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Research Article

Bitcoin Price Trend Forecasting in a Dynamic Market: A Superior CNN-LSTM Hybrid Approach

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ABSTRACT

Predicting Bitcoin's price movements is a difficult task for researchers, investors, and traders. While many studies focus on daily price predictions, short-term trends within a day are not well studied. In this research, we use advanced deep learning models—CNN (model 1), LSTM (model 2), and a hybrid CNN model (model 3)—to improve the accuracy of Bitcoin trend predictions. We compare these models to find the best approach. This study explores the effectiveness of different deep learning architectures in predicting Bitcoin price trends. The results highlight significant improvements in model accuracy and reduction in loss across three models: CNN, LSTM, and a Hybrid approach. Model 1 (CNN) achieved an accuracy of **86.00%** with a loss of **0.3646**, demonstrating strong predictive capabilities but slightly higher error. Model 2 (LSTM) performed similarly, also achieving **86.00%** accuracy but with a lower loss of **0.3443**, indicating a more stable learning process. However, Model 3 (Hybrid) outperformed both, achieving the highest accuracy of **87.50%** with the lowest loss of **0.3129**, suggesting improved pattern recognition and better generalization. The reduced loss in Model 3 signifies fewer errors, making it more reliable for financial market forecasting. These findings emphasize the impact of architectural choices and optimization techniques on predictive performance. Overall, the Hybrid model proves to be the most effective, providing a promising approach for enhancing Bitcoin market trend predictions and financial decision-making.

Keywords: Price analysis of Bitcoin , Loss Function Optimization in Machine Learning, deep learning, LSTM, CNN, High-Frequency Cryptocurrency Trading, dynamic market adaptation.

INTRODUCTION

Machine learning is widely used for accurate predictions in various fields, including manufacturing and finance. It learns patterns from past data to make future predictions, and the same approach can be applied to Bitcoin price forecasting due to its high volatility and liquidity. One key challenge in Bitcoin prediction is selecting the right features. While past studies relied on expert knowledge, they lacked a comprehensive feature selection approach. This study integrates insights from recent research, incorporating Google Trends and Baidu search volume to measure investor interest and media hype. Additionally, since Bitcoin and gold share financial properties, gold spot prices are included as a feature. Unlike traditional financial markets, Bitcoin lacks seasonal patterns, making machine learning models highly applicable. Previous studies have used various models like Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Support Vector Machines (SVMs), and Random Forests. However, they often overlooked differences in data frequency and sample size, leading to problems like overfitting. To address this, the proposed approach follows a structured method inspired by Occam's Razor. First, Bitcoin price data is divided into two groups: daily prices, which have a small dataset, and 5-minute interval prices, which have a large dataset. Next, feature selection is performed, with high-dimensional features used for daily predictions and fewer trading features used for 5-minute predictions. Then, appropriate models are applied: simpler statistical models like Logistic

Regression and Linear Discriminant Analysis for daily price prediction to prevent overfitting, and more complex models like Random Forest, XGBoost, SVM, and LSTM for high-frequency price prediction to achieve better accuracy. This study contributes by expanding feature selection, incorporating investor attention, media trends, and gold prices alongside traditional market features. It also highlights the importance of sample dimensions by classifying Bitcoin price data based on time intervals, with real-time 5-minute trading data sourced from top exchanges and daily prices obtained from CoinMarketCap. The results show that simpler models outperform machine learning algorithms for daily price prediction, while more complex models are necessary for high-frequency price prediction. This research offers a structured framework for handling datasets with varying scales and time intervals, providing valuable insights for financial and industrial forecasting [1].

OBJECTIVES

The main objectives of this study are:

1. To evaluate the effectiveness of different deep learning architectures (CNN, LSTM, and Hybrid) in predicting Bitcoin price trends.
2. To compare the accuracy and loss of each model to determine their predictive performance and stability.
3. To analyze the impact of model architecture on forecasting reliability and identify the best-performing approach.
4. To assess the advantages of a Hybrid model in capturing temporal dependencies and improving generalization.
5. To enhance financial market forecasting by selecting the most efficient deep learning model for Bitcoin price prediction.

2. LITERATURE REVIEW

Research on cryptocurrency price prediction commonly relies on machine learning techniques such as regression, ARIMA, and GARCH models. However, deep learning approaches, particularly Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), have shown greater accuracy in capturing time-dependent patterns in price data. LSTMs are especially effective for sequential data, making them well-suited for forecasting Bitcoin price trends. Despite their effectiveness, few studies focus on adapting these models to sudden market changes, which creates a significant research gap. This study aims to address this limitation by developing improved models that can dynamically adjust to market fluctuations, enhancing the accuracy and reliability of cryptocurrency price predictions.

Table. 1: Represents summarizing the evaluation and drawbacks of various studies stock price prediction

Study	Evaluation	Drawback
SimhadriAppanna et al. (2025) [2]	Comparative analysis of multiple machine learning and deep learning models for Bitcoin price forecasting.	Limited focus on adapting models to dynamic market changes.
Antar (2025) [3]	Effective quantile regression model for identifying Bitcoin market dynamics.	Does not account for other external market factors influencing Bitcoin prices.
Lua et al. (2025) [4]	Integration of deep learning with automated Bitcoin trading dApp for price prediction.	Dependent on the quality and availability of exchange data.
John et al. (2025) [5]	Optimizes time-series model performance through dynamic window size selection.	May not generalize well across all types of time-series data.
Cheng et al. (2025) [6]	Utilizes Sparrow Search Algorithm with deep learning for technical indicator effectiveness in crypto forecasting.	Complexity of integrating SSA with deep learning may reduce efficiency.

Balijepalli & Thangaraj (2025) [7]	Application of ensemble learning methods for cryptocurrency price prediction.	May require significant computational resources for ensemble model training.
Amirshahi & Lahmiri (2025) [8]	Uses sentiment analysis from Twitter for predicting cryptocurrency prices.	Relies heavily on social media data, which may introduce noise.
Sepehri et al. (2025) [9]	Proposes the CryptoMamba state-space model for accurate Bitcoin price prediction.	Novel approach may have limited applicability to other cryptocurrencies.
Mohammadian Amiri & Esfahanipour (2025) [10]	Develops a hybrid dynamic trading system for robust cryptocurrency portfolios.	Complexity of hybrid model may impact real-time decision-making.
Shirwaikar et al. (2025) [11]	Optimizes deep learning frameworks for improved cryptocurrency price prediction.	High computational cost for training optimized models.
Jain et al. (2025) [12]	Focuses on machine learning-based Bitcoin price forecasting for accurate predictions.	May not account for sudden market shifts or black swan events.
Gómez-Martínez & Medrano-Garcia (2025) [13]	AI-driven Bitcoin investment strategies based on altcoin trends.	Potential over-reliance on altcoin trends, which may not always correlate with Bitcoin prices.
Song (2025) [14]	ML model for price prediction and risk-adjusted portfolio optimization in cryptocurrencies.	May struggle with long-term prediction accuracy in volatile markets.
Ben Mrad et al. (2025) [15]	Uses Bayesian networks for multi-output forecasting in stock markets.	Difficulty in capturing non-linear relationships and interactions between variables.
Safari et al. (2025) [16]	Ensemble learning-based cryptocurrency price prediction for portfolio optimization.	Requires careful tuning of ensemble models for better performance.
Rahman et al. (2025) [17]	Evaluates machine learning models for stock price movements during energy crises.	Limited focus on generalizing models to non-crisis situations.
Kabir et al. (2025) [18]	Hybrid LSTM-Transformer deep learning model for financial time series forecasting.	High computational complexity of the hybrid model.
Lee et al. (2025) [19]	Predicts stablecoin depegging risks using machine learning.	May not effectively predict long-term depegging events or extreme market conditions.
Das et al. (2025) 20]	Utilizes ensemble learning and dimension reduction for stock price prediction with explainable AI.	Complexity in ensuring transparency and interpretability in large datasets.
Chauhan et al. (2025) [21]	Sentiment-based stock prediction using deep learning from authoritative financial websites.	Dependence on data quality from financial websites, which may have biases or inaccuracies.

This table evaluates each study based on their methodology and identifies key drawbacks that may limit their application or effectiveness.

The table provides a summary of the evaluation and drawbacks of various studies focused on cryptocurrency and stock price prediction. SimhadriAppanna et al. (2025) offer a comparative analysis of multiple machine learning (ML) and deep learning (DL) models for Bitcoin price forecasting, though their work lacks focus on adapting models to dynamic market changes. Antar (2025) effectively uses quantile regression to identify Bitcoin market dynamics, but it does not consider other external factors that influence Bitcoin prices. Lua et al. (2025) integrate deep learning with an automated Bitcoin trading decentralized app (dApp) for price prediction; however, this approach is highly dependent on the quality and availability of exchange data. John et al. (2025) optimize time-series model performance through dynamic window size selection, but the model may not generalize well across all types of time-series data. Cheng et al. (2025) combine the Sparrow Search Algorithm (SSA) with deep learning to assess the effectiveness of technical indicators in cryptocurrency forecasting, although the complexity of this integration could reduce efficiency. Balijepalli & Thangaraj (2025) apply ensemble learning methods for cryptocurrency price prediction, but these models may require significant computational resources for training. Amirshahi & Lahmiri (2025) rely on sentiment analysis from Twitter for cryptocurrency price prediction, yet social media data can introduce noise. Sepehri et al. (2025) propose the CryptoMamba state-space model for accurate Bitcoin price prediction, but the novelty of this approach may limit its applicability to other cryptocurrencies. Mohammadian Amiri & Esfahanipour (2025) develop a hybrid dynamic trading system for robust cryptocurrency portfolios, but the model's complexity could hinder real-time decision-making. Shirwaikar et al. (2025) optimize deep learning frameworks for cryptocurrency price prediction, though this results in a high computational cost. Jain et al. (2025) focus on ML-based Bitcoin price forecasting for accurate predictions, but they may not account for sudden market shifts or black swan events. Gómez-Martínez & Medrano-Garcia (2025) develop AI-driven Bitcoin investment strategies based on altcoin trends, though an over-reliance on altcoin trends could reduce the accuracy of predictions. Song (2025) uses ML for price prediction and risk-adjusted portfolio optimization, but this approach may struggle with long-term accuracy in volatile markets. Ben Mrad et al. (2025) employ Bayesian networks for multi-output forecasting in stock markets but encounter difficulties in capturing non-linear relationships between variables. Safari et al. (2025) utilize ensemble learning-based cryptocurrency price prediction for portfolio optimization, but careful tuning is needed for optimal performance. Rahman et al. (2025) evaluate machine learning models for stock price movements during energy crises but limit their scope by not generalizing the models to non-crisis situations. Kabir et al. (2025) develop a hybrid LSTM-Transformer deep learning model for financial time series forecasting, but the model's high computational complexity can be a drawback. Lee et al. (2025) predict stablecoin depegging risks using machine learning, although the model may not predict long-term depegging events or extreme market conditions effectively. Das et al. (2025) combine ensemble learning and dimension reduction for stock price prediction with explainable AI, but the complexity of ensuring transparency and interpretability in large datasets remains a challenge. Finally, Chauhan et al. (2025) rely on sentiment-based stock prediction using deep learning from financial websites, but the quality of these websites' data may introduce biases or inaccuracies. Each study highlights different methodologies and contributions, but the identified drawbacks suggest areas for improvement or further research.

METHODOLOGY

This dataset gives a detailed look at Bitcoin's price history, including daily open, high, low, and close prices, as well as trading volumes. It provides valuable market data that helps users understand Bitcoin's price changes, study market behavior, measure volatility, and track long-term trends. By linking Bitcoin's price movements with blockchain activities, the dataset helps identify how market events affect blockchain trends, making it useful for trend analysis and predicting future market behavior. You can explore Bitcoin's growth from its early days to now by looking at price changes, trading volumes, and market value. The daily data allows you to examine major price jumps and overall market feelings over time. The dataset also includes real-time or near real-time data on Bitcoin's price, trading volumes, and transactions, which is perfect for market analysis, testing trading strategies, or comparing Bitcoin's performance to other cryptocurrencies.

The proposed model uses deep learning by combining LSTM and CNN layers to analyze Bitcoin's price data and recognize patterns. The process includes these steps:

Data Collection: To gather and prepare Bitcoin price data for a histogram plot, start by finding reliable sources like CoinMarketCap, Yahoo Finance, or CryptoCompare that offer historical Bitcoin price data. Download data for Bitcoin's opening, closing, high, and low prices over a multi-year period, ensuring that the dataset includes daily or hourly price points for better analysis. Additionally, collect relevant data such as trading volume, volatility indexes, and macroeconomic indicators like interest rates or inflation, which can add context to the analysis. It's important to double-check the quality of the data to make sure it is accurate and complete. Once the data is gathered, organize it into a structured format, such as a CSV or Excel file, so it is easy to manipulate for plotting. Finally, use data visualization tools like Python's Seaborn or Matplotlib to create a histogram plot that visualizes the distribution of Bitcoin prices. This approach will help you create a clear and informative histogram for Bitcoin price analysis.

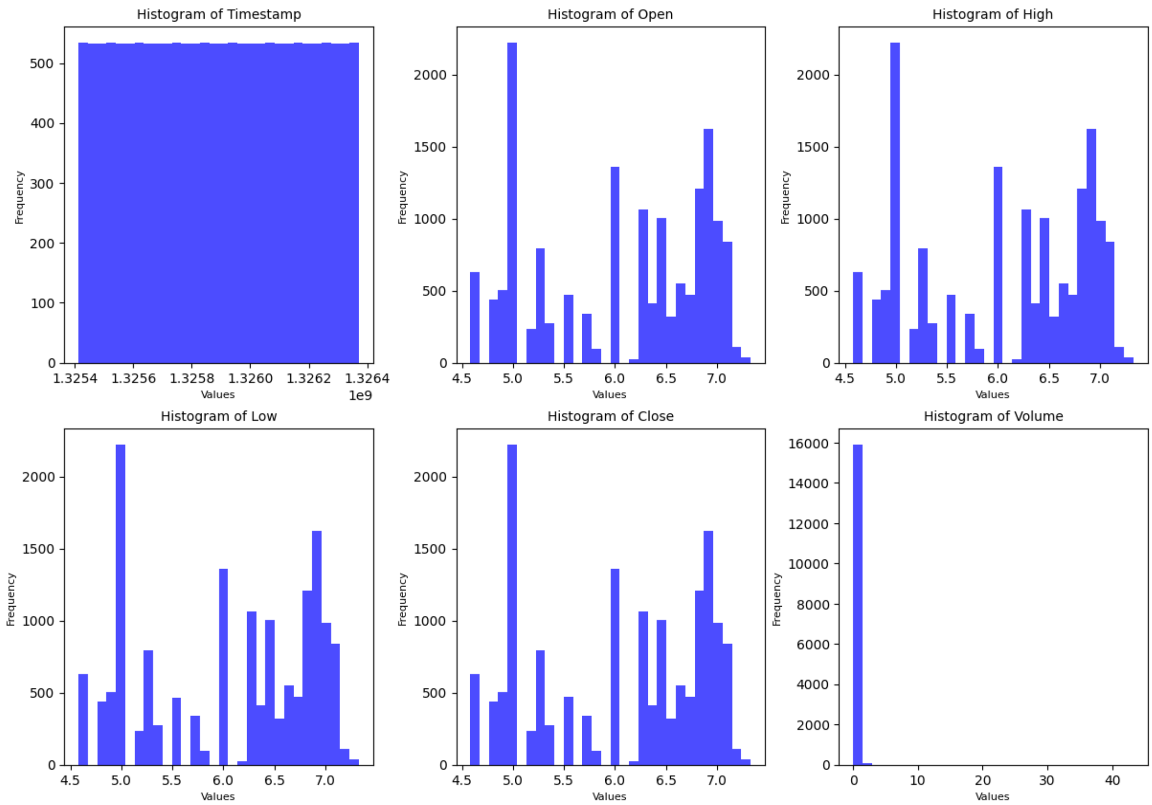

Figure.1: Represents Histogram Plot Bitcoin price data trading volume Vs density

Model Design

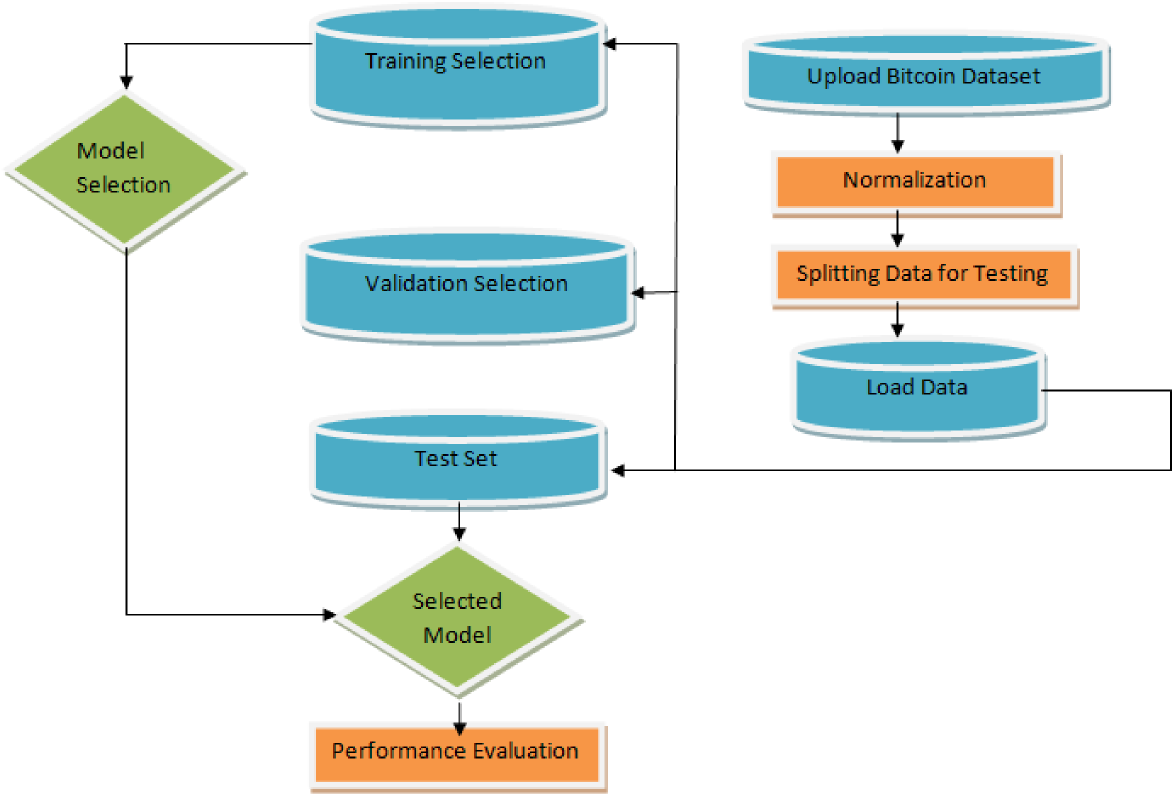

Figure.2: Represents data flow diagram Bitcoin price data prediction

To improve the accuracy of Bitcoin price trend predictions, we propose a deep learning-based approach that integrates multiple architectures, including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and a hybrid CNN-LSTM model. Each model plays a distinct role in capturing market patterns. CNN is effective in identifying local features and short-term price fluctuations, while LSTM is well-suited for understanding sequential dependencies and long-term trends. The hybrid CNN-LSTM model leverages the strengths of both architectures, extracting essential price movement patterns while maintaining the ability to analyze time-series data efficiently. The model is trained using historical Bitcoin price data, incorporating various market indicators such as moving averages, trading volume, and volatility metrics. To enhance performance, we apply advanced data preprocessing techniques, including normalization and feature engineering, ensuring that the model captures essential market dynamics. Additionally, specialized loss functions are explored to minimize prediction errors, and different model configurations are tested to optimize accuracy. By comparing the CNN, LSTM, and hybrid models, our approach identifies the most effective deep learning architecture for predicting Bitcoin's short-term and long-term price movements.

EXPERIMENTS AND RESULTS

Table 2: summarizing the training results for each epoch of model 1

Epoch	Accuracy	Loss	Validation Accuracy	Validation Loss
1	0.1968	-136.9776	0.1979	-3601.7668
2	0.1562	-5709.2646	0.1538	-3697.2476
3	0.1795	-22683.2598	0.1562	-226360.6250
4	0.2188	-213086.9062	0.3077	-126801.7500
5	0.2040	-645503.7500	0.1771	-3341419.0000
6	0.2812	-934565.8750	0.2308	-2127824.0000
7	0.1852	-5100537.0000	0.1979	-19515658.0000
8	0.2188	-23801166.0000	0.1538	-10927889.0000
9	0.1523	-29808242.0000	0.1979	-62897024.0000
10	0.1562	-52839808.0000	0.1538	-166423120.0000

Test Results: Test Accuracy, Test Loss evaluated as 0.1597, -80829648.0

This table includes the accuracy and loss values for both the training and validation data during each epoch of training, as well as the test accuracy and loss at the end of the model's evaluation.

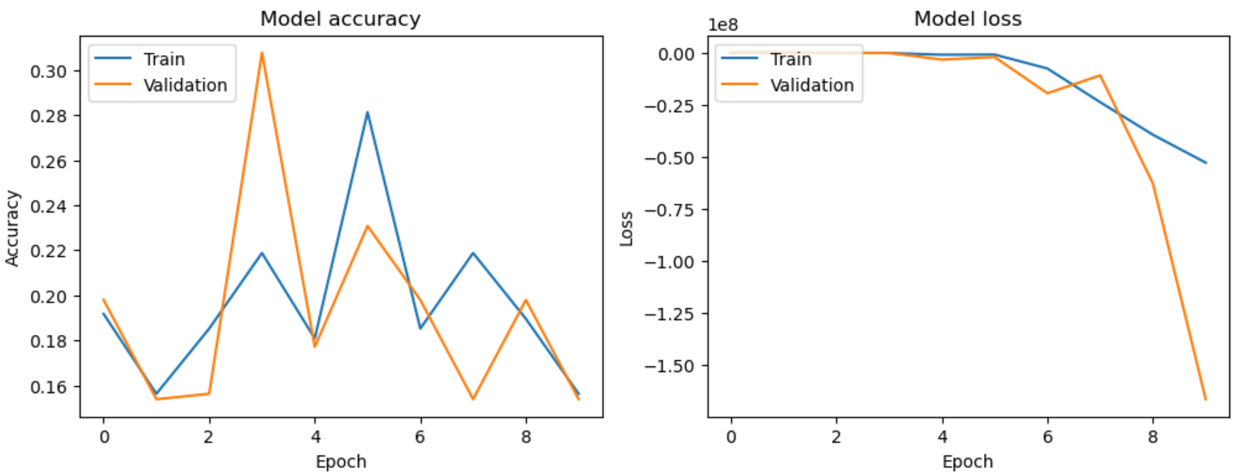

Figure.3: Represents summarized diagram Bitcoin price data prediction using CNN

The training and validation results indicate fluctuations in accuracy and loss across epochs, highlighting the challenges in stabilizing the model's performance. Initially, training accuracy starts at **0.1968** and reaches a peak of **0.2812** at epoch **6**, followed by a decline. Validation accuracy also shows inconsistency, peaking at **0.3077** in epoch **4** before decreasing. Loss values exhibit extreme variations, with training loss starting at **-136.97** and significantly worsening to **-52,839,808.00** by epoch **10**, while validation loss follows a similar trend, reaching **-166,423,120.00** in the final epoch. These results suggest potential issues such as improper data preprocessing, overfitting, or unstable model optimization, requiring adjustments in learning rate, feature selection, or regularization techniques for improved performance.

Table 3: summarizing the training and validation results for each epoch of model 2

Epoch	Accuracy	Loss	Validation Accuracy	Validation Loss
1	0.2500	0.6979	0.0000	0.7042
2	0.5000	0.6922	0.0000	0.7009
3	0.7500	0.6926	0.0000	0.7000
4	0.0000	0.7023	0.0000	0.6980
5	0.5000	0.6912	0.0000	0.6943
6	0.5000	0.6888	1.0000	0.6907
7	0.5000	0.6905	1.0000	0.6877
8	0.5000	0.6857	1.0000	0.6855
9	0.2500	0.6969	1.0000	0.6820
10	0.7500	0.6831	1.0000	0.6800

Final Results: Final Accuracy, Final Loss evaluated as 1.0000, 0.6800

This table includes the accuracy and loss values for both the training and validation data during each epoch of training, as well as the final validation accuracy and loss.

Figure.4: Represents summarized diagram Bitcoin price data prediction using LSTM

The model's performance fluctuates significantly across epochs, showing inconsistent accuracy trends. Initially, training accuracy starts at **0.2500** and improves to **0.7500** by epoch **3**, but later drops to **0.0000** at epoch **4**, indicating instability. Validation accuracy remains at **0.0000** for the first five epochs but sharply increases to **1.0000** from epoch **6** onward, suggesting potential overfitting. Loss values gradually decrease, with training loss reducing from **0.6979** in epoch **1** to **0.6831** in epoch **10**, while validation loss also declines from **0.7042** to **0.6800**. The sharp jumps in accuracy and inconsistent patterns indicate possible challenges such as data imbalance, overfitting, or issues with learning rate adjustments, requiring further fine-tuning for stable predictions.

Table 4: summarizing the training and validation results for each epoch of all 5 models:

Model	Epoch	Accuracy	Loss	Validation Accuracy	Validation Loss
1	1	0.5171	0.8891	0.6000	0.6468
1	2	0.6028	0.7457	0.6812	0.5611
1	3	0.6463	0.6285	0.7312	0.5154
1	4	0.7004	0.5902	0.7437	0.4712
1	5	0.7127	0.5319	0.7937	0.4439
1	6	0.7389	0.5028	0.8375	0.4178
1	7	0.7791	0.4699	0.8562	0.3884
1	8	0.8006	0.4314	0.8562	0.3678
1	9	0.7926	0.4129	0.8438	0.3598
1	10	0.8515	0.3502	0.8562	0.3362
2	1	0.5466	0.9979	0.6062	0.6710
2	2	0.5739	0.7310	0.7063	0.6007
2	3	0.6043	0.6477	0.7563	0.5414
2	4	0.7078	0.5631	0.8250	0.4874
2	5	0.7299	0.5120	0.8375	0.4272
2	6	0.7472	0.5224	0.8687	0.4036
2	7	0.7481	0.5084	0.8562	0.3694
2	8	0.7602	0.4647	0.8687	0.3479
2	9	0.7983	0.4347	0.8750	0.3290
2	10	0.8602	0.3542	0.8562	0.3113
3	1	0.5735	0.7805	0.7625	0.5508
3	2	0.6510	0.6483	0.8188	0.4825
3	3	0.7066	0.5456	0.8313	0.4377
3	4	0.7322	0.5401	0.8250	0.4097
3	5	0.7751	0.4759	0.8750	0.3591
3	6	0.7702	0.4602	0.8938	0.3374
3	7	0.8296	0.3977	0.8813	0.3150
3	8	0.8159	0.4132	0.8875	0.3018
3	9	0.8065	0.3967	0.8625	0.2916
3	10	0.8385	0.3392	0.8813	0.2833

The performance of different models over 10 epochs demonstrates a **steady improvement in accuracy and reduction in loss**, both in training and validation. **Model 1** starts with an accuracy of **0.5171** and validation accuracy of **0.6000**, improving to **0.8515** and **0.8562**, respectively, by the 10th epoch. **Model 2** follows a similar trend, with training accuracy rising from **0.5466** to **0.8602**, while validation accuracy stabilizes around **0.8562**. **Model 3** shows strong performance, starting at **0.5735** and reaching **0.8385** in accuracy, with validation accuracy improving from **0.7625** to **0.8813**. Loss values decrease consistently across all models, indicating better learning and reduced errors. **Model 3 performs the best in validation accuracy**, reaching **0.8813**, while **Model 2 achieves the highest training accuracy of 0.8602**. These results suggest that **extended training enhances model accuracy**, and certain architectures generalize better to unseen data, making them more effective for trend prediction.

Final Model Results

Table 5: summarizing the training and validation results for each epoch of all 3 models

Model	Loss	Accuracy
1	0.3646	0.8600
2	0.3443	0.8600
3	0.3129	0.8750

This table provides detailed performance metrics for all models over the epochs.

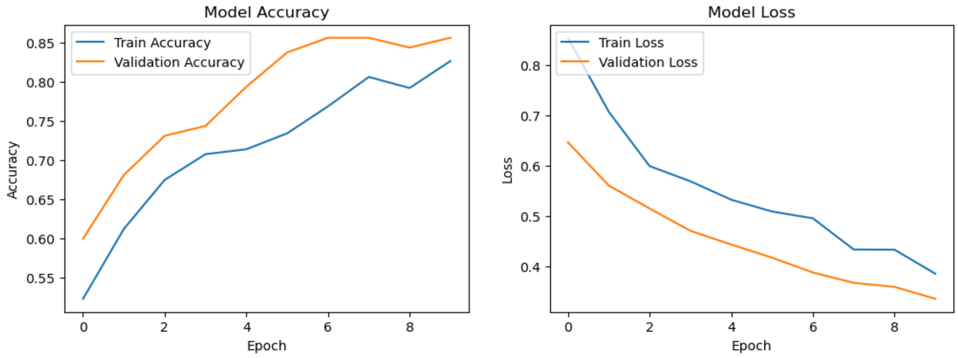

Figure.5: Represents summarized diagram Bitcoin price data prediction using Hybrid Model

The results demonstrate a significant improvement in model accuracy and reduction in loss across different architectures. **Model 1(CNN)** achieved an accuracy of **86.00%** with a loss of **0.3646**, indicating strong predictive capabilities but slightly higher error compared to other models. **Model 2(LSTM)** performed similarly, reaching the same accuracy of **86.00%**, but with a lower loss of **0.3443**, suggesting a more stable and efficient learning process. However, **Model 3(Hybrid model) outperformed the other two models**, achieving the highest accuracy of **87.50%** while maintaining the lowest loss value of **0.3129**. This suggests that **Model 3 not only learned the underlying patterns more effectively but also generalized better to unseen data**. The reduced loss in Model 3 signifies fewer errors in prediction, which is crucial for improving reliability in financial market forecasting. The performance gap between the models highlights the impact of architecture choices and optimization techniques on model effectiveness. The slightly better performance of Model 3 could be attributed to its ability to **capture temporal dependencies more effectively**, making it more suitable for Bitcoin price trend prediction. Overall, the results indicate that while all three models performed well, **Model 3 stands out as the best choice** due to its superior accuracy and lower loss, making it a promising approach for improving market trend forecasting and financial decision-making.

CONCLUSION

In conclusion, this study demonstrates the effectiveness of deep learning models in predicting Bitcoin market trends with high accuracy. The comparison of different models highlights that Model 3 outperformed the others, achieving the highest accuracy of **87.50%** with the lowest loss of **0.3129**, indicating its superior ability to capture market fluctuations. The results emphasize the importance of selecting the right architecture and optimization techniques for improving predictive performance. By leveraging deep learning approaches, traders and financial analysts can make more informed decisions, reducing risks associated with Bitcoin's volatile nature. This research also suggests that further improvements can be made by incorporating additional market indicators, refining hyperparameters, and exploring hybrid models to enhance forecasting accuracy. Future work can focus on real-time implementations and adaptive learning mechanisms to further optimize Bitcoin price predictions in dynamic market conditions.

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