Utilising Temporal Convolutional Networks for Cryptocurrency Price Forecasting

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Abstract

This research explores the use of Temporal Convolutional Network (TCN) for predicting cryptocurrency prices. Given the inherent volatility and complex patterns in cryptocurrency markets, traditional forecasting models often fall short. TCNs, being able to capture long-term dependencies in sequential data, are proposed as a superior alternative. The study analyses data from five cryptocurrencies at 15-minute intervals, develops a TCN-based forecasting model and evaluates its performance against baseline models, including Buy-and-Hold, Naïve Forecast, ARIMA, and Long Short-Term Memory (LSTM) networks. Results indicate that TCNs enhanced prediction accuracy and robustness, providing valuable insights for traders in making informed decisions.

CCS Concepts: • **Computing methodologies** → **Neural networks**; • **Applied computing** → **Forecasting**; • **Information systems** → *Data stream mining*; • **Mathematics of computing** → *Time series analysis.*

Keywords: Algorithmic Trading, Cryptocurrency, LSTM, Machine Learning, Price Prediction, Temporal Convolutional Networks

1 Introduction

Since the release of open-source Bitcoin software in 2009 [26], cryptocurrecies have undergone significant evolution, marked by pivotal developments that have expanded the overall financial market.

As the cryptocurrency market shifted from being perceived as an alternative investment, to becoming a mainstream avenue for profitable ventures [37], there has been a surge in the adoption of algorithmic trading to navigate the complexities of these markets. This approach has gained traction due to its ability to analyse vast datasets and uncover patterns overlooked by human traders [9, 13].

However, the inherent characteristics of financial data, such as large volumes, fuzzy information, non-linear patterns, and the diversity array of influential factors, often challenge the effectiveness of these conventional approaches [12]. This is especially the case in the cryptocurrency market, where alternative metrics, such as mining costs, sentiment analysis [22], and the lack of an underlying business or tangible assets associated with any coin [1, 22], continue to exacerbate the complexities of speculation, leading to intricate temporal dependencies.

Despite the growing prevalence of algorithmic trading via Machine Learning (ML) and Artificial Intelligence (AI), the cryptocurrency market still grapples with volatility and significant price fluctuations [3, 17]. Although unpredictability poses a considerable challenge for traders, it is also seen as an opportunity for higher profit [24].

In this study, the utilisation of Temporal Convolutional Network (TCN) is proposed for the prediction of cryptocurrency prices. TCN have shown remarkable effectiveness in capturing temporal dependencies in sequential data, which makes them well suited to model the dynamic nature of cryptocurrency markets [2].

The empirical evaluation conducted in this research demonstrates the superior performance of the TCN model compared to baseline approaches. Specifically, the TCN model with a Bagging ensemble method consistently outperforms the Naïve Forecast and ARIMA models in terms of prediction accuracy and trading performance across multiple cryptocurrencies. It also exhibits a higher profit margin than the Buy-and-Hold strategy, except for Ethereum (ETH). The Long Short-Term Memory (LSTM) model is also outperformed by TCN, providing higher profit from the simulations, better performance and efficiency, and a more ideal ratio of correct to incorrect overall trades.

1.1 Aims and Objectives

The primary aim of this research is to optimise the profitability of cryptocurrency trading strategies, by achieving superior accuracy and robustness when predicting cryptocurrency prices, thereby empowering traders with valuable insights for informed decision-making.

The objectives are therefore as follows:

- Develop and implement a forecasting model using TCN tailored for cryptocurrency price prediction, with the aim of enhancing the accuracy and reliability in forecasting future price movements.
- Train and optimise the model using historical price data from several cryptocurrencies.
- Evaluate the forecasting performance of the TCN based on metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R-Squared (R2).

- Compare the performance of the TCN with the more established Long Short-Term Memory (LSTM) model, as well as other baseline models, including Buy-and-Hold, Naïve Forecast, and the traditional ARIMA model.
- Conduct trading simulations to assess the real-world applicability and effectiveness of the forecasting models.

2 Background and Literature Review

In this section, an overview of existing literature on the use of various ML techniques in algorithmic trading will be presented, providing insights into the evolving role of AI and ML in trading practices, with a particular focus on the cryptocurrency market and its forecasting. The TCN model will also be discussed and evaluated through different studies.

2.1 Forecasting Financial Markets and Traditional Econometric Models

Forecasting financial markets is a complex endeavour that attempts to predict future prices or market movements. This prediction is based on a confluence of factors, both quantitative and qualitative. These factors include historical price data, economic indicators, market sentiment [1, 9, 18, 18, 22, 37], and overall macroeconomic conditions. The importance of incorporating these external economic indicators is underscored by studies such as [35], where their model outperformed others when incorporating macroeconomic variables. However, financial markets are often not fully efficient, which has led to the development and application of various forecasting models.

Traditional financial theories, such as Efficient Market Hypothesis (EMH), propose that market prices already reflect all available information. As a result, they argue that prices follow a random path, making any reliable forecast based solely on past data almost impossible [36].

These methods, which heavily relied on econometric models like Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) [40], have proven effective for short-term forecasting. However, they are increasingly being replaced by more sophisticated AI/ML techniques. This shift is driven by the superior ability of AI/ML to handle the complexities and non-linearities inherent in financial data.

2.2 Forecasting Cryptocurrency Prices

The cryptocurrency market commonly exhibits behaviours that are not typically observed in traditional financial markets [23], such as dramatic price swings triggered by speculative activities, regulatory news [1, 37], public sentiment online [18], or technological developments [22]. This volatility creates challenges for the creation of predictive models, as they must not only handle large data volumes but also adapt to rapid changes in market conditions.

With the novelty of cryptocurrency markets serving as an ideal testing ground for the newest forecasting models, there has been a recent surge in the application of AI/ML techniques to algorithmic trading within the cryptocurrency market [9, 34]. Countless studies are exploring how these techniques, employed to exploit the intricate and often non-linear patterns in financial data, thereby forecasting different aspects of this complex market, with many applying and analysing supervised ML models such as Decision Trees, SVM [29], the Bayesian Linear Regression [31] and Bayesian Neural Network (BNN) [14], Deep Learning [15, 16, 28, 32], Long Short-Term Memory (LSTM) [21, 23, 27] and Reinforcement Learning [16].

Decision Trees, one of the simplest models, have been widely utilised for this purpose. For example, studies by [25, 33] demonstrate the utility of this model and Regression Trees in predicting cryptocurrency prices, with [25] showing a higher precision than linear regression and ARIMA. These models, while straightforward, offer a baseline for more complex predictive frameworks.

An advanced approach to forecasting involves the use of Binary Autoregressive Tree (BART), which combines the strengths of traditional regression trees with autoregressive models like ARIMA, making it well-suited for the non-stationary and volatile nature of cryptocurrency time series data. This model is discussed in [6], where it achieves RMSE ranges of 4% to 8%, demonstrating the effectiveness of AI/ML for short-term forecasting. Further research by the same authors compared various ML models, including BART and Artificial Neural Networks (ANN), finding that these models achieve MAPE of around 3% to 4% and an average precision of 63% for daily predictions [7].

This author also discusses ensemble models in a later paper [5], which combine predictions from Random Forest (RF) and Stochastic Gradient Boosting Machines (SGBM) to improve performance, reaching MAPE as low as 0.92% to 2.61% for daily price predictions, showing promising results in various applications. Ensemble deep learning, which combines multiple models to improve prediction performance, has also been explored in the context of cryptocurrency forecasting. [21] evaluates ensemble learning strategies with deep learning models such as LSTM and Bidirectional LSTM (BiLSTM) for hourly price prediction. The results indicate that ensemble models, particularly those employing stacking with diverse meta-learners, provide a reliable forecast, demonstrating their utility in volatile markets.

[34] explores the application of a more conventional approach to deep learning techniques, using Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and BiLSTM models to forecast cryptocurrency prices. The study found that BiLSTM provides the highest accuracy, suggesting that

considering bidirectional context in time series data enhances predictive performance.

The application of AI techniques in stock market trading is also reviewed in detail by [9], covering various methods such as ANN, SVM, and Deep Learning. The study discusses the potential of these techniques in improving prediction accuracy and informed trading strategies, which are applicable to cryptocurrency markets.

[23, 27] combine RNN with LSTM algorithms to forecast daily closing prices of various cryptocurrencies. Same as previously mentioned studies, traditional methods like ARIMA were outperformed, as well as other ML models such as RF-Regressor, Multilayer Perceptron (MLP), Convolutional Neural Network (CNN) and the conventional LSTM model.

[30] focuses on forecasting Ether prices using a range of deep learning models, including LSTM, GRU, and TCN, as well as their hybrid and ensemble versions. The study achieves prediction accuracy up to 84.2%, indicating that hybrid and ensemble models outperform individual models, suggesting their potential for broader application in cryptocurrency price forecasting.

Such models were further examined in [4], specifically LSTM, GRU, Temporal Convolutional Network (TCN), and Transformers, to predict Bitcoin prices and returns. In addition to the previous study, feature engineering from market, macroeconomic, network, and social data are also incorporated, highlighting the importance of diverse input features in improving the robustness and accuracy of predictive models. In this study, the TCN model achieves the highest accuracy scores, but BiLSTM having the lowest amount of prediction errors.

[20] employs a Deep Reinforcement Learning (DRL) approach, specifically an LSTM-based agent, to predict Bitcoin prices and develop trading strategies. The study highlights the challenges of Bitcoin's price volatility and the effectiveness of LSTM in capturing long-term dependencies. The DRL agent demonstrated the ability to generate excess returns in high-frequency trading, outperforming SVM, Multilayer Perceptron (MLP), TCN, and Transformer models.

The study by [38] makes use of Graph Neural Networks (GNN), in combination with LSTM, to also forecast cryptocurrency prices. The findings reveals that integrating network effects from financial markets and cryptocurrencies substantially improves prediction accuracy, as indicated by lower Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and RMSE.

Network-based features derived from Bitcoin transaction data are used by [10] to forecast prices. By employing models like Bayesian regression, SVM, and RF, this paper shows that the characteristics of the transaction network could significantly improve the prediction accuracy over short time intervals.

2.2.1 External Influences.

These studies collectively demonstrate that ML models often outperform traditional random walk models in predicting price movements due to their ability to learn complex patterns in historical data. The potential of ML techniques in the cryptocurrency market is further enhanced by incorporating diverse data sources, such as social media sentiment and network-based features, which provide additional context and improve model robustness.

This can be shown in [18], where the predictive power of Twitter sentiment on cryptocurrency is directly investigated. By analysing over 24 million tweets and applying sentiment analysis techniques, the study found that Twitter sentiment and message volume were strong predictors of price returns. This study highlighted the influence of public sentiment and the potential of integrating social media data into financial forecasting models. [37] analyses the complex impact of mainstream media on Bitcoin returns, finding that Bitcoin narratives, particularly those related to politics and culture, can significantly drive demand. [1] discusses investor behaviour in cryptocurrency markets, also emphasising the influence of news and media on prices. This study highlights that negative news impacts investors more than positive news, and regulatory announcements can lead to adverse reactions in the market.

Such predictive power is used in [40], which presented the Weighted & Attentive Memory Channels (WAMC) model that efficiently models non-linear correlations between different cryptocurrencies and traditional assets. The model incorporates a GRU component and self-attention mechanisms to improve accuracy and reduce prediction errors. Considering sentiment data from Google Trends and Twitter, the WAMC model showed higher efficacy compared to traditional models like SVR and ARIMA, as well as various deep learning models.

Overall, the evolving landscape of cryptocurrency price prediction is marked by the integration of advanced ML techniques and the consideration of diverse data sources. These approaches not only enhance the accuracy and robustness of predictions but also provide valuable insights for informed decision-making in the highly volatile and dynamic cryptocurrency market.

2.3 Temporal Convolutional Networks (TCNs)

The advent of deep learning models, particularly RNNs and their variants such as LSTM and GRU, initially promised breakthroughs in handling sequential data such as stock prices. However, recent studies have highlighted the limitations of these models in achieving superior performance, especially in terms of memory retention and computational efficiency.

TCNs, first proposed by [19], offer a significant improvement over RNN for sequence modelling tasks. This advantage stems from their ability to handle longer sequences without the risk of vanishing gradients and their overall training efficiency. [2] directly compare TCN with LSTM, a popular type of RNN. They demonstrate that TCN achieve comparable or better performance with significantly lower computational complexity. This efficiency is particularly beneficial for processing the voluminous and high-velocity data characteristic of cryptocurrency markets.

Given this result, one of the key reasons for focusing on TCN in this research is their inherent ability to capture long-term dependencies in time series data without the drawbacks associated with RNN. TCN use causal convolutions to prevent information leakage from future to past, which is essential for accurate time series forecasting. Additionally, TCN utilise dilated convolutions to exponentially increase the receptive field, allowing the model to learn from long-range dependencies more effectively than traditional RNN and LSTM.

[8] utilises TCN to forecast gold prices, and when comparing its performance against models like ARIMA, CNN, LSTM, and hybrid CNN-LSTM approaches, is found to outperform them, reducing error by more than 27%. While this research underscored the robustness of TCN in more traditional financial forecasting, it suggested the potential applicability of this model in predicting other assets, particularly cryptocurrencies.

In the context of cryptocurrency forecasting, [11] introduces their model, WT-CATCN, combining Wavelet Transform (WT) and Casual Multi-Head Attention (CA) TCN to forecast Bitcoin prices. They demonstrate that this model improves forecasting performance by 25% compared to other state-of-the-art models. The research identifies significant predictors of Bitcoin prices, such as transaction volume differences between exchanges, and recommends validating the model with other cryptocurrencies and more granular data to generalise findings.

Furthermore, [39] explores the application of TCN to forecast stock volatility and VaR, finding that it significantly improves volatility prediction accuracy and generally reduces risk prediction errors. This study highlights the versatility of TCN in different financial forecasting contexts, indicating their potential utility in the highly volatile cryptocurrency markets.

[12] proposes an enhanced TCN model aimed at enhancing the accuracy and training speed of stock price predictions. By incorporating trading data and pre-processed financial news into a multichannel series prediction model, the model's accuracy is improved by reducing the convolution layers. The improved TCN shows better prediction accuracy and faster training times compared to the original TCN network, demonstrating its efficiency and effectiveness.

Overall, the incorporation of TCN in this research aims to leverage their strengths in handling long-term dependencies, computational efficiency, and robustness in volatile market conditions. These attributes make TCN particularly well-suited for the challenges posed by cryptocurrency price prediction, where traditional models such as ARIMA, LSTM, and even some advanced ML models often fall short. By focusing on TCN, this research seeks to enhance the accuracy and reliability of cryptocurrency price forecasts, thereby providing traders with valuable insights for informed decision-making.

In conclusion, while the existing literature demonstrates the potential of various ML techniques in financial forecasting, TCN stand out due to their ability to efficiently handle long-term dependencies and complex, non-linear patterns in the data. This research aims to build on these findings by developing a TCN-based model tailored for the unique characteristics of cryptocurrency markets, ultimately contributing to the field of financial forecasting and empowering traders with more accurate predictive tools.

3 Methodology

As mentioned, the focus of this research will be on developing a forecasting model using TCN tailored specifically for cryptocurrency price prediction.

Due to the extensive usage of the LSTM model in various studies [2, 4, 8, 20, 21, 23, 27, 30, 30, 34], an two-layered implementation of this method will be used to compare with the proposed TCN model. Ensemble methods, including Bagging and Boosting, are implemented on both models to enhance performance.

The Buy-and-Hold and Naïve Forecast strategies are used as baseline models for performance benchmarking. An ARIMA model [6, 8, 25, 27, 40] will also be developed and evaluated in order to be able to compare the proposed TCN model with a more traditional time-series forecasting method.

The performance of this model will be evaluated based on different metrics, particularly RMSE, MAE, MAPE and R2. Additionally, trading simulations are conducted on the LSTM and TCN models to assess the models' real-world applicability, using a strategy based on predicted prices to make buy or sell decisions, keeping in mind a 0.1% trading fee.

In the following subsections, a more detailed description will be provided of the datasets used, the general approach, proposed and baseline models, as well as the evaluation metrics used for continued discussion.

3.1 Methodology Overview

The methodology involves several key steps in order to address the research objectives as defined in Section 1.1.

1. *Data Collection and Preprocessing*: The initial step involved the gathering of historical price data of various cryptocurrencies, including information such as open, high, low, close (OHLC) prices, trading volumes, and market capitalisation.

2. *Baseline Models & LSTM*: The development and evaluation of baseline models to benchmark the performance of the TCN model. These include the Buy-and-Hold Strategy, Naïve Forecast and the LSTM model.
3. *Model Development*: The implementation of the TCN model tailored for cryptocurrency price prediction. This includes designing the architecture and selecting appropriate features.
4. *Model Training & Optimisation*: The training process involves splitting the dataset into training and validation sets. The TCN model undergoes hyperparameter tuning using the grid search technique to identify the optimal parameters, including the learning rate, batch size, and the number of layers and filters.
5. *Model Evaluation*: The final evaluation involves testing the TCN model on an out-of-sample test set to assess its generalisation performance. The model's accuracy is evaluated using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and R-Squared (R2) metrics.

3.2 Dataset Description

The dataset utilised in this research comprises historical price data from five cryptocurrencies, being Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Litecoin (LTC), and Ripple (XRP). This data was sourced from Binance[1] and spans the period from January 1, 2024, to May 30, 2024. Given the dynamic and volatile nature of the cryptocurrency market, particular emphasis is placed on intraday trading and relatively high-frequency trading strategies. Therefore, for the purposes of this research, the 15-minute interval data is selected for further analysis and modelling.

The resulting dataset contains the following information:

- *Open Timestamp*: The time indicating the start of the 15-minute interval, represented as a Unix Time Code.
- *Close Timestamp*: The time indicating the end of the 15-minute interval, represented as a Unix Time Code.
- *Open Price*: The price of the cryptocurrency coin at the beginning of the interval.
- *High Price*: The highest price of the coin recorded within the interval.
- *Low Price*: The lowest price of the coin recorded within the interval.
- *Close Price*: The price of the coin at the end of the interval.
- *Volume*: The total trading volume of the coin in Tether (USDT) during the 15-minute interval.
- *Count*: The total number of trades that occurred during the 15-minute interval.
- *Quote Volumes*: The total trading volume in the quote currency (USDT) during the 15-minute interval.

[1]Binance: https://www.binance.com/

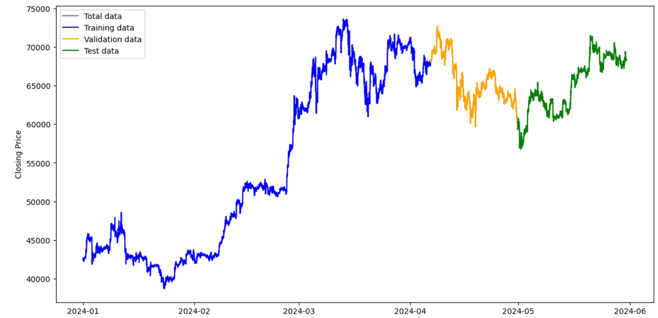

Figure 1. Bitcoin (BTC) closing price over time with Train-Test-Validate split

- *Market Buy Volumes*: The volume of the current cryptocurrency bought by takers (market buyers) during the 15-minute interval.
- *Market Buyer Quote Volume*: The volume of the quote asset (USDT) spent by takers (market buyers) during the 15-minute interval.

Tether (USDT) is a type of cryptocurrency known as 'stablecoin', designed to maintain a stable value tied to the US dollar [18, 38]. This makes it ideal for serving as a reliable base currency for comparing the volume of cryptocurrency coins overtime.

The dataset is imported into the analysis environment and organised into a DataFrames dictionary, facilitating further exploration and analysis. Additionally, to ensure consistency and comparability across intervals, data preprocessing techniques were applied, including the conversion of timestamps from Unix format to *datetime* format for increased readability and manipulation, the setting of the 'Open Timestamp' as the index for the time-series data, the use of the *MinMaxScaler* to scale the data, and the use of feature engineering to calculate the daily return and logarithmic return for the closing price.

The data is divided into training, validation, and testing sets to enable robust model evaluation. For each cryptocurrency, as shown in Figure 1, the data is split as follows: the training set includes data points from January 1, 2024, to April 6, 2024, 14:45 (64% of the total data), the validation set comprises data points from April 6, 2024, 15:00 to April 30, 2024, 18:45 (16% of the total data), and the testing set covers data points from April 30, 2024, 19:00 to May 30, 2024, 23:45 (20% of the total data). This division ensures that the model is trained on earlier data, validated on subsequent data, and tested on the most recent data, providing a realistic assessment of the model's performance on unseen data.

3.3 Model Descriptions

3.3.1 Baseline Models. To evaluate the effectiveness of TCN, three baseline strategies will be employed for comparison, the Buy-and-Hold, the Naïve Forecast strategy, and the ARIMA model.

The Buy-and-Hold strategy involves checking the cumulative return on investment if the coin was bought at the start and only sold at the end of the available dataset. This strategy helps to determine whether refraining from any trading would have been more profitable than using any trading model.

The Naïve Forecast model, on the other hand, assumes that the future price of a cryptocurrency will be equal to its most recent price. By comparing the predictions of the TCN model against this simple forecasting technique, the model's ability to capture more complex patterns and trends in the data can be more easily assessed.

Finally, the Autoregressive Integrated Moving Average (ARIMA) model is a widely used time series forecasting method, which has demonstrated effectiveness in capturing short-term trends and seasonality in financial data [6, 8, 25, 27, 40]. By analysing historical price sequences and incorporating lagged observations and differencing to achieve stationarity, the ARIMA model provides an ideal baseline for comparison of the deep learning models.

3.3.2 LSTM Model. The Long Short-Term Memory (LSTM) model is a type of Recurrent Neural Networks (RNN) specifically designed to handle time-series data and long-range dependencies. LSTM networks have been extensively used in various domains, especially finance, due to their ability to capture complex patterns over time. As discussed in Section 2, several studies have identified LSTMs as one of the most effective models for predicting cryptocurrency prices, owing to their capability to learn from historical price sequences and generalise well to unseen data.

The architecture of the LSTM model employed in this research is designed to optimise the prediction accuracy while maintaining computational efficiency. Initially, the historical price data underwent preprocessing, which involved scaling using a *MinMaxScaler* to normalise the data to a range of 0 to 1. Additionally, the data was organised into sequences with a length of 60 periods (15-minute intervals), where each sequence serves as an input to the model. Subsequently, the model parameters, including LSTM units, dropout rate, and learning rate, were fine-tuned using *KerasTuner*.

The model comprises the following layers:

1. *LSTM Layer*: The first LSTM layer includes 64 units, chosen through hyperparameter tuning, and is configured to return sequences, enabling the model to pass the temporal dependencies to the next LSTM layer.
2. *Dropout Layer*: A dropout rate of 0.2 is applied to prevent overfitting by randomly setting a fraction of input units to zero at each update during training.
3. *Second LSTM Layer*: The second LSTM layer, also with 64 units, processes the sequences from the previous layer and returns the final state, which captures the temporal dynamics of the input data. Another dropout layer with a 0.2 rate is applied to further reduce overfitting.
4. *Dense Layer*: A dense layer with a single unit is used to produce the final output, which represents the predicted cryptocurrency price.

The model is compiled using the Adam optimizer with a learning rate of 0.01 and the MSE loss function, ensuring robust training and convergence.

To enhance the performance and robustness of the LSTM model, the Bagging and Boosting ensemble method are implemented and compared.

1. *Bagging*: Bagging (Bootstrap Aggregating) involves training multiple LSTM models on different bootstrap samples of the dataset and averaging their predictions. This method helps reduce the variance and improve the model's generalisation ability. First, multiple bootstrap samples were generated from the original dataset, which were used to train an LSTM model on each of them. Averaging the predictions from all the trained models, the final forecast was obtained.
2. *Boosting*: This involves sequentially training LSTM models, where each subsequent model attempts to correct the residual errors of the previous model. This approach helps improve the accuracy by focusing on hard-to-predict instances. The first LSTM model is therefore trained on the original dataset, after which the residual errors from the prediction of this first model is calculated in order to be used to train additional LSTM models iteratively. The predictions from all the models are subsequently summer to produce the final output.

As shown in Table 4, the Boosting technique provided better results. Hence, the final LSTM model was implemented with the inclusion of the Boosting technique.

The LSTM model's performance was compared with the TCN model. While both models are capable of handling sequential data, they have distinct architectural differences. The LSTM model, with its recurrent nature, is adept at capturing long-term dependencies and patterns in the data. In contrast, the TCN model uses dilated convolutions to achieve a large receptive field, allowing it to model long-range dependencies without the risk of vanishing gradients that can affect RNNs.

3.3.3 TCN Model. The proposed forecasting model leverages the TCN model to capture long-term dependencies and handle the high volatility characteristic of cryptocurrency markets. TCN have demonstrated superior performance in handling sequential data with long-range dependencies while addressing limitations commonly encountered in traditional RNN, such as vanishing gradients and computational inefficiency.

The TCN architecture comprises multiple layers of dilated causal convolutions, followed by Rectified Linear Unit (ReLU) activation functions to introduce non-linearity. Causal convolutions ensure that information leakage from future data points is prevented, maintaining the temporal integrity required for time-series forecasting. By employing dilated convolutions, the model exponentially increases its receptive field, allowing it to capture long-range dependencies effectively. The model incorporates historical price data, as well as trading values, in order to enhance its predictive capabilities.

The TCN model is trained using historical cryptocurrency price data. The data is preprocessed using *MinMaxScaler* to scale the features and create input-output pairs for the model. This ensures that all input features are within a similar numerical range, preventing certain features from dominating the model's learning process. The model is then trained using the Adam optimizer with a MSE loss function. During training, the model learns to minimise the difference between the predicted prices and the actual prices in the training set.

Randomised hyperparameter search is once again conducted using the *KerasTuner* library to explore different combinations of hyperparameters, such as the number of filters in convolutional layers, kernel sizes, and learning rates. The best parameters were found to include 64 filters in the first convolutional layer, with a kernel size of 5, 32 filters with a kernel size of 5 in the second convolutional layer, and a learning rate of 0.001.

After applying the Bagging and Boosting methods to the TCN model, as previously done with the LSTM model, it appeared that the Bagging technique outperforms the Boosting technique, as shown in Table 5. To further investigate the impact of this technique on the TCN model's performance, separate experiments are conducted on the TCN model, one without Bagging and another with Bagging technique included.

3.4 Model Evaluation

3.4.1 Evaluation Metrics. To comprehensively compare and evaluate the LSTM and TCN models, the following metrics were employed:

1. *Root Mean Square Error (RMSE)*: This metric is the square root of the mean of the squared errors. It provides a measure of the magnitude of prediction errors and is more sensitive to large errors. It is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

   where:
   - n is the number of data points,
   - y_i is the actual value,
   - $\hat{y}_i$ is the predicted value.
2. *Mean Absolute Error (MAE)*: Measures the average magnitude of the errors in a set of predictions, without considering their direction. It is defined as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

3. *Explained Variance*: Assesses the proportion of the variability in the data that is accounted for by the model. It is defined as:

$$\text{Explained Variance} = 1 - \frac{\text{Var}(y - \hat{y})}{\text{Var}(y)} \tag{3}$$

   where:
   - $\text{Var}(y - \hat{y})$ is the variance of the errors,
   - $\text{Var}(y)$ is the variance of the actual values.
4. *Mean Absolute Percentage Error (MAPE)*: Expresses the accuracy as a percentage, measuring the average absolute percentage error between predicted and actual values. It is defined as:

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{4}$$

   where:
   - $\sum_{i=1}^{n}$ represents the summation over all actual values.
5. *R-Squared (R2)*: Indicates the proportion of the variance in the dependent variable that is predictable from the independent variables. It is defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{5}$$

3.4.2 Visualising Performance. To further illustrate the model's performance, the predicted versus actual prices are plotted over the test period. The plots highlight the price trend, with the predicted prices closely follow the actual price trend, indicating that the model successfully captures the overall movement of cryptocurrency prices; as well as an error analysis, by difference between predicted and actual prices over time, one can observe that the errors are relatively small and do not exhibit any systematic pattern, suggesting that the model generalises well to unseen data. Such a plot can be seen in Figure 2.

3.5 Trading Simulation

The methodology and results of the trading simulation are also conducted to assess the real-world applicability and effectiveness of the forecasting models, LSTM and TCN.

The trading simulations are executed using a simple strategy where the model's predicted prices are utilised to make buy or sell decisions at each time step. The simulations are conducted over a specified historical time period, with the model making trading decisions based on predictions made for each subsequent time step.

3.5.1 Simulation Parameters. In conducting the trading simulation, several key parameters were selected to ensure the robustness and reliability of the evaluation process. The trading fee, which represents the cost incurred for executing trades within the market, was set to 0.1%, as charged by Binance[2] for trading on their platform, in order to simulate a more realistic scenario.

Additionally, the initial capital allocated to the trading portfolio was set at 1000 USDT to provide sufficient liquidity and flexibility in executing trading strategies.

4 Results and Discussion

In order to have a baseline for the performance of the rest of the evaluated models, the Buy-and-Hold strategy was implemented, the results of which can be found in Table 1.The test period spanned from April 30, 2024, to May 30, 2024. During this timeframe, investments in cryptocurrency coins would have yielded a modest profit, with Ethereum (ETH) boasting the highest cumulative return of 26%. These returns will serve as a benchmark to ensure that the ML models do not outperform a simple passive investment strategy, which would indicate that investors would have been better off without using the models.

Coin	Starting Balance	Final Balance	Return
BTC	1000	1136.93	13.92%
ETH	1000	1266.49	26.90%
BNB	1000	1044.88	4.70%
LTC	1000	1077.8	8.00%
XRP	1000	1043.27	4.54%

Table 1. Performance Metrics for Buy-and-Hold Strategy

The Naïve Forecast model serves as another straightforward simplistic baseline to compare more complex forecasting models. It assumes that the future price of a cryptocurrency will be the same as its most recent observed price. As shown in Table 2, in particular the high MAE and MSE values, especially with Bitcoin (BTC), suggest that the model struggles to accurately predict cryptocurrency prices. Thus, there is significant room for improvement. The MAPE values suggest that the model's percentage errors range from 0.20% to 0.27%, indicating generally accurate predictions on average. Given these results, the Naïve Forecast's performance appears to be relatively good in terms of predicting the direction of price movements, with some variations in absolute error metrics across different cryptocurrencies.

Coin	MAE	MSE	RMSE	MAPE	DA
BTC	116.167	32336.4	179.823	0.1970	47.5235
ETH	7.0278	120.409	10.9731	0.2253	48.0477
BNB	1.0984	3.0866	1.7569	0.2293	44.4123
LTC	0.2185	0.1331	0.3648	0.2654	46.2541
XRP	0.0014	0.0000	0.0024	0.2411	44.8331

Table 2. Performance Metrics for the Naïve Forecast Model

Finally, Table 3 shows that the ARIMA model's performance varies across different cryptocurrencies. While it demonstrates relatively high RMSE values for BTC and ETH, indicating significant prediction errors in absolute terms, it achieves lower RMSE values for Binance Coin (BNB), Litecoin (LTC), and Ripple Coin (XRP). The MAPE values suggest that the model's percentage errors range from -1.64% to -3.98%, with negative values indicating overestimation and positive values indicating underestimation on average. The R2 values are relatively low for all coins, indicating that the model explains only a small portion of the variance in the data. Overall, the ARIMA model's performance appears to be mixed across different cryptocurrencies, suggesting that it may not be the most suitable model for all coins in this context.

Coin	RMSE	MAE	MAPE (%)	R2	MSLE
BTC	5798.9234	4883.3470	-1.6435	0.0082	-1.1614e-06
ETH	477.2762	322.8215	-0.6413	0.0200	2.2043e-07
BNB	22.9085	19.8092	-1.3187	0.0015	-3.1802e-06
LTC	4.8215	4.2595	-3.2210	0.0034	-1.0333e-05
XRP	0.0278	0.0250	-3.9776	0.0003	6.3184e-06

Table 3. Performance Metrics for the ARIMA Model

Having established the baseline models, the LSTM and TCN models will now be analysed and compared, using RMSE, MSE, MAPE, R2 and the Explained Variance. Through these results, shown in Table 6, one could better ascertain which model demonstrates superior performance.

Table 4 presents the comparative performance of the LSTM model using Bagging and Boosting techniques across various cryptocurrencies. It shows that the Boosting method consistently outperformed the Bagging method across all evaluated cryptocurrencies, with lower MAE and MAPE values, suggesting improved accuracy and better fit to the data. Additionally, the Boosting method consistently achieved higher R^2 and Explained Variance values, indicating a better explanatory power of the model. With this information, it was decided that the Boosting method will be implemented to the LSTM model to ensure the best possible results.

The Bagging and Boosting ensemble methods were also compared for use with the TCN method, the results of which

[2]Binance Spot Trading Fee Rate: https://www.binance.com/en/fee

Metric	BTC	ETH	BNB	LTC	XRP
Bagging Results					
RMSE	313.0836	15.8069	2.6740	0.4189	0.0025
MAE	243.0828	11.1054	1.7385	0.2548	0.0015
MAPE	0.0045	0.0037	0.0037	0.0031	0.0026
R^2	0.9991	0.9991	0.9995	0.9985	0.9973
Explained Variance	0.9992	0.9991	0.9995	0.9985	0.9974
Boosting Results					
RMSE	244.5636	14.1132	2.7558	0.4185	0.0032
MAE	158.4662	9.5927	1.8997	0.2514	0.0024
MAPE	0.0027	0.0032	0.0042	0.0031	0.0044
R^2	0.9995	0.9993	0.9995	0.9985	0.9955
Explained Variance	0.9995	0.9993	0.9996	0.9985	0.9972

Table 4. Bagging and Boosting Results for the LSTM Model

can be found in Table 5. Based on the results, Bagging performed better than Boosting for the TCN model, as it generally exhibits lower error metrics and higher goodness-of-fit metrics across the evaluated cryptocurrencies. Therefore, an additional model was created, incorporating the Bagging ensemble method, allowing for a comparison between the conventional TCN model, and the TCN model with Bagging.

Metric	BTC	ETH	BNB	LTC	XRP
Bagging Results for TCN Model					
RMSE	270.56	18.13	2.40	0.32	0.0018
MAE	197.76	11.06	1.80	0.23	0.0012
MAPE (%)	0.31	0.33	0.31	0.28	0.23
R^2	0.9942	0.9976	0.9744	0.9816	0.9782
Explained Variance	0.9953	0.9977	0.9805	0.9844	0.9782
Boosting Results for TCN Model					
RMSE	410.30	19.90	2.39	0.35	0.0019
MAE	268.58	12.48	1.70	0.25	0.0013
MAPE (%)	0.42	0.38	0.29	0.30	0.25
R^2	0.9867	0.9971	0.9747	0.9780	0.9751
Explained Variance	0.9868	0.9972	0.9762	0.9790	0.9751

Table 5. Bagging and Boosting Results for TCN Model

The TCN methods have a significantly shorter computation time when compared to the LSTM model, an important factor in any prediction model given the constant fluctuations present in the cryptocurrency market.

Although LSTM outperforms conventional TCN models in certain aspects, it still falls short when compared to TCN with Bagging. Additionally, the LSTM model yielded more incorrect trades than correct ones for the BTC and XRP coins, something that is not observed with either TCN model.

Based on these results, it can be concluded that the TCN models provided the best overall outcome, balancing prediction accuracy, as shown with the low RMSE, MAE, MAPE

Metric	LSTM	TCN	TCN+Bagging
	BTC		
RMSE	333.364	235.148	244.158
MAE	218.686	162.328	164.000
MAPE	0.00343988	0.00251681	0.00254024
R2	0.991228	0.995636	0.995295
Exp. Variance	0.991418	0.995680	0.995374
Final Balance (USDT)	1106.01	1165.74	1114.01
Total Trades	18	26	20
Time Taken	97.1055	20.9219	1.1946
Correct Trades	7	19	12
Incorrect Trades	11	7	8
	ETH		
RMSE	19.838	18.8497	17.087
MAE	12.8672	11.0289	10.1623
MAPE	0.00386244	0.00329898	0.00305542
R2	0.997168	0.997443	0.997899
Exp. Variance	0.997169	0.997451	0.997924
Final Balance (USDT)	1065.78	1152.72	1092.79
Total Trades	10	20	13
Time Taken	81.1	14.7502	1.28752
Correct Trades	6	14	8
Incorrect Trades	4	6	5
	BNB		
RMSE	2.54246	4.89165	2.35597
MAE	1.73044	3.49952	1.55133
MAPE	0.00294685	0.00595854	0.00264403
R2	0.971422	0.894211	0.97546
Exp. Variance	0.971461	0.901712	0.975524
Final Balance (USDT)	1086.28	1206.83	1187.5
Total Trades	12	28	23
Time Taken	83.4569	6.79155	1.18518
Correct Trades	7	15	13
Incorrect Trades	5	13	10
	LTC		
RMSE	0.412805	0.3438	0.297389
MAE	0.286721	0.239498	0.204766
MAPE	0.00347045	0.00289696	0.0024749
R2	0.968803	0.978361	0.983809
Exp. Variance	0.968814	0.978628	0.983977
Final Balance (USDT)	1494.71	1344.71	1097.47
Total Trades	34	32	12
Time Taken	53.1616	13.4675	1.36901
Correct Trades	20	19	6
Incorrect Trades	14	13	6
	XRP		
RMSE	0.00200041	0.00190634	0.00182593
MAE	0.00134972	0.00129222	0.00120851
MAPE	0.00258316	0.00247028	0.00231114
R2	0.973905	0.976301	0.978258
Exp. Variance	0.97391	0.976708	0.978283
Final Balance (USDT)	1219.45	1421.29	1388.2
Total Trades	41	55	53
Time Taken	93.0686	14.5011	1.18384
Correct Trades	20	32	30
Incorrect Trades	21	23	24

Table 6. LSTM & TCN Model Results

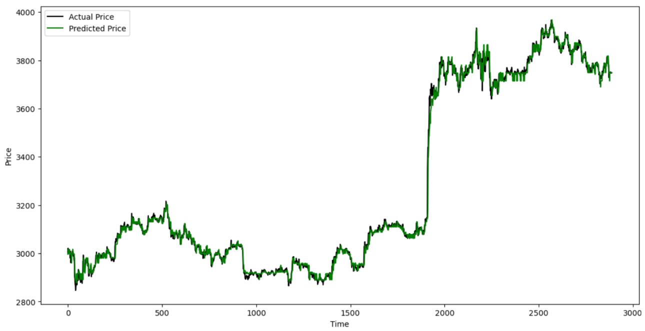

Figure 2. Predicted vs Actual Price for Bitcoin (BTC) using the TCN Model

and high R2, with a reasonable number of correct trades and computational efficiency.

In comparison to the Naïve Forecast, Buy-and-Hold, and ARIMA models, the TCN model with Bagging ensemble method offers several advantages. It outperforms the Naïve Forecast and ARIMA models in terms of prediction accuracy and trading performance, as well as provides a higher profit margin than the Buy-and-Hold strategy across all cryptocurrencies except for ETH.

Considering the findings from studies like [2, 4, 39], the results suggest a comparable performance between LSTM and the conventional TCN model with both demonstrating very similar metrics. However, the TCN model performed marginally worse in [4] but slightly better in [39]. This research reinforces such trend, however, it should be noted that the TCN outperformed the LSTM model in simulations, producing a higher final balance with all cryptocurrencies except LTC. It should again be noted that employing the Bagging ensemble method with TCN yielded consistently lower prediction errors, more accurate trades, and significantly faster computational speeds. Additionally, in simulations, the Bagging ensemble method showcased superior performance across all coins except LTC when compared to the LSTM model.

5 Conclusion

This research has demonstrated the effectiveness of TCN in forecasting cryptocurrency prices. By leveraging the ability of TCNs to capture long-term dependencies in sequential data, our model has shown superior performance in comparison to traditional methods such as Buy-and-Hold, Naïve Forecast, and ARIMA, as well as the more advanced LSTM networks. The TCN model with an integrated Bagging ensemble method not only achieved the best overall outcome in price prediction, but also demonstrated robustness in volatile market conditions. These findings underscore the potential of TCNs to provide valuable insights for traders, enhancing their decision-making processes in the dynamic cryptocurrency market.

5.1 Limitations and Challenges

Despite the promising results, several limitations and challenges were encountered in this study:

- *Data Quality and Availability:* Cryptocurrency markets are highly volatile, and the quality of data can significantly impact model performance, as shown with the BTC data in the results. A wider range of data would minimise the impact of volatility on the training of the data.
- *Market Anomalies:* Unpredictable market events, such as regulatory changes or significant technological advancements, can introduce anomalies that are challenging for models to account for, potentially leading to significant prediction errors.
- *Computational Complexity:* Although TCNs are more efficient than RNN-based models, the training process for large datasets is still computationally intensive. Further optimisations to the parameters could further decrease this complexity.
- *Model Generalisation:* While the TCN model performed well on the selected cryptocurrencies, its generalisability to other financial markets remains to be thoroughly investigated.

5.2 Future Works

Future works in cryptocurrency price prediction offer promising avenues for advancing research and enhancing prediction accuracy. Based on the insights from this study, several key areas for future exploration emerge.

One direction involves integrating technical indicators, such as MA, MACD, and RSI strategies, into prediction models could enhance their ability to identify trends, momentum, and potential buying or selling opportunities.

Furthermore, exploring additional features beyond historical price data and trading volumes, such as sentiment analysis of news articles, social media activity, or blockchain data, could provide valuable insights into market sentiment and enhance the predictive power of the models.

Implementing real-time forecasting capabilities could also be instrumental in enabling timely decision-making for traders. Furthermore, a larger dataset would allow for more comprehensive analysis and validation of predictive models under different market conditions and time periods.

Exploring advanced model architectures, including hybrid models that combine TCNs with other deep learning techniques, has potential to improve predictive performance. Extending the application of TCNs to other financial markets and incorporating risk management strategies within forecasting models present opportunities for further research.

In conclusion, while TCNs have shown great promise in the realm of cryptocurrency price forecasting, ongoing research and development are essential to address existing limitations and fully harness the potential of these advanced machine learning techniques.

The code used for this research is available on GitHub, and written in Python through Jupyter Notebook.

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Abbreviations

AI Artificial Intelligence
ANN Artificial Neural Networks
ARIMA Autoregressive Integrated Moving Average

BART Binary Autoregressive Tree
BiLSTM Bidirectional LSTM
BNN Bayesian Neural Network

CA Casual Multi-Head Attention
CNN Convolutional Neural Network

DRL Deep Reinforcement Learning

EMH Efficient Market Hypothesis

GARCH Generalized Autoregressive Conditional Heteroskedasticity
GNN Graph Neural Networks
GRU Gated Recurrent Unit

LSTM Long Short-Term Memory

MA Moving Average
MACD Moving Average Convergence Divergence
MAE Mean Absolute Error
MAPE Mean Absolute Percentage Error
ML Machine Learning
MLP Multilayer Perceptron
MSE Mean Squared Error

R2 R-Squared
ReLU Rectified Linear Unit
RF Random Forest
RMSE Root Mean Square Error
RNN Recurrent Neural Networks
RSI Relative Strength Index

SGBM Stochastic Gradient Boosting Machines
SVM Support Vector Machines
SVR Support Vector Regression

TCN Temporal Convolutional Network

VaR Value-at-Risk

WAMC Weighted & Attentive Memory Channels
WT Wavelet Transform

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