WWW.IJRPR.COM

**International Journal of Research Publication and Reviews**

Journal homepage: www.ijrpr.com ISSN 2582-7421

# Crypto Currency Price Prediction using Bitcoin LSTM Model along with Sentiment Analysis

***Harsh Kumar [a], Kevin Benjamin [a], Santosh Kumar [a], Rayala Viswanath [a]****

[a] *Faculty of Engineering and Technology, Department of Information Science and Engineering, JAIN Deemed-to-be University*

*DOI : https://doi.org/10.55248/gengpi.6.0425.16138*

**A B S T R A C T**

Crypto Currency (such as Bitcoin, LiteCoin, Ethereum) is a decentralized currency not attached to any governing body which functions on the Block-Chain technology. It has gained a lot of popularity and value in the past few years and has become a valuable asset to invest in. It is a highly volatile asset that is easily swayed by public opinion via tweets. We used a Database of influencers tweets in cryptocurrency (2021-2023) downloaded from Mendely data and analysed it. We also downloaded Bitcoin historical price data for the same date range and then we combined the sentiment data with price data to build our model for it which we later used for the prediction purposes. We achieved an MSE of 2.67 and R2 of 0.79.

## 1. Introduction

Crypto – currency is a decentralized currency which can be something that can be traded between individuals or groups. Investment is possible through different commercial centers known as Bitcoin trades. These enable individuals to trade on Bitcoins utilizing various currencies. Mt. Gox is the biggest Bitcoin exchange, where Bitcoin is stored as a virtual digital bank. The record of the considerable number of exchanges, the timestamp information handled in this market is called Block chain. Each record of block chain information is encrypted. Trades done by the client's name are made private only wallet ID is made open. The only need to predict the Crypto prices is because crypto has no governing body so any rumors or news about crypto results in the prices variation rapidly. So, there is a need to predict the prices of the crypto based on previous trends so that one can reduce the loss.

## 2. Literature Survey

### *2.1. Forecasting Directional Bitcoin Price Returns Using Aspect-Based Sentiment Analysis on Online Text Data*

**Objective:**

- The main objective of this study is to forecast the weekly direction of Bitcoin price movements determining whether prices will go up or down in the upcoming week.
- Evaluating the performance of machine learning (ML) models in comparison to the conventional 'buy and hold' strategy.
- It aims to assess whether ML-based predictions can offer better accuracy and improved financial returns over traditional investment methods.

**Methodology:**

The research employed four machine learning algorithms: Logistic Regression, Random Forest, Decision Trees, and Support Vector Machines (SVM), including both Linear and Radial Basis Function (RBF) kernels. The dataset consisted of weekly Bitcoin price data from October 2017 to August 2021. Google Trends data were used as a proxy for gauging public interest and sentiment. Historical data is split into two parts: one for training the models, and the rest for testing. Evaluation Metrics follows, Accuracy – Correct predictions overall, Prediction Rate – Success rate of forecasting positive movements, Specificity Correctly identifying negative movements, ROC Curve – A graphical plot that illustrates the diagnostic ability of a classifier by plotting True Positive Rate (Sensitivity) vs. False Positive Rate (1 - Specificity) at various threshold settings.

**Results:**

Among the evaluated models, the Support Vector Machine (SVM) classifier demonstrated the highest predictive accuracy on the test set, achieving 67.74%. Remarkably, it recorded no false positives during bullish weeks, indicating a high reliability in forecasting upward price movements. The Random Forest model ranked second, with a test accuracy of 61.29%, reflecting moderate consistency in its predictions. In contrast, Logistic Regression exhibited the lowest performance, attaining an accuracy of only 38.7%, which can be attributed to its limitations in modeling complex, non-linear patterns within the data. In addition to predictive accuracy, the financial viability of each model was examined. The machine learning-driven trading strategy achieved a return on investment (ROI) of 56.05%, substantially surpassing the traditional 'buy and hold' approach, which delivered an ROI of merely 18.84%.

**Gaps:**

- Logistic Regression and Decision Tree classifiers demonstrated subpar performance, indicating their inadequacy in capturing the complex, nonlinear patterns associated with Bitcoin price fluctuations. Moreover, several models exhibited imbalanced precision, excelling in predicting either upward or downward trends, but not both—limiting their reliability under varying market conditions.
- The effectiveness of these models was also found to be highly dependent on the quality, consistency, and representativeness of the input data. Data inconsistencies across different time periods and the presence of market noise significantly affected model robustness and hindered their ability to generalize to unseen scenarios.
- A key challenge identified was the reduction of false positives, particularly in forecasting bullish trends. In practical trading settings, such errors can result in poor investment decisions and financial losses, highlighting the necessity for enhanced precision in predictive models operating in high-risk environments.

### *2.2. Bitcoin, Sentiment Analysis and the Efficient Market Hypothesis*

**Objective:**

The primary objective of this study is to assess the predictability of Bitcoin's weekly price movements and, in doing so, test the validity of the Efficient Market Hypothesis (EMH) within the cryptocurrency market. The research integrates technical, asset-based, and sentiment-based indicators—specifically Google Trends data—into machine learning models. By examining the forecasting power of these models, the study aims to determine whether the inclusion of sentiment analysis can produce superior trading strategies compared to traditional buy-and-hold investment approaches

**Methodology**:

The study utilizes weekly Bitcoin data from September 2017 to August 2021, encompassing 198 observations. To minimize market noise inherent in daily data, a weekly frequency was selected. Four distinct datasets were constructed:

- Dataset 1: Only Bitcoin's past prices (autoregressive structure).
- Dataset 2: Bitcoin prices alongside macroeconomic indicators like S&P 500, DAX, Gold prices, foreign exchange rates (USD/EUR, GBP/USD), and the federal funds rate.
- Dataset 3 and 4: Extension of dataset 2 with the addition of Google Trends indicators, moving averages, and momentum-based features.

The machine learning models employed included Logistic Regression (Logit), Support Vector Machines (SVM) with linear and RBF kernels, Decision Trees, and Random Forests. The data were split into training (in-sample) and testing (out-of-sample) sets, with the 2021 data used exclusively for testing to evaluate model generalization.

Model performance was evaluated based on sensitivity (true positive rate), specificity (true negative rate), overall accuracy, and the ROC curve. The main focus was on models that exceeded a minimum performance benchmark derived from the proportion of unchanged Bitcoin price direction over the training and testing periods.

**Results:**

- Best Performing model was the SVM model which gave the accuracy of 67.74% during the testing phase.
- This model also made no false predictions of the price increases which is a very important aspect.
- While other models such as Random Forest gave an accuracy of 61.29% and the Logistic regression performed poor with accuracy rate of 38.7% only
- Returns after investing using these models were 56.05% whereas the buy and hold strategy gave only 18.84% of returns.

**Gaps:**

Models like Logistic regression and simple decision trees did not work well and did not meet the requirement levels. Some models had high accuracy rate but did not predict price increase and false prediction together, where both things are very important on real world use. Another thing noticed clearly was the model only worked well when it has good-quality data and data can vary many times so it could limit how widely this model can be used as complexities could occur.

### *2.3. Enhancing Bitcoin Price Direction Prediction Using Deep Learning and On-Chain Data*

**Objective:**

- To evaluate the impact of feature selection methods (Boruta, GA, LightGBM) on deep learning model performance.
- To compare CNN–LSTM, LSTNet, and TCN models—underexplored in this context—for Bitcoin price direction prediction.
- To backtest and analyze the profitability of model-based trading strategies compared to traditional MACD-based strategies

**Methodology:**

- The dataset used for this analysis was sourced from Glassnode (2013–2023), comprising 87 on-chain Bitcoin metrics. To address missing values, two imputation strategies were applied: listwise deletion (MCAR), while regression-based techniques handled values missing not at random (MNAR). The prediction problem was structured as a binary classification task, where a label of 1 indicated an expected price increase in the following week, and 0 denoted either a decline or no significant change.
- To improve model performance and reduce redundancy, three feature selection methods were utilized. The Boruta algorithm, was used to identify and retain all statistically relevant features. A Genetic Algorithm (GA) was also implemented, optimizing feature subsets by using a Random Forest model to evaluate fitness. In addition, LightGBM, a Gradient-boosted embedded selector ranking features by importance.
- Deep learning architectures employed to handle the temporal and spatial complexities in the data. A hybrid CNN–LSTM model was designed to combine the feature extraction capabilities of CNN with the sequence modeling strength of LSTM units. The LSTNet model further incorporated CNN, LSTM, and an autoregressive component to capture both short-term fluctuations and long-term patterns. Moreover, a TCN was utilized, which uses dilated convolutions to model long-range dependencies effectively without relying on recurrent layers.
- For benchmarking purposes, the ARIMA model (AutoRegressive Integrated Moving Average) was used. As a well-established statistical forecasting method, ARIMA provided a comparative baseline for evaluating the accuracy of machine learning and deep learning approaches.
- The entire dataset was divided chronologically into training and testing sets with an 80/20 split to preserve the temporal structure. Model performance was assessed using multiple evaluation metrics, including Accuracy, Precision, Recall, F1 Score, Area Under the Receiver Operating Characteristic Curve (AUC-ROC), and Matthews Correlation Coefficient (MCC), offering a holistic view of classification quality.
- Model tuning was conducted through a randomized search strategy, supported by cross-validation. This approach allowed efficient navigation of the hyperparameter space and helped in identifying optimal configurations for each model, enhancing both stability and performance.
- To analyze the real-world applicability of the models, three trading strategies were simulated: a simple buy-and-sell mechanism, a variation of buy-and-sell incorporating loss mitigation tactics, and a MACD-based baseline trading approach.

**Results:**

The CNN–LSTM model, enhanced with features selected via the Boruta algorithm, emerged as the most effective in this study, achieving a test accuracy of 82.44%. This hybrid deep learning architecture effectively captured both spatial and temporal dependencies in Bitcoin price movements. Statistical validation using the Wilcoxon signed-rank and Friedman tests confirmed its superiority over other evaluated models. Key performance metrics included: Precision of 83.09%, Recall of 80.78%, F1 Score of 81.92%, AUC-ROC of 82.42%, and a Matthews Correlation Coefficient (MCC) of 0.6489, indicating strong predictive reliability. The Long-and-Short Buy-and-Sell strategy delivered the best performance—yielding an Annual Return of 6653%, a Sharpe Ratio of 1.86, and a Maximum Drawdown (MDD) of -7.04%. The model also maintained a Market Exposure of 55.83% and Volatility of 3.18%, highlighting its effectiveness for real-world trading while ensuring sound risk management.

**Gaps:**

Research on TCN and LSTNet in the cryptocurrency domain remains limited, presenting opportunities for further exploration. Notably, prior studies have often overlooked the integration of on-chain data and advanced feature selection methods, such as Boruta and Genetic Algorithms (GA), which are essential for enhancing model accuracy and robustness. The link between model performance and trading profitability has been insufficiently addressed, leaving a gap in evaluating real-world applicability. There is also a need to incorporate sentiment analysis and technical indicators alongside on-chain metrics to improve predictive performance. While short-term forecasting has been extensively studied, long-term predictions in the cryptocurrency market remain largely unexplored

### *2.4 Twitter Sentiment Analysis-Based Adjustment of Cryptocurrency Action Recommendation*

**Objective**:

The authors propose an adjustment mechanism that corrects the recommendation model's output only when prediction certainty *is low, using real-time Twitter sentiment* improve the accuracy and profitability of cryptocurrency action recommendation models (Buy, Sell, Wait) by incorporating Twitter-based sentiment analysis. *to influence decision-making*

**Methodology:**

- Bitcoin price data and Twitter sentiment data are primary dataset . The Bitcoin price data, sourced from Investing.com, spans 1,481 days (April 21, 2018, to May 10, 2022). The Twitter dataset, obtained from Kaggle, comprises 3,337,635 tweets referencing "BTC" over 444 days (February 21, 2021, to May 10, 2022). Preprocessing was performed using regular expressions to remove elements such as emojis, URLs, and hashtags. Sentiment classification was carried out using Flair, a deep learning-based tool, to label tweets as positive, neutral, or negative.

- The model used in this study is an LSTM-based classification model, selected for its proven effectiveness in time-series forecasting. The input features for the model include Bitcoin price data (e.g., P (Price), O (Opening Price), H (High), L (Low), and V (Volume)), along with calculated profit features, such as sellProfit, buyProfit, and maxProfit. The model also incorporates an adjustment mechanism based on the confidence level of its predictions. If the model's confidence is lower than a predefined threshold (e.g., 60%), it adjusts its actions using the sentiment derived from Twitter data. In cases of positive sentiment, the model suggests a "Buy" action, whereas, with negative sentiment, it opts for a "Sell" action. If the predicted profit is insufficient, the model recommends a "Wait" decision.
- The performance of the model was evaluated using the following metrics:
  - Accuracy: To measure the overall correctness of the predictions.
  - F1 Score: To account for the balance between precision and recall, particularly in cases of class imbalance.
  - Confusion Matrix: To analyze the model's classification performance, including true positives, false positives, true negatives, and false negatives.
  - F-Test and T-Test: For statistical validation, ensuring the model's results are significant when compared to other baseline models.
- The impact of varying the length of the sentiment analysis window was investigated using three rolling windows, 1-day, 3-day, and 7-day rolling windows were evaluated to determine the optimal period of tweet history for model performance. The results demonstrated that the 1-day rolling window yielded the least noise and the best overall performance, which is especially important in the volatile nature of the cryptocurrency market.

**Results:**

The baseline model achieved an accuracy of 81.31% and an F1 Score of 77.86%, offering solid performance but without considering prediction confidence. Sentiment adjustments improved model performance. The 1-day tweet window achieved the highest accuracy at 84.01% and an F1 Score of 80.03%, a +2.7% improvement over the baseline. The 3-day window showed a +2.0% increase, and the 7-day window had a smaller +0.6% improvement. The 1-day window provided the best results, while longer windows added noise and reduced precision. The F-test confirmed significant variance between baseline and adjusted models, and the T-test ($p < 0.05$) confirmed the improvements were statistically significant. Adjusted models predicted more correct actions than the unadjusted version.

**Gaps:**

The study has several gaps that could be addressed in future work. First, it relies solely on Twitter data for sentiment analysis, limiting its robustness. Incorporating additional sources like Reddit or news articles could enhance prediction accuracy. Second, the focus on short-term, daily predictions leaves room for exploring longer investment horizons, such as 3-day or weekly actions. The model is also centered on Bitcoin (BTC), and extending it to include other cryptocurrencies would improve its generalizability. Additionally, the absence of a real-time adaptive threshold based on market conditions limits the model's flexibility in volatile markets. Lastly, while different sentiment windows are tested, larger or more dynamic rolling windows could be explored to better capture market trends. These gaps provide valuable opportunities for future research and model refinement.

### *2.5. Cryptocurrency Price Prediction Using Lstm*

**Objective:**

This review aims to evaluate the potential of machine learning techniques for forecasting Bitcoin price movements. It focuses on analyzing different ML models, comparing data sources such as sentiment indicators and blockchain metrics, and examining the role of optimization strategies and computational advancements in enhancing predictive accuracy.

**Methodology:**

The studies reviewed employed various ML algorithms including Support Vector Machines (SVM), Random Forest, Generalized Linear Models (GLM), Artificial Neural Networks (ANN), and Recurrent Neural Networks (RNN) such as Long Short-Term Memory (LSTM). These models were trained using a mix of social sentiment data (e.g., Twitter, Wikipedia), online search trends (e.g., Google Trends), and blockchain-specific features (e.g., mining difficulty, hash rate). Optimization tools like genetic algorithms and GPU-based training were also investigated for improving model performance and efficiency.

**Results:**

- Latent source models showed strong profitability, achieving up to 89% returns with a Sharpe ratio of 4.1.
- SVMs and ANNs, when relying solely on blockchain data, had moderate directional accuracy around 55%.

- RNNs and LSTMs were more effective in modeling sequential or time-based data, making them suitable for financial forecasting.
- GPU acceleration significantly improved model training and testing speeds, with reports of performance being up to 80 times faster than CPU-based training.

**Gaps:**

Several models lacked adequate validation, leading to concerns about their reliability across different scenarios. Sentiment-based predictions were impacted by misinformation and sample bias. Some models, while accurate, failed to consistently predict upward price movements or gave false signals. Additionally, the success of these models heavily depended on the availability of clean and consistent data, which may not always be feasible in real-world applications.

***2.6. Sentiment-Driven Cryptocurrency Price Prediction: A Machine Learning Approach Using Historical and Social Media DataObjective:***

The primary goal of this study is to evaluate the impact of incorporating social media sentiment data, particularly from Twitter, into machine learning models for predicting Bitcoin price movements. By leveraging historical Bitcoin market data, on-chain blockchain statistics, and sentiment scores generated using the VADER and Twitter-roBERTa models, the research aims to develop optimized predictive models. A key focus is the implementation of a Multi-Modal Fusion framework that combines diverse data sources to improve forecasting accuracy and assist in more informed cryptocurrency trading decisions

**Methodology:**

The research utilized three principal datasets: Bitcoin's historical market prices, blockchain on-chain metrics, and Bitcoin-related tweets, covering the period from 2014 to 2022. The tweet dataset underwent comprehensive cleaning, including the removal of user mentions, URLs, stopwords, punctuation, and duplicate entries, followed by tokenization, stemming, and lemmatization.

Sentiment analysis was performed using two different models: VADER, a rule-based sentiment analysis tool tailored for social media text, and Twitter-roBERTa, a fine-tuned transformer-based model specifically trained on Twitter data. Sentiment scores were aligned with Bitcoin's market prices to assess the relationship between social sentiment and price movements.

For modeling, all features were lagged by one day to predict whether the following day's closing price would increase or decrease. Feature normalization was achieved using MinMaxScaler to standardize the data. Five traditional classification models—Support Vector Machine (SVM), Logistic Regression (LR), K-Nearest Neighbors (KNN), Gaussian Naïve Bayes (GNB), and Extreme Gradient Boosting (XGBoost)—were developed, alongside a Multi-Modal Fusion model combining sentiment and on-chain data.

The Multi-Modal Fusion model consisted of two branches: one processing sentiment data through dense neural network layers and the other processing on-chain attributes via an LSTM layer. Outputs from both branches were merged and passed through additional dense layers to make final predictions. Hyperparameter tuning was conducted using techniques such as GridSearchCV, RandomizedSearchCV, and Bayesian Optimization to enhance model performance. Evaluation metrics included Accuracy, F1 Score, Precision, and Recall, both with and without sentiment integration.

**Results:**

Including sentiment data notably improved model performance across all evaluation metrics. Models incorporating Twitter-roBERTa sentiment scores consistently outperformed those using VADER. The Multi-Modal Fusion model integrated with Twitter-roBERTa achieved the highest performance, recording an accuracy of 90%, an F1 score of 0.85, along with precision and recall values also reaching 0.85. Among the conventional machine learning models, XGBoost with Twitter-roBERTa sentiment data delivered the next best results, achieving an accuracy of 87%. Logistic Regression, Support Vector Machine, and Naïve Bayes models also showed marked improvement when sentiment information was included. In contrast, the K-Nearest Neighbors model showed relatively modest gains even after sentiment integration.

**Gaps:**

The analysis was limited to Bitcoin alone and may not necessarily generalize to other cryptocurrencies or financial assets, the study focused solely on Twitter as the sentiment source, excluding other potentially influential platforms such as Reddit, Telegram, or financial news outlets. Although a fixed one-day lag was applied for predictive modeling, different assets or market conditions might benefit from dynamic or variable lag structures, suggesting a potential area for future research.

## 3. Problem Definition

Crypto Currency (such as Bitcoin, LiteCoin, Ethereum) is a decentralized currency not attached to any governing body which functions on the Block-Chain technology. It has gained a lot of popularity and value in the past few years and has become a valuable asset to invest in. It is a highly volatile asset that is easily swayed by public opinion via tweets. These tweets made by influential people both in and out of the crypto space lead to huge sways in the value of Bitcoin. A single tweet from Elon Musk can cause a huge bull run in the market or a huge fall. There is a need to develop a prediction tool that can help retail investors of all kinds to navigate this volatile market.

## 4. Proposed Work

Our work will be focused on Bitcoin only and not any other crypto currency. We aim to create a tool that can predict the movement of the price of Bitcoin using tweets made in the previous day. For this purpose we plan to use a Database of influencers tweets in cryptocurrency (2021-2023) downloaded from Mendely data and analyse it. The analysis will involve data cleaning and identifying trends. Then we download historical Bitcoin price data of the same date range and merge it with the processed dataset. This new dataset set will be passed to a Machine Learning model called BitcoinLSTM. We split the data into training and testing sets and then run the model. We will evaluate the model using MSE and $R^2$ metrics.

## 5. Software Used

- Pandas - This library helps to load the data frame in a 2D array format and has multiple functions to perform analysis tasks in one go.
- Numpy - Numpy arrays are very fast and can perform large computations in a very short time.
- Matplotlib - This library is used to draw visualizations.
- PyTorch - This library offers fast GPU-accelerated tensor computation and dynamic deep neural networks using a tape-based autograd system.
- Scikit – learn – This library provides simple, easily accessible and efficient tools for predictive data analysis which is reusable in many contexts.
- BitcoinLSTM – It is PyTorch neural network builder model which is suited for Bitcoin price prediction based on historical price and sentiment data.

**System Architecture**

**Fig. 1 – System Architecture;**

## 6. Results

The model was able to work efficiently on the test set providing satisfactory results. We recorded the following metrics:

- MSE: 2.67
- $R^2$: 0.79.

## 7. Future Scope

We aim to build this into a tool with a GUI and give it a real time prediction feature by analyzing tweet sentiments in real time.

***Acknowledgements***

We extend our deepest gratitude to our university professors, especially our guide Dr. Chayapati A R. Their guidance has been invaluable. We also thank JAIN (Deemed-to-be University), Faculty of Engineering & Technology for giving us access to great resources for the same. We are thankful to everyone who contributed to this project; their insights and support were crucial to its timely completion.

**References**

Bhatt, Sandeep, Ghazanfar, Muhammad, & Amirhosseini, Mohammad Hadi. (2023). *Sentiment-driven cryptocurrency price prediction: A machine learning approach utilizing historical data and social media sentiment analysis*. Machine Learning and Applications: An International Journal (MLAIJ), 10(2/3), 1–19.

Loginova, Ekaterina, Tsang, Wing Kam, van Heijningen, Gert, Kerkhove, Louis-Paul, & Benoit, Dominique F. (2024). *Forecasting directional bitcoin price returns using aspect-based sentiment analysis on online text data*. Machine Learning, 113, 4761–4784.

Park, Jinwoo, & Seo, Young-Sik. (2023). *Twitter sentiment analysis-based adjustment of cryptocurrency action recommendation model for profit maximization*. IEEE Access, 11, 44828–44841.

Mounika, S., Aravind, B., Sai Charan, K., & Kiran, B. (2023). *Cryptocurrency price prediction using LSTM*. International Research Journal of Modernization in Engineering, Technology and Science, 5(2), 1182–1184.

Toulias, Georgios, Sofianos, Elias, & Gogas, Periklis. (2023). *Bitcoin, sentiment analysis and the efficient market hypothesis: A machine learning approach*. Empirical Economics Letters, 22(1), 31–44.

Omole, Oluwatosin, & Enke, David. (2024). *Deep learning for Bitcoin price direction prediction: Models and trading strategies empirically compared*. Financial Innovation, 10, Article 117.

Paszke, Adam, et al. (n.d.). *PyTorch: An open source machine learning framework*. Retrieved April 30, 2025, from https://pytorch.org

Scikit-learn Team. (n.d.). *Scikit-learn: Machine Learning in Python*. Retrieved April 30, 2025, from https://scikit-learn.org