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Real-Time Bitcoin Price Prediction using XGBoost and LSTM Model

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ABSTRACT: The necessity for precise and timely price forecasting has grown due to the swift expansion of cryptocurrency marketplaces, particularly for extremely volatile commodities like Bitcoin. This project introduces a real-time A system for forecasting The worth of bitcoin that combines LSTM, or extended short-term memory and XGBoost models. To improve data quality, both historical in addition to current Data on bitcoin prices are gathered and preprocessed using noise reduction and normalization techniques. While LSTM is used to learn long-term sequential relationships within time-series data, XGBoost is used to find intricate nonlinear patterns and short-term price changes. Prediction robustness and reliability are increased by integrating these models. The Streamlit framework is used to deploy the system, which offers an interactive web-based interface that shows real-time prices, anticipated trends, and analytical insights. Experimental. Based on experimental data, The recommended approach provides a useful tool for bitcoin price analysis and decision support and successfully captures market behavior.

KEYWORDS: XGBoost, LSTM, time-series forecasting, real-time analytics, and Bitcoin price prediction

I. INTRODUCTION

By offering decentralized and digital forms of money, the rise of cryptocurrencies has drastically changed the global financial scene. Bitcoin continues to be the most popular and commonly used cryptocurrency, making its price behavior an important topic of study. However, market mood, trading volume, macroeconomic variables, and speculative activity all have an impact on the severe volatility of Bitcoin values. This volatility emphasizes the necessity for advanced forecasting technologies and makes accurate price prediction a difficult endeavor.

The nonlinear and dynamic structure of cryptocurrency markets is frequently difficult to model applying traditional statistical techniques such as linear regression and ARIMA. Because of their capacity to extract complex designs from extensive financial time-series data, Deep learning and artificial intelligence approaches have drawn interest. Deep learning models such as Long Short-Term Memory (LSTM) networks are especially good at modeling temporal relationships as well as sequential trends in time-series data, gradient boosting models like XGBoost are renowned for their effectiveness. in capturing nonlinear relationships and managing feature interactions.

This study proposes a hybrid method for instantaneous Forecast for the price of bitcoin that combines XGBoost and LSTM. The system makes use of real-time and historical market data that has been pre-processed using noise reduction and normalization methods to enhance data quality. While LSTM concentrates on learning long-term dependencies in price sequences, XGBoost is used to detect short-term price changes and significant features. The suggested approach seeks to improve forecast accuracy and stability over individual models by combining both models.

The Streamlit framework is used to implement the prediction system in order to close the gap between model development and practical usage. Streamlit makes it possible to create an interactive web-based interface that offers visual analytics, real-time pricing updates, and prediction results. This eliminates the need for technical knowledge and makes it simple for users to understand market patterns and model results. The suggested system provides insightful information for investors, analysts, and researchers while showcasing the useful application of hybrid machine learning methods for bitcoin price predictions.

II. LITERATURE SURVEY

1) **Title:** Prediction and Machine learning-based analysis of the price of bitcoin and Deep learning models

Authors: Ashish Kumar Priyanka Kumari Ravi Ranjan (2023)

Abstract: This study studies Predicting the price of bitcoin via machine learning and deep learning models. The dataset provides historical market values with preprocessing processes for accuracy. Multiple algorithms such as SVM, LSTM, and ARIMA are evaluated to measure predicting efficiency. The results reveal models for deep learning, especially LSTM, outperform standard approaches in handling volatility and time-dependent patterns in cryptocurrency price behavior.

2) Title: Predicting the Price of Bitcoin with Long Short-Term Memory

Authors: Muhammad Ihsan Fawzi, Halim Umar, Taufiq Ihsan, Salsabila Nurul Fadhilah (2024) **Abstract:** This research predicts Bitcoin prices using the LSTM model by analyzing historical datasets, technical indicators, and market fluctuations. The study compares prediction performance and demonstrates that LSTM effectively captures sequential patterns and volatility in cryptocurrency markets. Results indicate significantly improved forecasting accuracy compared to traditional statistical approaches, supporting the suitability of deep learning techniques for financial time-series prediction.

3) Title: Forecasting Bitcoin Price by Tuned Long Short Term Memory Model

Authors: Aleksandar Petrovic, Luka Jovanovic, Miodrag Zivkovic, Nebojsa Bacanin, Nebojsa Budimirovic, Marina Marjanovic

Abstract: The interest for cryptocurrencies is high and hence this work focuses on providing a practical real-world application of the swarm metaheuristics and long short-term memory model (LSTM). The goal is price forecasting which is interesting due to the high volatility of the cryptocurrencies. The authors apply LSTM for the solution of the problem which has been proven to reap results with this type of problem. The LSTM is further optimized by a swarm metaheuristic - arithmetic optimization algorithm (AOA). The solution was tested alongside familiar high-performing competitors with the use of standard metrics mean absolute error (MAE), mean squared error (MSE), mean absolute percentage error (MAPE), and root mean squared error (RMSE).

4) Title: Forecast for the Price of Bitcoin Based on Transformer, LightGBM and Random Forest

Authors: Yihan Tu(2024)

Abstract: This article analyzes Forecast for the price of bitcoin utilizing Transformer, LightGBM, Random Forest, and OLS regression models. The dataset includes historical price and technical indicators provided from Yahoo Finance. The Transformer model outperforms conventional statistical and tree-based models in capturing long-term volatility, particularly in capturing sequential patterns and long-range dependencies, according to the results. The work emphasizes the potential of attention-based deep learning models for boosting cryptocurrency forecasting accuracy.

III. METHODOLOGY

Existing Problem:

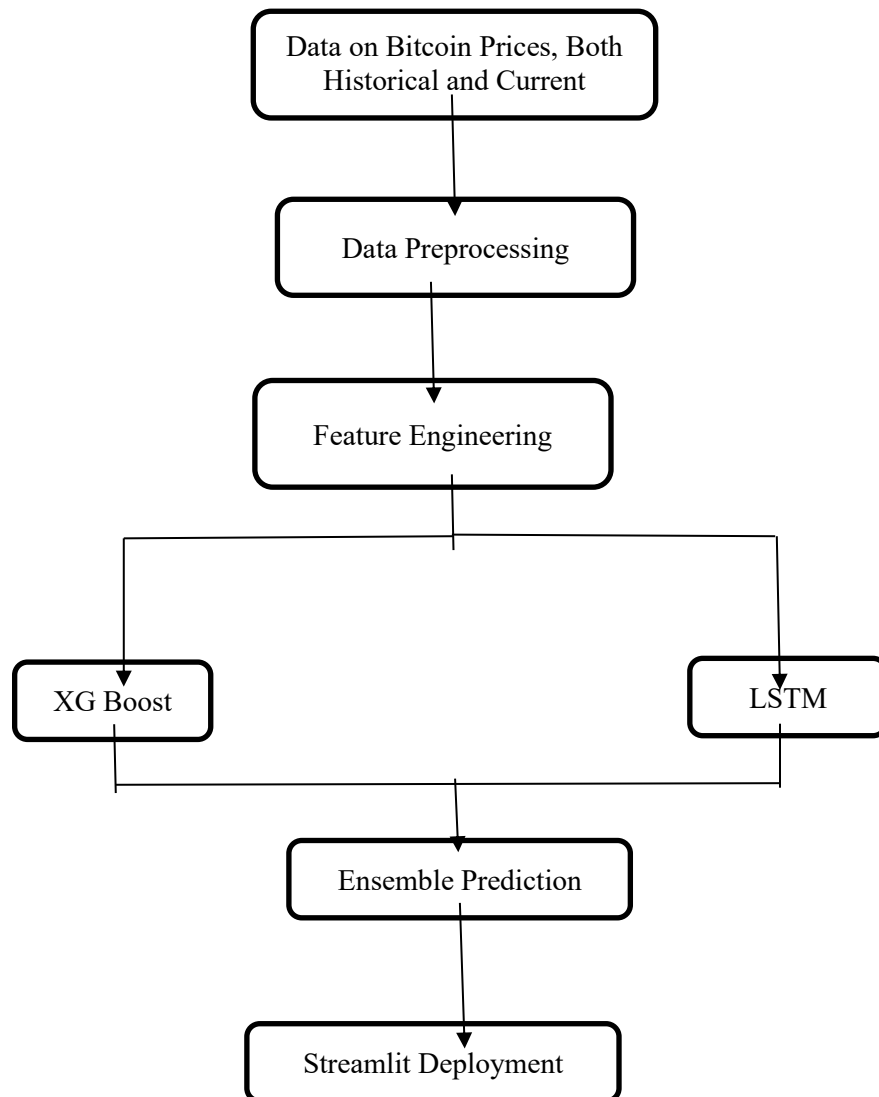
Because of its extreme volatility and nonlinear market behaviour, forecasting the value of bitcoin is still difficult. Both short-term variations and long-term trends are not adequately captured by conventional statistical and single-model machine learning techniques. Furthermore, the majority of current systems have limited practical applicability due to their reliance on offline data and lack of interactive visualization and real-time prediction.

Proposed Solution:

In order to capture both short-term price fluctuations and long-term temporal trends, this study suggests a hybrid strategy for a real-time A system for Forecasting the Bitcoin price that incorporates XGBoost and LSTM models. To improve forecast accuracy, the system applies efficient preprocessing and feature engineering techniques to both historical and current market data. Real-time prices and anticipated trends are visualized using an interactive Streamlit-based interface, making bitcoin price analysis useful and approachable.

Proposed Methodology:

The recommended method to combines Long Short-Term Memory (LSTM) and XGBoost models to produce a hybrid framework for predicting the Bitcoin price. To guarantee data quality, historical as well as current Data on bitcoin prices are gathered and preprocessed using feature extraction, cleaning, and normalization. While LSTM is employed to learn long-term temporal dependencies from sequential data, XGBoost is employed to simulate short-term price fluctuations and nonlinear interactions. The final forecast is produced by combining the forecasts from both models using an ensemble approach. The Streamlit framework is employed in the system's deployment to facilitate user interaction, visualization, and real-time prediction.

**Fig 1: Proposed Methodology****IV. SYSTEM DESIGN**

The suggested method, which is integrated into a Streamlit web application, uses a combination of LSTM and XGBoost models to deliver current price of Bitcoin prediction. APIs are utilized to gather both Bitcoin data, both historical and current, include timestamps, trading volume, and OHLC values. Preprocessing of the data includes normalization, treatment of missing values, as well as feature engineering using technical indicators like RSI and moving averages. While XGBoost mimics short-term market volatility, LSTM captures long-term sequential dependencies. Live Bitcoin prices, forecasted values, and trend visualizations are shown on the Streamlit interface, which is updated dynamically when new data is received. A dependable tool for traders and analysts, this modular architecture guarantees scalability, maintainability, and real-time responsiveness.

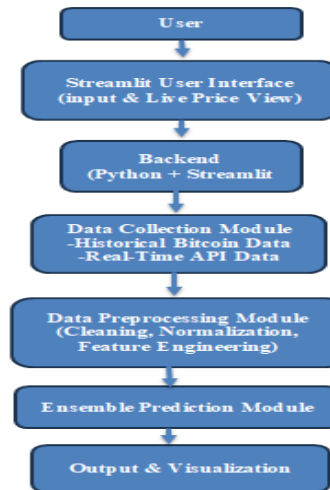


Fig 2: System Design

V. SYSTEM ARCHITECTURE & DESIGN

Through an effective and modular framework, the system architecture is intended to provide prediction of the price of Bitcoin in real time. It's starts with a data collecting layer that continuously gathers current and historical data on Bitcoin prices from reputable cryptocurrency APIs. feature engineering, normalization, and data cleansing are carried out in the preprocessing layer to improve the caliber of the gathered data. Two models make up the prediction layer: Long Short-Term Memory (LSTM), which learns long-term temporal connections in time-series data, and XGBoost, which captures short-term price changes and nonlinear correlations. A final estimated price is produced by combining the results between the two models. The Streamlit framework is employed to deploy the system, which offers an interactive online interface with real-time prices, forecasts, and graphical insights for efficient analysis.

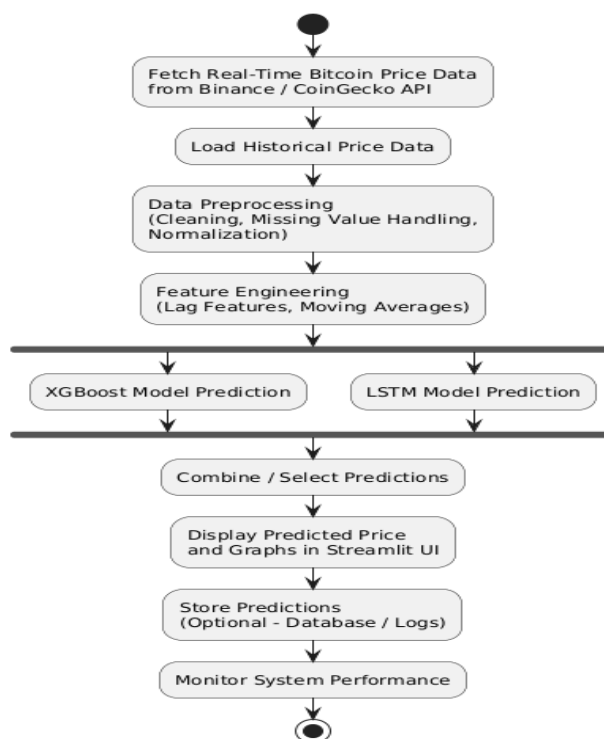


Fig 3: Activity Diagram

VI. IMPLEMENTATION

The Streamlit framework, LSTM, and boosting Algorithms are employed in The evolution of the Forecasting the price of Bitcoin in real time system. An interactive online program that shows current Bitcoin prices and forecast outcomes is created using Streamlit. Cryptocurrency APIs are used to gather and store both historical and real-time data for processing. After being cleaned and standardized, the data is transformed into formats that are appropriate for model input. While the boosting algorithm (XGBoost) increases prediction accuracy by learning from engineered features, the LSTM model is used to learn time-series patterns and capture price trends over time. The system makes it simple for users to track and analyze price fluctuations by continuously updating predictions and visualizing them through charts and graphs.

VII. RESULTS & DISCUSSION

The Experimental results demonstrate that the recommended approach, which utilizes LSTM and boosting algorithms, successfully forecasts Bitcoin price changes in real time. The LSTM model is appropriate for time-series forecasting since it effectively captures long-term price variations and temporal relationships. The boosting algorithm (XGBoost) makes quick and precise predictions by effectively learning nonlinear relationships from manufactured features. When examined separately, XGBoost exhibits greater accuracy for short-term price changes, while LSTM performs better for long-term trend prediction.

Overall forecast reliability is increased by combining the two models. Real-time depiction of actual versus expected pricing is enabled by the Streamlit framework, which makes it simple for consumers to understand trends through interactive charts. Metrics like RMSE and MAE are used to evaluate performance and reveal decreased prediction error, which indicates increased accuracy. All things considered, the system offers a scalable and approachable solution for real-time Bitcoin price analysis and decision assistance.

VIII. CONCLUSION

By incorporating LSTM and boosting algorithms into a Streamlit architecture, the suggested system effectively forecasts Bitcoin prices in real time. While the boosting method uses feature-based learning to increase prediction accuracy, LSTM efficiently captures time-series patterns. When compared to individual models, the combined method improves reliability. Streamlit offers a real-time representation of projected and current pricing through an interactive and user-friendly interface. All things considered, the system exhibits efficient performance, scalability, and usefulness for real-time bitcoin price analysis and decision assistance.

IX. FUTURE ENHANCEMENTS

By combining other data sources like technical indicators, trade volume, market sentiment from social media, and on-chain blockchain metrics, the suggested real-time Bitcoin price prediction system can be further enhanced. By including these qualities, forecast accuracy can be improved and external influences impacting price fluctuations can be captured. To enhance long-term forecasting performance, more sophisticated models for deep learning like GRU, Transformer-based architectures, or mixed ensemble techniques can be investigated. Furthermore, expanding the system to include several cryptocurrencies would increase its adaptability and usefulness.

Future deployment improvements could include automated model retraining, cloud-based real-time data streaming, and performance monitoring to adjust to quickly shifting market conditions. Better decision assistance for users can be achieved by integrating trading signals, risk assessment modules, and alert messages. Adding configurable dashboards and predictive analytics to the Streamlit interface will increase its usefulness and practicality.

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