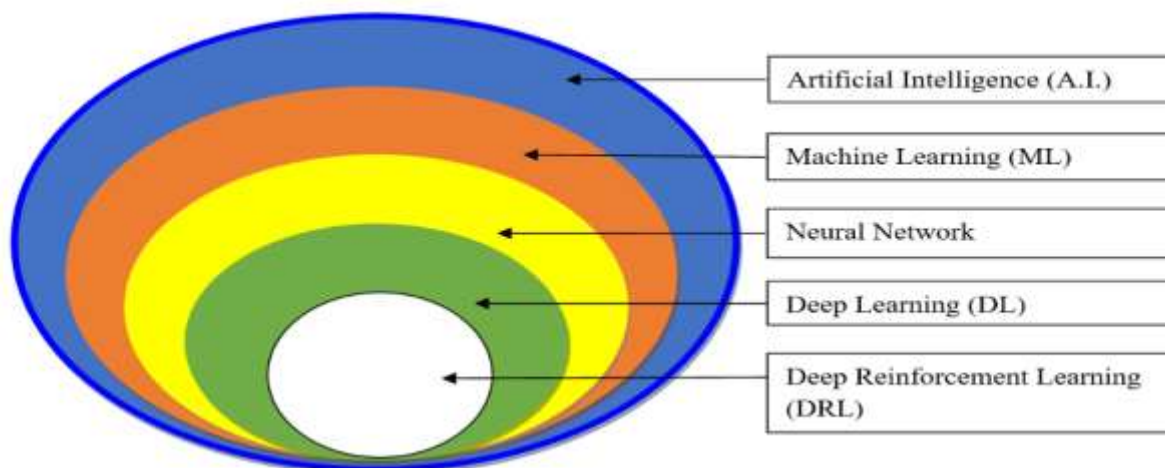
The Evolution of Artificial Intelligence:

In 1956, John McCarthy introduced the term, Artificial Intelligence, during a summer research project at Dartmouth College (McCarthy et al., 2006). It was established as a research field aimed at creating machines capable of replicating all aspects of learning and other forms of intelligence that can be formally described (Dick, 2019). Artificial Intelligence (AI) harnesses computers to imitate humans' intelligence by solving problems and making decisions (Amirzadeh et al., 2022).

AI has improved corporate productivity by empowering machines to mimic human behaviors (Bughn et al., 2017). The adoption of this technology is expanding rapidly across industrial sectors, like healthcare and manufacturing, as well as real-time evaluation of enormous datasets (Whittaker et al., 2018; Helm et al., 2020).

The subcategories of artificial intelligence are visualized in Figure 1, which is adopted from Amirzadeh et al. (2022), to explain the models that are utilized to predict prices in the cryptocurrency market. These categories include Machine Learning (ML), Neural Networks, Deep Learning (DL), and Deep Reinforcement Learning (DRL).

Figure 1: A Subset of Artificial Intelligence



Source: Amirzadeh et al (2022)

Machine Learning is an algorithm that enables machines to discover patterns without explicit programming instructions (*Rasekhschaffe & Jones, 2019*). This method carries out experience-based learning similar to human intelligence and possesses the ability to enhance its analytical performance through computational algorithms (*Helm et al., 2020*). Researchers from computer science, mathematics, statistics, and data science have been designing and improving the algorithm of machine learning which derives insights from data, with the goal of building reliable and precise models for predicting price trends and market movements in the crypto market (*Amirzadeh et al., 2022*).

The neural network is a computational model that replicates the human brain's ability to process information by interconnecting nodes to learn from data. It consists of three categories, i.e., Artificial Neural Network, Convolutional Neural Network, and Recurrent Neural Network. This network is used to learn salient features for detecting cyber-attacks, rather than handcrafted approaches (*Amirzadeh et al., 2022*). This method analyses the historical data and predicts the future price of cryptocurrency by analysing the patterns. Deep Learning focuses on training artificial neural networks with multiple layers. This model is effective in handling large-scale unstructured data and provides a foundation for researchers interested in future research on this technology. Deep Learning encompasses network design, training, and evaluation to optimize techniques and to perform analysis (*Heaton et al., 2018*). Deep Learning is a subcategory of machine learning (ML) that trains artificial neural networks (ANN) on large datasets. These neural networks can learn and make decisions on their own as they are inspired by the human brain's structure and function. These algorithms have a crucial impact on forecasting prices by analysing pattern-image of the historical data (*Seabe et al., 2023*).

Deep Reinforcement Learning (DRL) is an approach in which machines learn by interacting with an environment through trial and error. An intelligent agent learns to take optimal actions and receives rewards for desirable outcomes and penalties for undesired ones. DRL employs deep learning networks, which guide the agent on how to act in complex scenarios (*Arulkumaran et al., 2017*) and develop the ability to make trade decisions, such as when to buy, hold, or sell, by continuously interacting with the market.

Artificial intelligence and its advanced branches, such as ML, DL, DRL, and Neural Networks, play a sustainable role in price prediction by offering efficient, adaptive, and data-driven forecasting solutions. Neural networks and deep learning algorithms enhance sustainability and promote more consistent and transparent decision-making by minimizing human bias. These branches identify hidden patterns and predict market fluctuations with higher precision by learning from historical and real-time datasets. Artificial Intelligence promotes sustainable financial systems that support informed investment decisions, improve predictive accuracy, and encourage responsible market participation, allowing trading agents to establish self-learning optimal strategies that adapt to changing market conditions, reducing resource waste and speculative errors, which contributes to long-term sustainability.

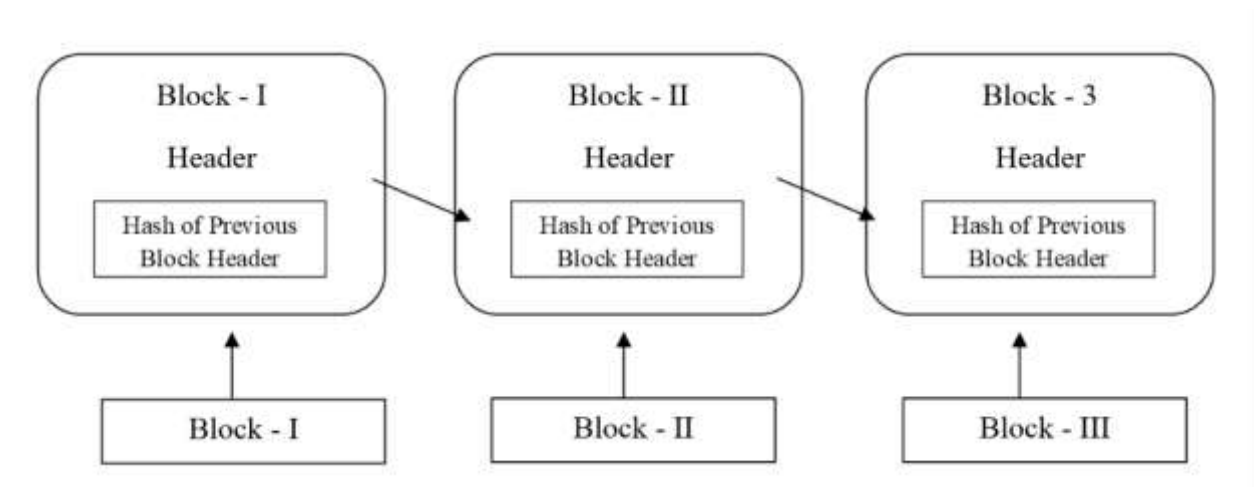
Theoretical Background of Cryptocurrency:

Digital assets refer to resources that can be digitally stored and can be transferred, traded, and stored digitally, while retaining identifiable economic value (*Ante, 2021*). Digital assets, like cryptocurrencies, have emerged as a transformative class, reshaping financial transactions and decentralized economic systems. Cryptocurrencies have attracted the attention of many investigators who predicted that these assets could have adverse consequences on the economy (*Karim et al., 2019*). These assets have unpredictable behavior, which makes it complex to predict their future acceptance in the global financial system (*Ragab, 2025*).

Cryptocurrency was introduced by Satoshi Nakamoto in 2008 in a white paper, "Bitcoin: A Peer-to-Peer Electronic Cash System" (*Nakamoto, 2008*). Cryptocurrency was introduced to transfer money from one person to another without involving financial intermediaries. Cryptocurrency includes technologies like blockchain and smart contracts. But technophiles gradually converted its functioning into an investment portfolio. Because of its high volatility and decentralized nature of transactions, many governments consider it as a matter of serious concern. However, EL Salvador (*Krause, 2025*) and the Central African Republic (*Bola Bongo, 2023*) accepted Bitcoin as legal tender in 2021 and 2022, respectively. Many governments are still evaluating whether to adopt cryptocurrency or to leverage their underlying technology to remain competitive in the global economy. In order to harness the technologies behind cryptocurrencies, governments are making efforts to develop a deeper understanding of how these innovations operate.

Blockchain technology serves as the foundational technology for cryptocurrency by enabling secure, transparent, and decentralized recording of digital transactions without intermediaries (Nakamoto, 2008). Blockchain is a distributed ledger system that records every transaction. These transactions are recorded in the form of blocks, which are cryptographically linked to previous blocks, forming a chain (Nawari & Ravindran, 2019). The “chain of blocks” is crucial to the technology as it can’t be breached by any malicious activity and provides transparency to the system. When a member transfers a coin to another member, they need a private key and a public key, which is then verified by the miners in the system (Nakamoto, 2008). After getting nodes from the miner, the transaction is added to the ledger. Blockchain follows a consensus mechanism, which creates a unique linear path from the first block ever posted to the current block that exists (Nakamoto, 2008). Figure 2 represents the overview of blockchain technology.

Figure 2: Blockchain Overview



Source: Author's Contribution

In 1994, Nick Szabo introduced smart contracts in his article “Smart Contracts: Building Blocks for Digital Markets” to build a digital economy without the involvement of third parties (A.I & I.A, 2021). It is a self-executing agreement written digitally and includes the terms of the contract directly in computer code. These contracts enforce, verify, and execute obligations automatically when predefined conditions are met, without requiring intermediaries (Szabo, 1996; Buterin, 2014). Once deployed, the contracts autonomously monitor and enforce compliance by executing predefined actions when specific conditions are fulfilled. Smart contracts operate in a decentralized environment, removing the need for centralized authorities or intermediaries and reducing the potential for manipulation, increasing the efficiency of transactions across the globe. On the other hand, their immutability and transparency build trust among investors (Christidis & Devetsikiotis, 2016).

Role of AI in Crypto-space:

Between November 2017 and March 2022, the capitalisation of the cryptocurrency market rose to \$1.664 trillion from \$267.8 billion, excluding bitcoin, whereas altcoin capitalisation grew from \$86.31 billion to \$1.007 trillion (Amirzadeh et al., 2022), and by 2024, market capitalisation increased to \$2.6 trillion USD (Chauhan & Saxena, 2026). Many international companies have invested in crypto-based businesses, e.g., by purchasing merchandise using Dogecoin. Cryptocurrencies have attracted investors’ interest and, due to their digital features, have become a new form of currency (Ergen & Kozat, 2019). In this period, many investors made a fortune solely by analysing the crypto market, but due to its volatile nature, many of them incurred losses. For example, the market capitalization of bitcoin dropped from 1.18 trillion to 935 billion USD in ten days in April 2021, then almost halved to 602 billion USD over the next three months in July 2021 (Amirzadeh et al., 2022).

Artificial Intelligence influences the crypto market positively and integrates the system with traditional financial assets (Abraham et al., 2018; Cianin et al., 2016). Artificial Intelligence helps in real-time portfolio adjustment, whereas Deep Reinforcement Learning (DRL) improves investment decisions and supports automated cryptocurrency portfolio management (Kl & Ramachandra, 2026). The integration of artificial intelligence within the cryptocurrency sector mirrors the major shift toward data-driven innovation

in the modern economy (*Yahia et al., 2025*). This technological evolution allows the analysis of vast datasets to predict market prices and optimize trading operations (*Andriushchenko et al., 2025*). Sophisticated compliance frameworks improve real-time monitoring and identification of suspicious patterns to mitigate the risk of financial crime (*Rodriguez et al., 2025*).

AI-powered learning technologies have improved commercial performance (*Saxena et al., 2022*). Indonesia has integrated Artificial Intelligence into platforms to demonstrate a legal process to combat anti-national financing via crowdfunding (*Putranti & Pramoto, 2025*). These AI-driven measures enhance public trust by ensuring financial tracking, which is perceived as a reliable defense against illicit activities (*Alrasheed, 2025*). The primary challenge is to prevent industries from cybercrimes, like phishing-as-a-service, through AI-driven risk engines (*Sulochana & De Silva, 2025*). The community must remain vigilant against scientific misconduct, which represents ‘academic fake money’ analogous to fraudulent cryptocurrency creation (*Haiech, 2025*).

This hybrid intelligence creates feedback loops between human judgment and algorithmic autonomy to establish institutional legitimacy (*Alibašić, 2025*). Blockchain technology serves as a foundation by providing a distributed ledger that documents transactions in an immutable format (*Ahamed et al., 2025*). The emergence of “Blockchain 5.0” proposes next-generation architectures allowing the sharing of artificial intelligence models directly on-chain in a privacy-preserving manner (*Tulkinbekov & Kim, 2025*).

Artificial Intelligence identifies patterns beyond human capability, improving forecasting accuracy of the crypto market (*Piravesh & Sallan, 2024*) and contributing to smarter and faster financial prediction (*Malhotra et al., 2024*). Machine learning improves trading signals and reduces risks in intraday trading (*Shastri, K. A., 2024*). An effective price predictor must integrate multiple features, such as price and volume, to maintain accuracy in volatile conditions (*Liu et al., 2025*). Hybrid deep learning techniques, by combining CNN and LSTM networks, have proven superior at capturing spatial and temporal dependencies in Bitcoin Price behavior (*Bouzari et al., 2025*).

The role of Artificial Intelligence (AI) in crypto-space is defined by its ability to enhance efficiency, promote market resilience, and hedge against risk, which nurtures trust and facilitates opportunities for development in a volatile market (*Paskaleva, 2025*). AI adoption spans multiple sectors globally and has become an integral element of innovation. Models like machine learning, deep learning, and CNNs help to predict prices with more precision, while LSTMs capture time-series financial patterns and predict short-term price movements (*Cvetkovic, 2024*). Another adoption of AI in crypto-space is to prevent illicit activities by analysing blockchain transaction patterns to identify suspicious transactions.

Artificial Intelligence has transformed the traditional financial market by developing trading algorithms that can analyse massive volumes of data and execute deals with unprecedented speed and precision (*Anumandla & Reddy, 2018*). These algorithms enable investors to create investment strategies, and due to their untraceable nature or privacy policies, some users indulge in illicit activities. To prevent these illicit activities, Artificial Intelligence stands as an optimal solution that includes machine learning and deep learning models. These models analyse the vast datasets to detect hidden fraud patterns (*Usman, 2025*).

The contribution of Artificial Intelligence in crypto-space is to enhance the efficiency and optimization of investment strategies and ensure transparency and security. The adoption of AI, like CNN, ANN, Deep Learning, and LSTM, into the crypto market enhances the ability of the investor to make informed decisions by accurately forecasting the fluctuation in the market and promotes the efficiency to mitigate the risk of loss, leading the investor to make efficient investment strategies and risk management (*Choithani et al., 2024*). These models analyse the factors causing fluctuation in the price of cryptocurrency due to technological development, market sentiment, and regulatory changes (*Paskaleva, 2025*).

AI-based trading systems reduce human intervention and support automated high-frequency trading strategies (*Brini & Kolm, 2026*). The purpose of AI-enhanced trading algorithms is to maximise profits and building efficient investment strategies in the highly volatile nature of the market, resulting in the convergence of AI and cryptocurrency trading. This system empowers the investor to make informed investment decisions in a highly volatile market and enables the investor to maximise profit from unpredictable market (*Koehler et al., 2018*). Artificial Intelligence predicts stock returns more accurately than traditional methods (*Cvetkovic, 2024*); separates portfolio optimization from execution decisions (*Li et al., 2026*). Advanced machine learning forecasting model predicts the change in the price of cryptocurrency and contributes valuable insights to the emergence of artificial intelligence and digital economy development (*Paskaleva, 2025*).

Cryptocurrency does not behave like traditional fiat currency because of its high volatility and requires investors to develop their own specific trading strategies (*Amirzadeh et al., 2022*). Cryptocurrency portfolio management is employed by deep reinforcement learning, which suggests a long-term approach to handle digital assets (*An et al., 2021*). The AI-enhanced algorithms improve automation and efficiency in bitcoin trading by enabling transactions to be executed quickly and precisely by removing human-based bias in decision-making. This results in more disciplined and consistent trading strategies (*Koehler et al., 2018*) and identifies durable and fragile market conditions and improves risk management in uncertain markets (*Thomson, A. D., 2025*).

Investors adapting modern innovations are able to address the evolving landscape by utilizing new trends and enhancing their strategies in this highly volatile digital economy. AI evaluates large-scale financial data and identifies high-return investment opportunities (*McIntyre et al., 2026*). AI leverages machine learning algorithms to analyse market patterns and execute trades automatically via smart contracts, leading to continuous learning and performance improvement (*Choithani et al., 2024*) and enhancing market transparency and decision-making (*Kirky & Andrean, 2024*).

Cryptocurrency is embedded with a cryptographic technique, which is a mathematical computation-based algorithm, making it difficult for hackers who try to enter into the blockchain. With the introduction of Artificial Intelligence, every sector of the global economy is making efforts to utilize it in their businesses. Decentralised nature of cryptocurrency transactions ensures security and protects the privacy of the investor. But scammers are able to commit fraud, like phishing attacks, against new investors. Adopting Artificial Intelligence in the cryptocurrency market has enhanced security and protected investors' trust by providing financial security and timely protection from potential threats to both traders and investors by identifying, assessing, and managing potential risk, and improving investment experiences (*Andriushchenko et al., 2025*).

Artificial intelligence techniques learn from vast data, which humans can't analyse efficiently, to analyse and detect patterns that ease and secure trading and mining (*Sabry et al., 2020*). These techniques are applied to address fundamental challenges like fraud detection, volatility prediction, portfolio construction, and cybersecurity. The integration of AI into cryptocurrency monitoring is transforming the fight against financial crimes such as money laundering, terrorism financing, and fraud. AI-based approach includes machine learning (ML), deep learning (DL), and natural language processing (NLP) techniques to outperform traditional rule-based systems in detecting fraudulent patterns (*Tairov & Stefanova, 2024*).

AI helps regulatory institutions to learn from data related to potential financial fraud and threats. AI systems can increase efficiency in Anti-Money Laundering (AML) monitoring by reducing false positives in suspicious activity reports (*Sabry et al., 2020*). AI techniques also contribute to analysing and assessing the security and privacy level of cryptocurrencies and identifying potential threats (*Sabry et al., 2020*). Consensus-based solutions utilizing AI can mitigate issues like cryptocurrency arbitrage bots in intelligent blockchain environments (*Zhang et al., 2025*).

Research Gap:

Existing studies have attempted to predict the volatility of the cryptocurrency market by using machine learning and deep learning. However, no prior studies have amalgamated predicting price volatility with fraud detection. Prior research provides accurate short-term predictions but fails to address fraud detection. This study is an attempt to bridge this gap by integrating an AI-based LSTM model to predict price volatility and a CNN model to detect fraudulent transactions, ensuring investor security and mitigating risk.

Table 1: Research Gap Analysis

Prior Study	Fraud Detection	Price Prediction	Unified Framework	Gaps Analysed
Bouzari et al., (2025)	No	Yes	No	Focuses on price prediction; not on fraud detection.
Seabe et al., (2023)	No	Yes	No	Compares DL models for forecasting; not discussed fraud detection
Tairov & Stefanova (2024)	Yes (ML\DL)	No	No	Examines AI for fraud detection but not on price prediction

Choithani et al., (2024)	Yes	Yes	No	Comprehensive survey; does not test models
Sabry et al., (2020)	Yes	Partial	No	Broad AI-crypto review; no unified empirical framework
Paskaleva (2025)	No	Yes	No	Addressing sustainability in Price Prediction; no fraud detection

Source: Author's Contribution

Table 1 illustrates that prior studies focused either on price prediction or on fraud detection. There are limited studies focusing on both, i.e., Price Prediction and Fraud Detection, in a unified framework. *Bouzari et al. (2025)* studied price prediction by applying CNN and LSTM to study price behaviour. *Sabry et al. (2020)* contribute an overview of Artificial Intelligence in both segments, but lack empirical analysis.

Methodology

Research Design:

This study adopts quantitative research to analyse fraud detection patterns in financial transactions with a deductive approach to test the hypothesis related to fraudulent and non-fraudulent transactions that are formulated based on existing literature and tested using statistical techniques. This paper utilized two different datasets sourced from a widely used open data platform for research and analytics, i.e., Kaggle.com, to analyse the essence of artificial intelligence in detecting fraud and as a price predictor. These datasets were selected based on their relevance, availability, and sustainability to the research objective, containing both fraudulent and non-fraudulent observations and other data. The dataset includes variables such as transaction amount, minimum value received, and fraud status, which are to be examined to identify the differences between fraud and non-fraud cases. The researcher also used a purposive sampling technique, selecting data that are clearly labelled as fraudulent or non-fraudulent. Fraud status is treated as a binary dependent variable, while transaction-related attributes, like minimum value received, are included as independent variables. A structured dataset was used to analyse and predict price trends using an artificial intelligence-based long short-term memory (LSTM) model.

Data Collection:

To understand the role of AI in the cryptocurrency space, the researcher included research papers, conference proceedings, and publications related to the objective of the study by using the terms, i.e., machine learning, deep learning, natural language processing, cryptocurrency, bitcoin, price prediction, fraud detection, from the Scopus database. A systematic strategy is utilized to narrow down the manuscripts obtained earlier, which ensures the accuracy of the study. This strategy includes citation chaining and reference tracking to find papers that were missed in the first database searches, which helps to study the creation, application, and assessment of AI-enhanced cryptocurrency trading algorithms and their effects. Then, the obtained literature is run through Python to obtain the final analysis of the study. This paper utilized two different datasets sourced from a widely used open data platform for research and analytics i.e. Kaggle. The First dataset comprised a total no. of 9841 observations to detect fraudulent activities, and the second dataset consists of 3010 observations to examine the ability to forecast prices. This dataset includes historical price-related variables structured sequentially to support predictive modelling. These datasets were selected based on their relevance, availability, and sustainability of the research objective, containing both fraudulent and non-fraudulent observations.

Tools and Techniques:

The study employs statistical tools to analyse and visualize fraud detection patterns in financial transaction data. Google Colab is used as the primary research tool due to its integration with Python libraries. The distribution of transaction values between fraudulent transactions and non-fraudulent transactions is compared with the help of box plots. These box plots help to visualize the data to identify variability, skewness, and the presence of outliers, which provide preliminary insights into differences across fraud categories.

Long Short-Term Memory neural network implements temporal dependencies in transaction data to capture sequential patterns. This model visualizes learning behaviour and forecasts trends with the help of training and validation graphs, which support fraud detection analysis in a time-dependent context.

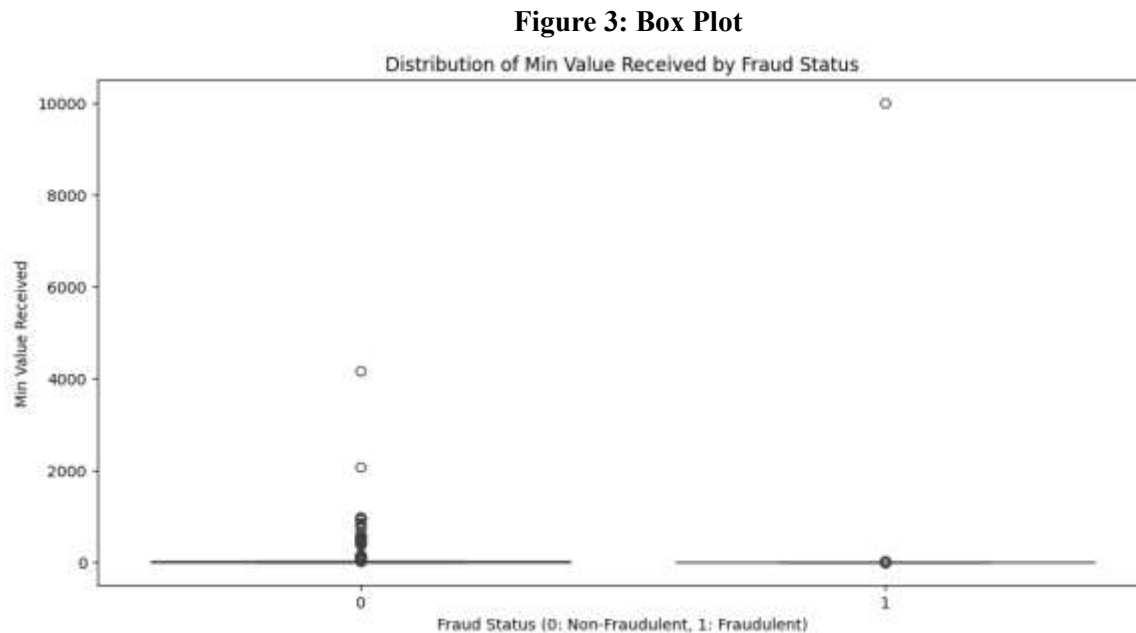
Result and Analysis

1. Box Plot:

This plot compares the distributions of minimum values received between non-fraudulent transactions and fraudulent transactions labelled as 0 and 1, respectively. The distribution shows a wider spread with high-value outliers, which indicates genuine transactions are involved. A broad range of minimum received values is visualized under a non-fraudulent transaction. Multiple outliers in the plot suggest higher variability in legitimate transaction behavior. While the fraudulent transaction indicates a highly concentrated distribution near the lower end of the scale, i.e., closer to zero, it represents that fraudulent activities are generally associated with lower values received and reflect an attempt to minimize detection risk. It also reveals a clear difference in distribution between fraudulent transactions and non-fraudulent transactions. It also suggests that the minimum value received is a useful indicator for fraud detection.

Figure 3 represents a comparison of the minimum value received between two groups through a box plot. In this figure, the y-axis indicates the minimum value received as Min Value Received, and the x-axis includes non-fraudulent transactions and fraudulent transactions as 0 and 1, respectively.

i. General Distribution: The plot indicates that both transaction types are highly concentrated near minimum value received. The narrow cluster near zero indicates that most transactions involve small amounts irrespective of fraud status, while higher values occur infrequently and appear as outliers.



Source: Google Colab

ii. Presence of Outliers: It also highlights the presence of extreme outliers in both groups. Several observations fall far above the central distribution, ranging from 500 to 4000 in non-fraudulent category. This indicates occasional high-value legitimate transactions. While in fraudulent category, it contains a single large outlier near to 10,000. These extreme values stretch the y-axis significantly, making the central tendency of both groups appear closer to zero.

Interpretation:

The box plots indicate the minimum received value is very small in both categories, i.e., non-fraudulent transactions and fraudulent transactions. The observation in both categories is clustered tightly near to zero, which suggests that this variable does not exhibit a strong central tendency between the fraudulent and non-fraudulent categories, resulting minimum value received that may have limited discriminatory power when used as an isolated indicator of fraud.

A. An extreme anomaly is reflected by a large outlier, which is displayed in fraudulent groups and suggests that fraudulent transactions involve low minimum values. Sometimes they include high-value transactions,

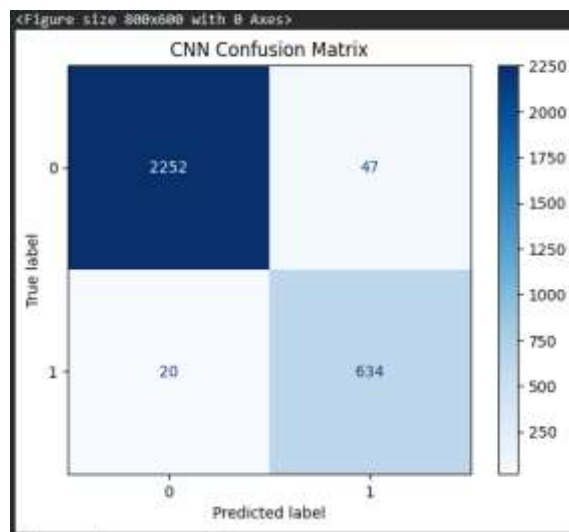
occasionally representing attempts to manipulate transaction patterns. Such extreme deviations are important for anomaly detection.

B. The presence of outliers in the non-fraudulent group simultaneously indicates that fraud cases often have high minimum values. It implies that outliers cannot identify fraudulent activity alone.

2. CNN Confusion Matrix:

This matrix summarises the performance of the CNN model for fraud detection. Figure 4 visualizes the comparison between the true and predicted class labels. This matrix enables the evaluation of the model's classification accuracy, error, and overall reliability in detecting fraudulent transactions from non-fraudulent transactions. The main diagonal represents the correct classifications; on the other hand, the other diagonal represents misclassifications. This matrix allows the clear visualization of identifying false positives and false negatives. This matrix helps to assess the accuracy of the model and its reliability and error distribution, which indicates the effectiveness of deep learning models for fraud detection tasks.

Figure 4: Confusion Matrix of CNN Model for Fraud Detection



Source: Google Colab

Interpretation:

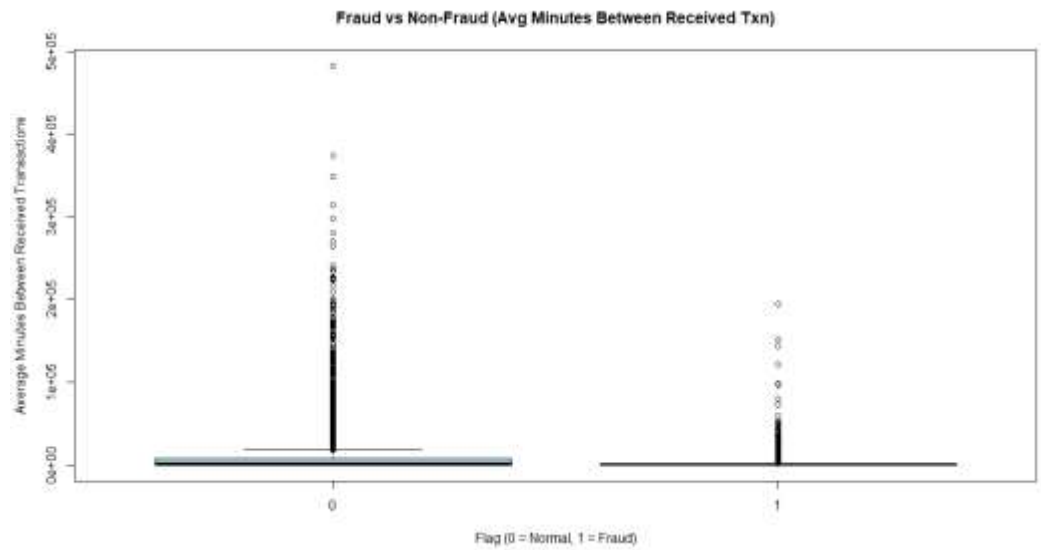
The CNN confusion matrix represents the role of artificial intelligence in detecting fraudulent transactions. AI successfully identified 2,252 cases, with 47 misclassified as fraud from non-fraudulent cases, indicating a low false-positive rate. It also detected 634 fraudulent transactions with only 20 cases classified as non-fraud, indicating a low false-negative rate. Such a difference is also important for detecting fraud, where missing fraudulent cases can be costly.

3. Box Plot (Average Time Gap):

The average time gap box plot, Figure 5, compares the average time difference between consecutive received transactions for non-fraudulent (0) and fraudulent (1) cases. The role of transaction timing is very crucial for fraud detection. It reflects how often transactions occur within an account. In non-fraudulent transactions, the distribution exhibits a wider spread, indicating that genuine users experience irregular and widely spaced transaction intervals.

Fraudulent transactions are highly concentrated near very low time intervals with a narrower spread. This pattern suggests that fraudulent activities often occur in rapid succession, consistent with automated behaviour aimed at exploiting systems quickly. Overall, the visual evidence indicates that the average minutes between received transactions is a meaningful temporal indicator that can help distinguish fraudulent behaviour, particularly when combined with other transactional features in predictive models.

Figure 5: Box Plot (Average Minutes Between Received Txn.)

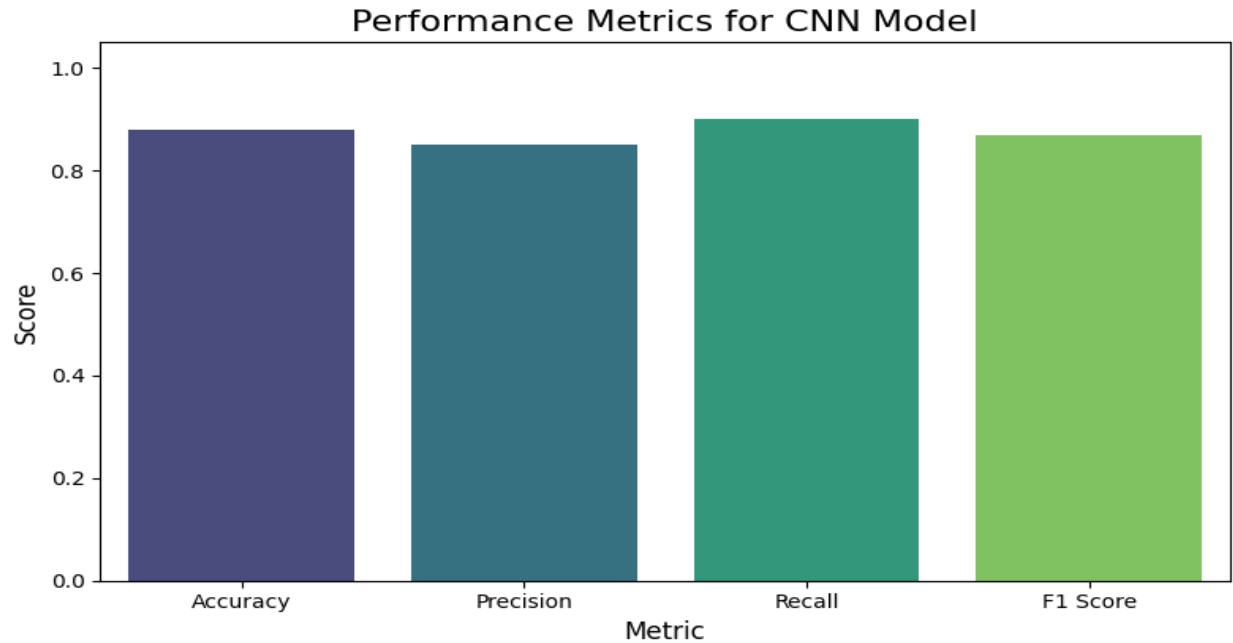


Source: Google Colab

4. Accuracy, Precision, Recall, F1 Score

Figure 6 indicates the values of Accuracy (0.88), Precision (0.85), Recall (0.90), and F1 Score (0.87) for a CNN-based model, which is used in detecting fraud and implicit activities. The high accuracy indicates that the AI system is reliable in distinguishing between legitimate and fraudulent activities. The recall score indicates that the model’s ability to identify fraudulent activities, which is crucial for fraud detection, because missing a fraudulent transaction can result in significant financial and reputational losses. The precision score is marginally lower than the recall score, but it remains strong, suggesting that the CNN model has flagged most activities as fraudulent. This precision helps to reduce false alarms, which are essential for maintaining operational efficiency and avoiding unnecessary investigations. The balanced F1 score demonstrates an effective trade-off between precision and recall, indicating that the AI model does not favor detection at the expense of accuracy.

Figure 6: Accuracy, Precision, Recall, F1 Score

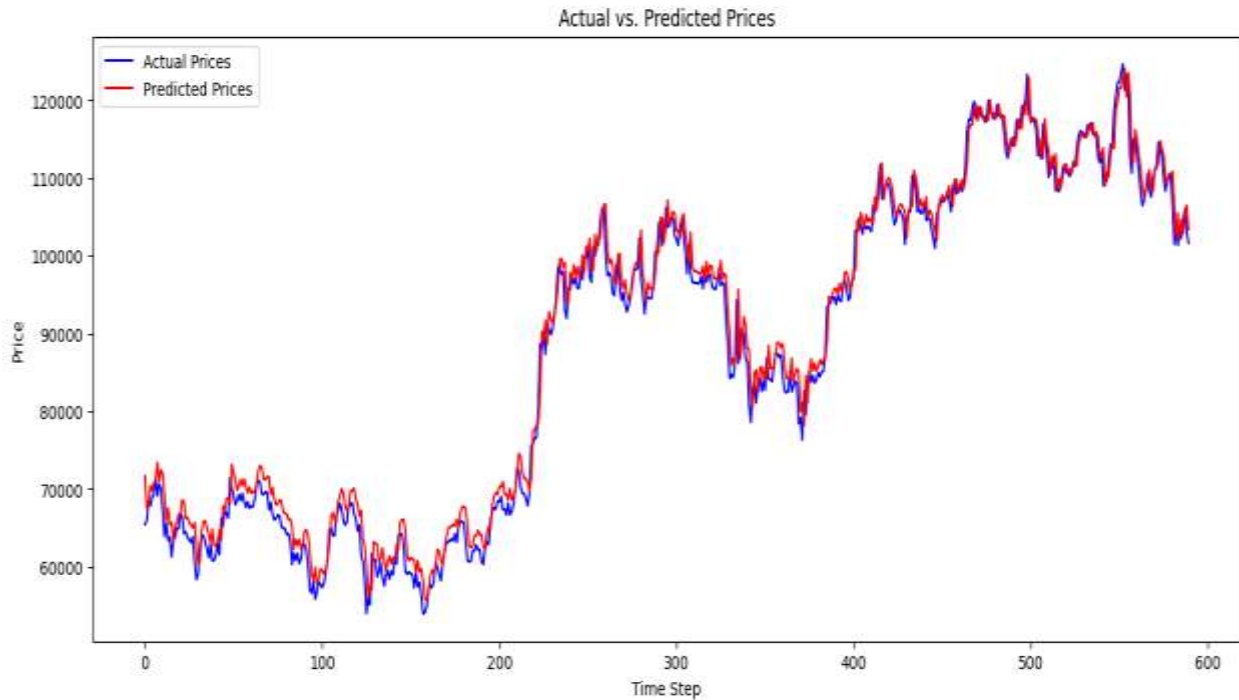


Source: Google Colab

5. Long Short-Term Memory neural network:

Long Short-Term Memory (LSTM) neural network is a subcategory of Recurrent Neural Network (RNN) developed to model sequential and time-dependent data. The purpose of LSTM is to conceptualise the internal flow and its impact on future forecasting (Yiying & Yeze, 2019). It comprises three layers, each containing ten nodes. Each node represents one memory cell. One memory cell includes three gates, i.e., forget gate, input gate, and output gate. It regulates which information should be removed or incorporated through the gates, which allows the system to selectively forget or retain information, which makes it suitable for cryptocurrency price time series prediction (Yiying & Yeze, 2019).

Figure 7: Using LSTM



Source: Google Colab

6. RMSE, MAE, R-SQUARED, MAPE:

RMSE is utilised to evaluate the accuracy of a predictive model. Lower RMSE indicates better model performance and higher prediction accuracy. MAE measures the difference between actual values and predicted values. Lower MAE values represent better predictive performance and improved model reliability. R^2 indicates the portion of variance in the dependent variable that is explained by the independent variable. MAPE calculates the average percentage of this difference. A lower MAPE value indicates higher forecasting accuracy and better predictive efficiency.

TABLE 2: RMSE, MAE, R-SQUARED, MAPE

Evaluation Metrics:

	Metric Value
RMSE	2386.5848
MAE	1903.8431
R-squared	0.9868
MAPE	2.3735

Source: Google Colab

Interpretation:

The above metrics, Table 2, demonstrate the strong predictive capability of the AI-based LSTM model calculated by utilising Google Colab. This table highlights the effectiveness of time-series forecasting and predictive analytics.

The RMSE (2386.5848) and MAE (1903.8431) indicate that the magnitude of prediction errors remains comparatively small to the overall scale of the data. RMSE penalizes larger errors more firmly. The difference between RMSE and MAE indicates that extreme prediction errors are limited, reflecting stable and consistent model performance.

The R-squared value (0.9868) indicates that the LSTM model explains 98.68% of the variance in the target variable. This reflects the model's excellent ability to learn complex temporal patterns and dependencies in sequential data, which is a core strength of LSTM-based AI systems.

The MAPE value (2.3735%) is low, suggesting that the model's predictions deviate slightly from actual values and demonstrating high forecasting accuracy and robustness. Such a low percentage error is particularly desirable in financial, demand forecasting, risk prediction, and operational planning contexts.

Findings

The findings of this study highlight that AI-based LSTM models can predict prices in a highly volatile crypto market. The integration of Artificial Intelligence into the cryptocurrency market helps to enhance investors' trust by maximizing their profit and protecting them from unpredicted losses. LSTM model mitigates the risk for new investors who are susceptible to market losses in the cryptocurrency ecosystem. New investors are vulnerable to digital scammers and become victims of attacks like phishing and fake wallets. CNN model demonstrated their significance by accurately detecting fraudulent transactions or implicit activities from non-fraudulent transactions by analysing patterns beyond human mind. This model supports the crypto exchange organizations and financial institutions to detect fraudulent transactions and secure investors' trust from cyberattacks like phishing and fake wallets.

To answer the research question, the researcher identified a few studies that align with the research question and explained their contribution and how they align with this study.

R.Q. 1: What is the role of artificial intelligence in detecting implicit activities?

The integration of AI in cryptocurrency transaction monitoring represents a transformative development in combating illicit financial activities (*Nelson, 2025*). Gradually, the fight against financial crimes has relied on artificial intelligence solutions, which include Deep Learning and Machine Learning (ML). These models have the ability to analyze vast datasets to detect hidden fraud patterns and adapt to emerging threats (*Usman, 2025*).

The researcher adopted a CNN model to address RQ1 by utilizing Google Colab. The results, Figure 6, indicate that the CNN-based model shows Accuracy (0.88), Precision (0.85), Recall (0.90), and F1 Score (0.87), which are used for detecting fraud and implicit activities. Therefore, the result highlighted that the integration of the CNN model under Artificial Intelligence is significant to detect fraudulent transactions. Artificial intelligence evaluates and detects patterns in vast data, which makes trading and mining more efficient. It can identify patterns in fraudulent trading and money laundering. The use of cryptocurrencies for criminal activities is reduced due to concerns about security and privacy (*Tairov & Stefanova, 2024*).

R.Q. 2: What is the ability of artificial intelligence to predict price fluctuations?

AI-enhanced algorithms have transformed investment techniques, allowing investors to mitigate risks, manage diversified portfolios, and make informed decisions (*Koehler et al., 2018*). AI methods like NLP, Deep Learning, and ML show potential in improving Bitcoin trading tactics (*An et al., 2021*).

This study employs LSTM models by utilising Google Colab to address RQ2. The results, Figure 7, demonstrate strong visual alignment between the actual values (black) and the predicted values (red). This model indicates the model's ability to learn stable patterns and changes with minimal prediction error. This suggests high predictive accuracy in low-volatile conditions. Table-2 presents the results of RMSE, MAE, R^2 , and MAPE, and highlights the effectiveness of time-series forecasting and predictive analytics. *Seabe et al. (2023)* had argued that cryptocurrency prices can be predicted effectively by utilising deep learning algorithms.

Implications

The integration of artificial intelligence (AI) into transaction monitoring requires global standards for using ethical AI. The CNN-based fraud detection model highlights the model's ability to detect hidden patterns within transactional data that are often difficult to detect. The LSTM models confirm that they are well-

suited for capturing long-term temporal dependencies in price data, resulting in accurate and reliable forecasts. These findings can be utilised by stakeholders, investors, and market participants and enable investors and financial institutions to identify future price trends, reduce uncertainty, and optimise investment decisions.

Financial Institutions and banks can use the fraud detection model to strengthen real-time monitoring systems and reduce financial losses by enabling them to identify anomalous transaction behavior, assess potential security threats, and implement risk-mitigation strategies. Policymakers and regulators must work together to develop regulatory frameworks that ensure responsibility, equity, and openness in algorithmic trading. The price prediction model can benefit investors, portfolio managers, and financial analysts by providing accurate forecasts for informed investment decisions.

Limitations

This study has the following limitations that should be acknowledged:

1. This study relies on secondary datasets, which limits the research to measuring the effectiveness of the artificial intelligence models in the cryptocurrency market.
2. The fraud detection and price prediction models were evaluated on historical data, which may not capture current market shifts, emerging fraud patterns, or real-time behavioral changes.
3. The research focuses on Ethereum and monitors the price fluctuations during a certain period of time, i.e., August, 2017 to December, 2025. Future research can apply the experiment to other crypto investments, like Bitcoin and Litecoin.
4. The role of AI is considered as “intelligent infrastructure” which manages the vast data and decentralized crypto-space and provides a system that provides navigation to forecast price fluctuations and ensures the safeguard of investors’ privacy and enables them to make efficient investment strategies.

Future Scope

Artificial Intelligence is transforming the technological environment and requires continuous improvement. The major challenge is that the high price fluctuations make short-term prediction difficult. Therefore, future research may extend this work by incorporating real-time data and explainable artificial intelligence models, which enhance the robustness and practical applicability. The framework can be extended by incorporating larger and more diverse datasets across different industries and geographic regions to improve generalizability.

Conclusion

This study examined the application of AI-based deep learning models for addressing two significant challenges in the cryptocurrency ecosystem (Fraud detection and Price Predictor). By utilising CNN for fraud detection and LSTM for price prediction, the study demonstrated the capability of AI techniques to analyse complex datasets.

The paper highlights that the CNN model successfully detected fraudulent and implicit activities and shows its potential to enhance existing fraud monitoring systems. The model has the ability to replace traditional rule-based approaches to detect fraud; instead, it captures hidden patterns in data, which makes it valuable. The LSTM-based price prediction model exhibited strong predictive accuracy, as reflected by high explanatory values and low errors value and confirms that LSTM networks are suitable for modelling temporal dependencies and forecasting price trends with reliability.

By integrating fraud detection and price prediction within a unified AI-driven framework, this research contributes to existing literature and provides practical insights for financial institutions, regulatory bodies, researchers, and technology developers. The research paper highlights the transformative role of AI in enhancing efficiency, accuracy, and strategic planning across financial and data-intensive domains.

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