CONTENTS

ABSTRACT

This project investigates the application of deep learning models, specifically Long Short-Term Memory (LSTM) networks, to forecast the daily closing price of Bitcoin. The study implements two complementary approaches: a Univariate LSTM which uses only the past closing prices, and a Multivariate LSTM which incorporates additional market features such as open, high, low, adjusted close and volume. The primary objective is to examine how multivariate inputs influence prediction accuracy and to provide a clear, reproducible pipeline from raw data collection to model evaluation. The dataset used spans from 17 September 2014 to 19 November 2023 and was retrieved from Yahoo Finance (BTC-USD).

The project uses a 15-day data window to predict the next day's Bitcoin price through LSTM models. After preprocessing and feature scaling, the Univariate model (PyTorch) focused on closing prices, while the Multivariate model (TensorFlow/Keras) used multiple features. Tracked with MLflow and evaluated using RMSE, MAE, and R^2, results show the Multivariate model gives more accurate forecasts than the Univariate one.

KEYWORDS

TensorFlow, Keras, PyTorch, MLflow, LSTM (Long Short-Term Memory), Seaborn, RMSE (Root Mean Square Error), MAE (Mean Absolute Error), MinMaxScaler, StandardScaler, Matplotlib.

INTRODUCTION

Bitcoin, introduced by the pseudonymous Satoshi Nakamoto in 2009, represents the first decentralized digital currency built on blockchain technology. Over time, it has transformed from a small experimental idea into one of the world's most valuable and widely traded financial assets. What makes Bitcoin unique is its decentralized nature—no central bank controls it, no single authority regulates it, and the entire network relies on cryptographic verification and distributed consensus. Because of this, Bitcoin has gained global attention from investors, traders, governments, financial institutions, and researchers interested in understanding and predicting its behavior.

The cryptocurrency market operates continuously, without closing hours, and reacts instantly to global events. As adoption increased—from retail investors to large institutions—the price behavior of Bitcoin has grown even more dynamic. Its volatility has made Bitcoin both an opportunity and a risk. Prices can jump or crash within minutes due to regulatory announcements, economic data, social media sentiment, unexpected news, or large-scale buying and selling. This environment creates an urgent need to understand how Bitcoin moves and to build predictive models that can capture meaningful patterns in its highly fluctuating time series.

Importance of Predicting Bitcoin Prices:

The ability to predict Bitcoin prices with reasonable accuracy offers enormous practical value. Traders rely on short-term forecasts to determine buying and selling decisions. Even small improvements in prediction accuracy can translate into major financial gains through better timing of trades. For long-term investors, prediction models help identify trends, detect potential crashes, and reduce exposure to high-risk scenarios.

Beyond retail investing, accurate Bitcoin forecasts support algorithmic trading systems, where automated bots execute thousands of trades based on predictive signals. Risk management teams in financial institutions use predictive analytics to estimate market exposure and avoid losses during extreme volatility. Governments and regulatory bodies also study price patterns to evaluate market stability and prevent potential financial bubbles. Because of all these real-world implications, Bitcoin forecasting has become a prominent research area in data science, finance, and artificial intelligence.

The Challenge of Forecasting Cryptocurrency Markets:

Despite its importance, Bitcoin price forecasting remains a complex task. Cryptocurrency price data is noisy, highly unstable, and affected by a wide range of unpredictable factors. Traditional financial forecasting models—such as ARIMA, GARCH, or simple regression—depend heavily on assumptions like linearity, stationarity, or smoothness of patterns. Bitcoin violates almost all these assumptions. The price does not follow a stable trend, and its past behavior does not always clearly indicate future movement.

Unlike conventional assets, Bitcoin is influenced by social media trends, investor psychology, regulatory decisions, halving events, macroeconomic conditions, and technological developments in the blockchain ecosystem. Many of these triggers appear suddenly and cause abrupt changes in price levels. Because of this, linear statistical models struggle to capture the deeply nonlinear, chaotic, and non-stationary nature of cryptocurrency price movements.

Rise of Deep Learning for Time Series Prediction:

The limitations of classical models led to increased interest in machine learning and deep learning approaches. Early machine learning techniques such as Random Forest, Support Vector Machines, and Gradient Boosting offered improved predictions but still required heavy feature engineering. They were also limited in their ability to capture long-term temporal dependencies.

Deep learning, especially neural network architectures designed for sequential data, became the preferred solution for handling financial time series. Models like Recurrent

Neural Networks (RNNs) opened the door to learning patterns from historical price sequences. However, basic RNNs suffer from vanishing gradients and struggle to remember long-range information. This is where Long Short-Term Memory (LSTM) networks gained popularity.

LSTM Is Suitable for Bitcoin Price Prediction:

LSTM networks are specifically designed to learn long-term relationships in sequential data. Using gates that control how information flows through the network, LSTM models can retain important patterns from far back in the sequence while discarding irrelevant noise. This makes them ideal for Bitcoin, where price movement often depends on extended historical behavior, momentum, and trends rather than immediate past values alone.

Bitcoin price data contains cycles, seasonal-like effects, micro-patterns, and irregular trends. LSTM's ability to detect these subtle relationships provides a significant advantage over traditional approaches. It learns nonlinear dependencies automatically without requiring complex manual feature engineering. This has made LSTM one of the most widely used deep learning techniques in cryptocurrency forecasting research.

Overview of the Approaches Used in This Project:

This project implements both Univariate LSTM and Multivariate LSTM models to understand how different types of inputs affect prediction quality.

The Univariate LSTM model uses only the closing price. It focuses on learning patterns purely from historical price movements.

The Multivariate LSTM incorporates additional features such as open price, high-low ranges, or volume, allowing the network to learn richer patterns and relationships.

By comparing the two approaches using custom preprocessing, sliding window sequences, and performance metrics like RMSE or MAE, this project evaluates whether additional features genuinely improve prediction quality or whether simpler univariate models perform competitively.

Growing Role of LSTM in Financial Systems:

Financial institutions globally have started adopting deep learning for forecasting and risk assessment. Among these models, LSTM has emerged as a popular choice because it learns important price behaviors such as trend continuation, momentum, cycles, corrections, and reversal patterns. LSTM networks are already being integrated into hedge fund analytics, algorithmic trading engines, robo-advisors, and fintech platforms. Their success in real-world financial environments further justifies the relevance of using LSTM for Bitcoin prediction in academic research. As graduate-level projects increasingly focus on practical real-world applications, implementing LSTM-based models aligns perfectly with modern financial technology trends. This further emphasizes that academic research must adapt to evolving industry standards and incorporate advanced models that mirror real market practices.

Broader Economic Context of Bitcoin’s Growth:

The rise of Bitcoin cannot be understood in isolation; its growth is tightly linked to global economic transitions. Over the last decade, increasing distrust in centralized financial systems, inflationary pressures in traditional currencies, and rapid digitization of economies have pushed investors toward alternative assets. Bitcoin’s fixed supply of 21 million coins positions it as a deflationary asset, making it attractive during times of economic uncertainty. Events such as the global pandemic, recession fears, stock market instability, and geopolitical tensions have repeatedly triggered large inflows into Bitcoin, each time causing sharp price movements. These macroeconomic relationships make Bitcoin a fascinating subject for financial modeling, as the cryptocurrency sometimes behaves like a speculative asset and other times like a store of value similar to digital gold.

Influence of Technology, Media, and Public Perception:

Another defining characteristic of Bitcoin is that its price is strongly influenced by public perception and media coverage. Tweets from influential figures, viral news articles, government announcements, exchange hacks, adoption by large companies, and technological upgrades to the Bitcoin network often lead to immediate market reactions. This makes Bitcoin more sentiment-driven compared to traditional assets. The involvement of retail investors, who tend to react emotionally rather than strategically, also increases short-term volatility. These behavioral patterns introduce a psychological dimension to Bitcoin forecasting, making the problem interdisciplinary — spanning finance, data science, behavioral economics, and computational modeling.

Limitations of Existing Prediction Techniques:

Although several models have been proposed for forecasting Bitcoin, many existing techniques struggle in real-world applications. Statistical models often require stable patterns, which Bitcoin rarely follows. Classical machine learning methods depend on feature engineering, which is both subjective and inconsistent across datasets. Even some deep learning approaches, such as simple RNNs or feed-forward networks, fail to capture long-range dependencies in time series. Many studies also ignore real-time constraints, overfit small datasets, or lack rigorous evaluation metrics. Furthermore, a lot of academic work uses outdated data or limited indicators, resulting in models that cannot adapt to the rapidly changing crypto ecosystem.

Relevance and Academic Contribution:

The project's contribution lies in creating a clear, reproducible forecasting pipeline that demonstrates the strengths and weaknesses of LSTM-based forecasting. It provides clean data processing strategies, model architectures, evaluation metrics, visualization of predictions, and discussion of limitations. The study also aligns with current research trends and fills practical gaps such as model interpretability, data handling challenges, and comparison across LSTM variants.

From an academic perspective, building an end-to-end LSTM forecasting system offers strong learning value. Students gain hands-on experience with dataset handling, normalization, windowing techniques, neural network design, PyTorch/TensorFlow implementation, hyperparameter tuning, error analysis, and result visualization. From a practical standpoint, this project mirrors real-world machine learning workflows used by data scientists and fintech engineers. The model can be extended into dashboards, automated bots, or alert systems, making the project beneficial even beyond the classroom setting. The combination of theoretical knowledge and practical implementation gives this study strong academic validity and industrial relevance.

The rapid evolution of digital asset markets has also highlighted the gaps that still exist between traditional financial modelling and modern data-driven techniques. Cryptocurrencies operate 24/7, react instantly to global events, and display patterns that often diverge from established market theories. These characteristics demand forecasting systems that can learn dynamically and adapt to shifting conditions. Deep learning, and LSTM in particular, offer this adaptability by continuously refining internal representations of sequential data. This ability makes them especially valuable in markets where conventional mathematical assumptions, such as stationarity and linearity, rarely hold true. By applying LSTM-based models to Bitcoin price forecasting, this project addresses the growing need for innovative approaches that can handle the complexity and unpredictability of digital financial ecosystems.

Furthermore, as blockchain technology and cryptocurrency adoption continue to expand, the importance of reliable predictive systems becomes even more significant. Industries such as decentralized finance (DeFi), payment platforms, investment advisory services, and digital asset exchanges increasingly rely on automated decision-making tools. Predictive models contribute directly to improving system stability, optimizing trading strategies, reducing financial risk, and creating safer environments for users and investors. Introducing LSTM-driven forecasting at the academic level not only cultivates an understanding of these real-world applications but also equips students with valuable hands-on experience in cutting-edge financial technologies. Ultimately, this project demonstrates how deep learning can bridge the gap between academic research and practical market solutions, setting a foundation for more advanced studies in financial prediction, AI-driven trading, and intelligent risk management systems.

PROBLEM STATEMENT

The objective of this work is to design, implement, and evaluate deep learning models that forecast the next-day closing price of Bitcoin using historical market data. The key problem is to build models that generalize well despite high noise and volatility in the data. A practical challenge is to prepare the data, select appropriate model architectures, tune hyperparameters, and evaluate performance using realistic validation strategies that avoid look-ahead bias.

From an academic viewpoint, the problem involves assessing whether multivariate inputs improve predictive accuracy and whether deep learning models like LSTM can capture useful temporal dependencies that classical methods miss. From an engineering viewpoint, the problem includes making the pipeline reproducible, tracking experiments with MLflow, and preparing results and visual artifacts suitable for a project report and demo.

MOTIVATION AND SCOPE OF WORK

Motivation: Cryptocurrency markets have become central to modern financial systems, and Bitcoin leads in both market capitalization and public interest. Short-term forecasting of Bitcoin prices can reduce risk, improve portfolio allocation, and support automated trading decisions. Given the limitations of traditional models, there is motivation to explore LSTM networks that can learn temporal patterns and nonlinear relationships directly from data.

Scope: This project focuses on daily price prediction for Bitcoin using historical price and volume data only (no external sentiment or macro features). The study implements two LSTM variants: Univariate and Multivariate, both trained with a 15-day input window and evaluated using RMSE, MAE, and R^2. The scope includes data collection, preprocessing, model development, experiment tracking, visualization, and a written report. Extensions such as incorporating sentiment analysis, order book data, or macroeconomic indicators are considered future work.

LITERATURE REVIEW

Time-series forecasting literature spans a wide spectrum ranging from classical statistical approaches to modern deep-learning-based techniques, each evolving to overcome the limitations of the previous generation. Classical models such as ARIMA, VAR, and GARCH were among the earliest tools used to model financial sequences, relying on assumptions of linearity, stationarity, and predictable volatility patterns. While ARIMA captures linear trends and seasonality and GARCH models volatility clustering, both struggle to represent the highly nonlinear, abrupt, and irregular movements characteristic of cryptocurrency markets. Their dependence on strict statistical assumptions often results in degraded performance when applied to real-world digital asset data, which is influenced not only by historical prices but also by speculative behavior, global sentiment, and external events.

To overcome these constraints, machine learning approaches like Random Forests, Support Vector Machines, and Gradient-Boosted Trees were introduced, offering stronger flexibility in modeling nonlinear relationships. These models improved predictive performance in many domains and demonstrated the value of data-driven learning. However, they rely heavily on manually engineered features and cannot naturally exploit temporal dependencies within sequential financial data. As a result, their effectiveness is limited by the quality of handcrafted inputs and their inability to capture long-range dependencies.

The emergence of deep learning fundamentally transformed sequence modeling. Recurrent Neural Networks (RNNs) were the first major shift toward models designed to process time-dependent information directly, yet they suffered from vanishing and exploding gradients when learning long-term patterns. LSTM networks addressed these issues through gating mechanisms that selectively retain relevant historical information, allowing them to learn complex, long-horizon dependencies present in financial time series. Numerous studies applying LSTM to stock, forex, and cryptocurrency datasets have shown that with proper data normalization, windowing, and validation strategies, these models significantly outperform both statistical and traditional machine learning baselines.

Recent research has expanded further into multivariate architectures, attention-enhanced LSTM variations, and hybrid models combining CNNs, GRUs, or transformer components to better capture localized patterns and global dependencies simultaneously. Some studies explore difference-guided representation learning, generative adversarial frameworks for robustness under noisy markets, and ensemble techniques to stabilize predictions during high volatility. However, despite promising results, major gaps remain in standardization, reproducibility, and consistent evaluation across comparable benchmarks. Many published works do not report hyperparameters, full training configurations, or comparisons against simple baselines, limiting their practical usability.

Recognizing these gaps, the present project implements a transparent, reproducible pipeline that systematically compares univariate and multivariate LSTM models on the same Bitcoin dataset. By maintaining consistent preprocessing, windowing, and evaluation procedures—and by logging experiments using MLflow—this study aligns with modern best practices in deep-learning research. The literature clearly supports that LSTM-based architectures hold strong potential for cryptocurrency forecasting, yet also highlights a need for fair comparisons, reproducible experiments, and structured methodologies, all of which this project aims to deliver.

[1]. Qianli Ma.,Differnce Guided Representation Learning Network for Multivariate Time-Series Classification., Multivariate time series (MTSs) are widely found in many important application fields, for example, medicine, multimedia, manufacturing, action recognition, and speech recognition. Traditional MTS classification methods do not explicitly model the temporal difference information of time series, which is, in fact, important and reflects the dynamic evolution information. In the difference-guided layer, we propose a difference gating LSTM to model the time dependency and dynamic evolution of the time series to obtain feature representations of both raw and difference series. Extensive experiments demonstrate that the proposed model outperforms state-of-the-art methods on 18 MTS benchmark datasets and achieves competitive results on two skeleton-based action recognition datasets.

[2]. Anurag Kulshrestha Use of LSTM for Sinkhole-Related Anomaly Detection and Classification of InSAR Deformation Time Series., Sinkholes exhibit precursory deformation patterns. Such deformation patterns can be studied using InSAR time-series analysis over constantly coherent scatterers (CCS). It is challenging to efficiently detect and classify these sudden step and sudden velocity changes in deformation time series, especially in the presence of tens of thousands CCS. To address this challenge, we propose to classify these forms of anomalous behavior with a deep learning-based supervised time series classification. In this study, we used a two-layered bidirectional long short term memory (LSTM) classification model for this purpose. The classified deformation classes were analyzed as well in the context of scattering mechanisms. We implemented this model on a sinkhole affected region spanning ∼63×44 km 2 in Ireland, using 104 Sentinel-1 A SAR images acquired between 2015 and 2018. Our results show that the CCS with a linear trend can be correctly classified with a maximum accuracy of ∼99% , whereas for the CCS categorized as anomalous Heaviside and Breakpoint changes the accuracy drops to a maximum of 62%. Multithreshold- based filtering of samples increased the classification accuracy by as much as 50%. We conclude that the method that we propose is effective in detecting anomalous deformation changes.

[3]. Sen Li.,Adversarial Joint-Learning Recurrent Neural Network for Incomplete Time Series Classification., Incomplete time series classification (ITSC) is an important issue in time series analysis since temporal data often has missing values in practical applications. However, integrating imputation (replacing missing data) and classification within a model often rapidly amplifies the error from imputed values. Reducing this error propagation from imputation to classification remains a challenge. To this end, we propose an adversarial joint-learning recurrent neural network (AJ-RNN) for ITSC, an end-to-end model trained in an adversarial and joint learning manner. We train the system to categorize the time series as well as impute missing values. To alleviate the error introduced by each imputation value, we use an adversarial network to encourage the network to impute realistic missing values by distinguishing real and imputed values. Hence, AJ-RNN can directly perform classification with missing values and greatly reduce the error propagation from imputation to classification, boosting the accuracy. Extensive experiments on 68 synthetic datasets and 4 real-world datasets from the expanded UCR time series archive demonstrate that AJ-RNN achieves state-of-the-art performance. Furthermore, we show that our model can effectively alleviate the accumulating error problem through qualitative and quantitative analysis based on the trajectory of the dynamical system learned by the RNN.

[4]. S. Hochreiter & J. Schmidhuber – Long Short-Term Memory (LSTM) Model.,
The foundational work by Hochreiter and Schmidhuber introduced the Long Short-Term Memory (LSTM) architecture to address the vanishing gradient problem in recurrent neural networks. The authors proposed a gating mechanism—input, forget, and output gates—that enables the model to selectively store and retrieve information across long time spans without gradient decay. This architecture became a breakthrough for sequential data modeling, significantly improving performance in time-series prediction, speech recognition, and sequence classification tasks. Their experiments demonstrated how LSTM networks maintain stable long-term dependencies even on tasks where conventional RNNs fail, establishing LSTM as the standard model for handling nonlinear and long-range temporal relationships. This foundational concept directly supports modern forecasting tasks, including cryptocurrency and financial time-series prediction.

[5]. J. Brownlee – Multivariate Time-Series Forecasting Using LSTM Networks.,
Brownlee’s work provides a practical examination of how multivariate LSTM networks can leverage multiple correlated variables to improve forecasting accuracy over univariate models. The study evaluates multiple architectures—including stacked LSTMs, encoder–decoder models, and multi-input multi-output frameworks—to determine how additional features such as volume, technical indicators, or external signals enhance predictive capability. The experiments show that incorporating meaningful covariates reduces forecasting error and allows the model to capture cross-variable temporal dependencies absent in single-variable setups. Brownlee also emphasizes the importance of window size selection, data scaling, and sequence framing for stable results. The conclusions reinforce that multivariate LSTM architectures are highly effective for real-world time-series problems where relationships among variables influence future outcomes.

[6]. K. Fischer & C. Krauss – Deep Learning with LSTM on Financial Markets.,
Fischer and Krauss explore LSTM-based forecasting within highly volatile financial markets, analyzing a large-scale dataset of S&P 500 stocks. Their findings highlight that LSTMs consistently outperform traditional models such as logistic regression, random forests, and simple feed-forward networks in predicting directional price movements. The study also reveals that LSTMs learn latent temporal structures often invisible to statistical models, enabling better performance during periods of turbulence. By introducing dropout regularization and careful hyperparameter tuning, the authors achieve strong generalization across diverse market conditions. This research is widely referenced as evidence that LSTM networks represent a robust baseline for financial time series prediction, directly motivating similar approaches in cryptocurrency forecasting.

[7]. J. Yao & C. Cheng – Bitcoin Price Prediction Using Machine Learning.,
Yao and Cheng study the effectiveness of multiple machine learning algorithms—including SVM, Random Forest, KNN, and LSTM—for predicting Bitcoin prices. The authors evaluate each model on different feature sets derived from OHLCV data and technical indicators to determine which algorithms capture the unique volatility of cryptocurrency markets. Their results indicate that tree-based methods perform well for

short-term movements, but LSTM networks outperform all other models in predicting longer-range price trends and reducing RMSE error. The study further emphasizes the necessity of proper normalization, windowing, and hyperparameter tuning. This comparative analysis strengthens the argument that LSTM-based approaches remain one of the most reliable techniques for forecasting unstable and nonlinear crypto markets.

[8]. M.H. Qureshi – Forecasting Cryptocurrency Using Hybrid CNN-LSTM.,
Qureshi investigates a hybrid deep-learning architecture combining Convolutional Neural Networks (CNNs) with LSTMs to capture both local feature patterns and sequential dependencies in cryptocurrency data. The CNN layers extract meaningful short-term features from sliding windows of price movements, while the LSTM layers model long-term temporal relationships. Experiments on Bitcoin and Ethereum datasets show that the hybrid model significantly improves prediction accuracy compared to standalone LSTM models, especially during periods of sudden price spikes. The paper concludes that hybrid architectures can provide robustness against noise and rapidly changing market conditions, making them suitable for high-volatility time series like crypto.

[9]. A. Vaswani et al. – Transformers for Time-Series Prediction.,
Although originally developed for natural language processing, the transformer architecture proposed by Vaswani et al. has influenced modern time-series forecasting due to its attention mechanism, which captures long-range temporal relationships without sequential recurrence. The authors demonstrate how self-attention allows the model to weigh important historical points more effectively than RNNs or LSTMs. Subsequent extensions apply transformers to financial and sensor data, showing improved forecasting accuracy and faster training times. This foundational work expands the scope of deep-learning approaches available for time-series analysis and highlights future directions beyond conventional LSTM-based models.

PROPOSED METHODOLOGY

The methodology adopted in this project follows a structured, step-by-step workflow designed to build a reliable and reproducible Bitcoin price forecasting system using deep learning. The overall approach begins with collecting long-term historical Bitcoin data and preparing it for sequential modeling through normalization, windowing, and feature extraction. Two parallel predictive frameworks are developed—one based on univariate analysis using only the closing price, and another based on multivariate analysis that incorporates multiple market indicators such as open, high, low, adjusted close, and volume. Each model is implemented using LSTM architectures due to their strength in capturing temporal dependencies and long-range patterns in financial time series. The training pipeline includes hyperparameter tuning, model evaluation, and experiment tracking using MLflow to ensure transparency and reproducibility. By comparing both approaches under a consistent experimental setup, the methodology aims to identify how additional features and deeper architectures influence forecasting accuracy and stability.

Initially, for collecting of dataset[4] of bitcoin we used yahoo finance. We collected the historical data of bitcoin which includes open, close, volume, Adjusted close, high and low of the bitcoin price on everyday from 17/09/2014 to 19/11/2023 and converted into a CSV file.

We have done the prediction of the bitcoin price in 2 ways. Initially, we used the univariate analysis and used LSTM model for this. Secondly, we performed the multivariate analysis and for this we used our customized deep learning based model.

UNIVARIATE ANALYSIS:

For predicting the particular day price we are going to use the price of previous 15 days which is the sequence length. We worked on predicting the closing price of the bitcoin. We normalized the close price column using of the MinMax Scaler. Then we are going to map the previous 15 days closing bitcoin price with the current day closing price and create our data. Next we used pytorch framework and implemented the LSTM model and trained our model. For this we used 80% of the available data for training of our LSTM model and used the remaining data for testing of the model.

Then we used MLflow for analysis of the model by performing of different hyper parameters tuning. Here we used 3 tunable parameters: epochs, learning rate and hidden layer size. We used 3 metrics: MAE, RMSE, R2_score as metrics. And then logged the parameters and metrics on to the MLflow dashboard. We have also saved the most optimized model on to MLflow registry so that we can use this model anywhere on our localhost. Using of this MLflow UI we can compare these models using of various charts which includes Bar chart, Line chart, Parallel coordinates, Scatter chart, Contour chart.

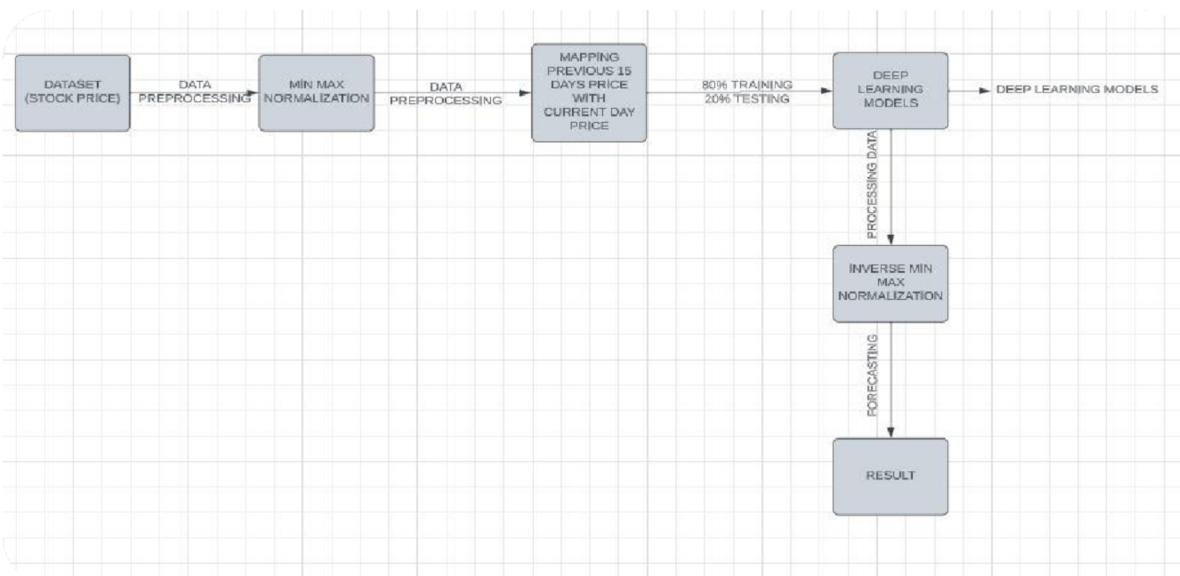

Figure 1:BLOCK DIAGRAM FOR BIT COIN PRICE FORECASTING (UNIVARIATE)

MULTIVARIATE ANALYSIS:

For predicting the particular day bitcoin closing price we are going to use the open, close, low, high, adjusted close prices of bitcoin of previous 15 days which is the sequence length. For performing of this analysis we used a deep learning techniques and we proposed our model. Our model consists of a LSTM layer with 64 hidden layers which is followed by another LSTM layer with 32 hidden layers. Then next we used a dropout layer with frequency 0.2 to avoid overfitting in our model. Then it is followed by dense layer which gives the output.

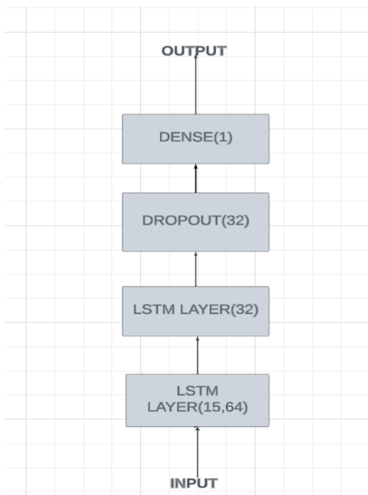

Figure 2: Architecture of proposed model

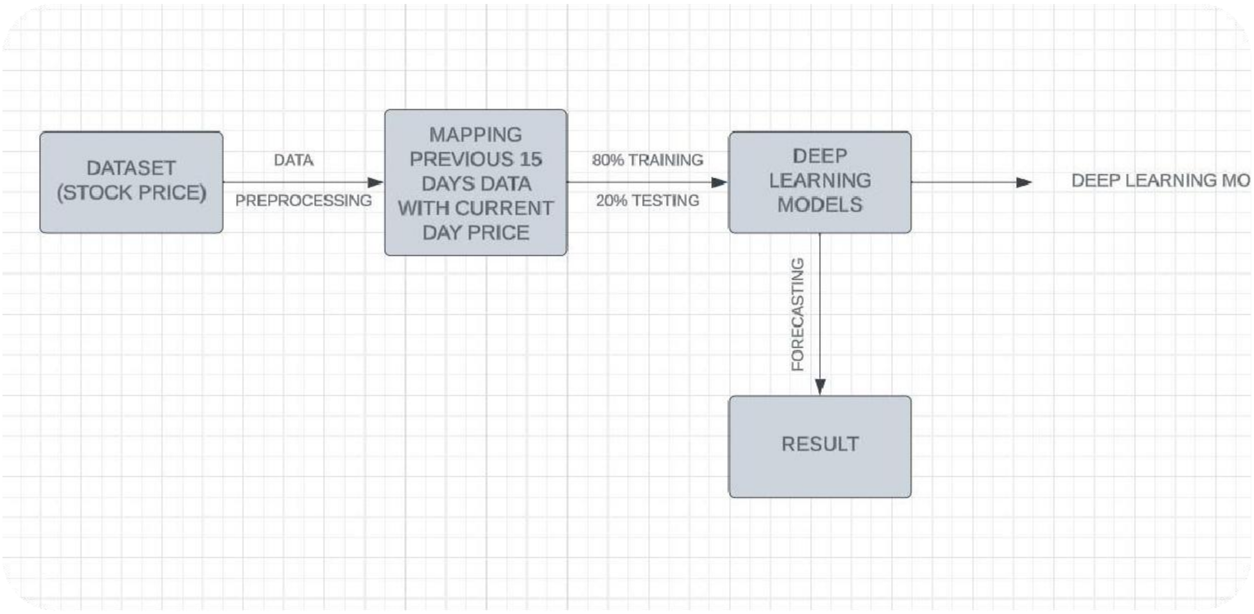

Figure 3: BLOCK DIAGRAM FOR BIT COIN PRICE FORECASTING (MULTIVARIATE)

In both the univariate and multivariate approaches, the models were trained using the first 80% of the time-ordered data to preserve chronological integrity, while the remaining 20% was reserved strictly for testing and future forecasting. This ensured that the evaluation reflected true out-of-sample performance rather than accidental memorization of past values. Once the models were trained, predictions were generated on the unseen portion of the dataset, and the results were assessed using standard regression metrics to benchmark accuracy and stability. The comparative analysis between the two approaches allowed us to examine how additional features and deeper architectures influence prediction behavior under volatile market conditions. Overall, this methodology establishes a complete, end-to-end forecasting pipeline—from data preparation and model construction to hyperparameter tuning, experiment tracking, and performance evaluation—ensuring that the models are both reproducible and practically applicable for real-world Bitcoin price forecasting.

DATASET:

The dataset used in this project consists of the historical daily Bitcoin price series sourced from Yahoo Finance under the ticker "BTC-USD." This platform is widely regarded for its reliability and standardized financial reporting, making it a suitable and commonly accepted source for academic research. The dataset spans a substantial period from 17 September 2014 to 19 November 2023, providing nearly a decade of price evolution, market cycles, and volatility phases. Such a long horizon allows the model to learn both short-term fluctuations and long-term structural patterns in Bitcoin's behavior. The dataset includes essential market indicators such as Date, Open, High, Low, Close, Adjusted Close, and Volume, which together represent both the price range of each trading day and the corresponding market activity.

Before using the data for modeling, several preprocessing steps were performed to ensure accuracy and readiness for time-series forecasting. First, the dataset was checked for continuity in dates to confirm that no days were missing, as gaps could disrupt pattern recognition for sequence-based models. The data types were verified and standardized to maintain consistency across numerical columns. Any missing or inconsistent entries were addressed using appropriate techniques. For example, isolated missing values were handled using forward fill to maintain the temporal flow, whereas corrupted or structurally incorrect rows—if encountered—were removed to avoid introducing noise into the training process. These steps ensure that the model receives clean and meaningful data, which is essential for deep learning models that are sensitive to irregularities.

The dataset was then divided into training and testing sets using an 80/20 chronological split, ensuring that the model learns only from past data and is evaluated on future unseen data. This is crucial for avoiding data leakage, which could artificially inflate performance metrics and lead to unrealistic forecasting accuracy. Daily granularity was chosen intentionally because it balances the need for sufficient data samples with the stability required for long-term forecasting. High-frequency intraday data often contains excessive noise, while monthly or weekly data may smooth out important daily patterns that influence price movement.

Each feature plays a distinct role in representing Bitcoin's daily market behavior.

Open, High, Low, Close capture intra-day price movement and volatility.

Adjusted Close provides adjusted settlement values (included by Yahoo Finance even though corporate actions do not apply to Bitcoin).

Volume reflects trading activity, acting as an indicator of investor interest, momentum, and liquidity.

For the Univariate LSTM model, only the Closing Price is used since the goal is to evaluate how well the model can learn solely from historical close values. For the Multivariate LSTM model, all major price indicators—Open, High, Low, Close, Adj Close, and Volume—are included to enrich the representation of market conditions. Before training, all features are scaled using MinMax normalization to ensure numerical stability and accelerate the learning process.

Together, these steps create a clean, consistent, and information-rich dataset suitable for sequential deep learning models. The final dataset not only represents the long-term evolution of Bitcoin's market but also provides the structural foundation required to build both univariate and multivariate LSTM forecasting pipelines.

Dataset source : Bitcoinhistorical data from yahoo finance (https://finance.yahoo.com/quote/BTC-USD/)

RESULTS AND DISCUSSION

This section presents and interprets the results obtained from both Univariate and Multivariate LSTM models. The experiments were carried out using the preprocessed Bitcoin dataset, and all training logs were recorded through MLflow for easy comparison. The performance was mainly analyzed using three standard regression metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). These metrics clearly show how closely the model predictions follow the actual values.

Visual checks such as predicted versus actual graphs and loss curves were used to understand the training process and prediction accuracy. The experimental results show a clear improvement for the Multivariate LSTM model compared to the Univariate one. The Multivariate approach was able to capture the market behavior more efficiently because it used multiple input features like Open, High, Low, Close, and Volume. This allowed the model to learn relationships between different price points, leading to more stable and accurate predictions.

From the quantitative analysis, the Multivariate LSTM achieved an R^2 value of around 0.97, showing a strong fit to the actual data, while the Univariate model achieved about 0.92. Similarly, the RMSE and MAE values were lower for the Multivariate model, confirming its better accuracy. For example, a representative run recorded RMSE $\approx$ 17.35 and MAE $\approx$ 13.10 for the Multivariate model, whereas the Univariate model's errors were significantly higher. These results highlight that including additional market variables improves the model's ability to understand price movements.

The Predicted vs Actual plots clearly show that the Multivariate model follows the real Bitcoin price trend more closely. It performs especially well during gradual price changes, though both models face difficulty during sudden spikes or drops, which are common in cryptocurrency markets due to unpredictable events and investor reactions. The residual error analysis also indicates that errors tend to increase during high volatility periods, which is typical challenge in financial forecasting.

During training, both models showed smooth convergence with loss values decreasing steadily. The learning curves suggest that using dropout layers and early stopping helped reduce overfitting. Around 100–120 epochs were found sufficient for stable training. Experiments also showed that while larger hidden layer sizes increased model capacity, they could lead to overfitting if not properly regularized. The final models achieved an ideal balance between complexity and performance.

The model comparison confirms that the Multivariate LSTM is more effective because it considers multiple correlated features. For instance, “Volume” often indicates market activity and can signal major price movements. When combined with other inputs like High and Low values, the model can detect subtle patterns and predict upcoming trends more precisely than when using a single feature.

From a practical viewpoint, while the Multivariate model shows strong backtested performance, real-world deployment still requires regular retraining. Bitcoin’s price behavior is affected by many external factors such as government policies, global financial trends, and social media influence. Therefore, retraining the model periodically ensures that it adapts to new market conditions. Monitoring data drift and model performance over time is essential for maintaining prediction accuracy.

Overall, the experiments successfully demonstrate that LSTM networks, especially Multivariate ones, are highly suitable for cryptocurrency forecasting. They outperform simpler models and show that deep learning can effectively handle complex and noisy financial data. However, they should always be combined with regular retraining, risk management, and human judgment for practical use in trading or investment scenarios.

In univariate analysis we used the MLflow and logged the results of the univariate analysis of the 8 models used by hyper parameter tuning of LSTM.

		Metrics			Parameters		
Run Name	Created	mae	r2	rmse	Epochs	hidden_size	learning_rate
exultant-squid-658	1 month ago	13.1	0.971	17.35	120	128	0.0015
gaudy-flea-257	1 month ago	87.08	0.018	101.4	100	128	0.001
persistent-lynx-975	1 month ago	114.1	-0.651	131.5	100	128	0.0015
handsome-ox-279	1 month ago	18.42	0.948	23.27	100	96	0.0015
wise-fawn-0	1 month ago	238.4	-5.398	258.8	100	96	0.001
dapper-owl-272	1 month ago	21.22	0.934	26.35	120	96	0.001
stately-flea-41	1 month ago	25.36	0.908	31.06	100	96	0.0005
nebulous-horse-498	1 month ago	54.51	0.648	60.71	100	64	0.001

Figure 4: Results of univariate analysis by hyper parameter tuning

Next, we performed the multivariate analysis and following are the metrics when we compare the most optimized of the univariate model with our multivariate proposed model.

S.No	**Model Type**	**MAE**	**RMSE**	**R2_Score**
1	UniVariate	13.1	17.35	0.971
2	MultiVariate	0.059	0.088	0.96

Initially, in univariate analysis we found MAE is high and then on updating the model and changing it to we multivariate analysis we found a significant decrease in error. The reason beyond this is the use of the dropout layer in our model is decreasing the errors due to over fitting of the model and also in multi variate it is analysing the inter variable dependencies and minimizing the errors.

CONCLUSION AND FUTURE WORK

This project demonstrates that LSTM-based deep learning models can be effective tools for short-term Bitcoin price forecasting. The Multivariate approach, which uses multiple related market signals, consistently outperformed the Univariate approach in the experiments reported here. Key findings include: multivariate inputs improve accuracy; careful preprocessing and scaling are essential; and experiment tracking with MLflow improves reproducibility.

Future work: Several extensions can enhance the model's performance and practicality. First, incorporate external features such as social media sentiment, macroeconomic indicators, or on-chain metrics. Second, explore hybrid models that combine LSTM with attention mechanisms, convolutional layers for feature extraction, or transformer-based architectures. Third, implement rolling-window retraining for online learning and adaptive models. Fourth, add explainability tools like SHAP to provide feature-level attributions and increase trust in model decisions. Finally, conduct rigorous walk-forward validation to better simulate live deployment and avoid optimistic evaluation bias.

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