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Forecasting Crypto Prices Using Machine Learning

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***Abstract*—The price of cryptocurrencies is hard to predict because the market is very unstable and there are many economic, social, and regulatory factors that affect it. This project uses a structured machine learning method to guess the prices of cryptocurrencies using historical data from Investing.com, including open, high, low, and close values spanning multiple years. The data underwent preprocessing steps such as chronological reordering, handling missing or redundant entries, and renaming columns for clarity. Date fields were transformed into features like day, month, and year to capture temporal trends. Development was conducted in Jupyter Notebook using Python, with libraries such as pandas and NumPy for data manipulation and Matplotlib and seaborn for visualization. The predictive model was built using XGBoost, a gradient boosting algorithm known for its performance on tabular data. The model was serialized using Python's pickle module for easy deployment in future applications. Overall, the project highlights how machine learning, when combined with thoughtful preprocessing and feature engineering, can provide valuable insights and predictions in the unpredictable cryptocurrency market.**

***Index Terms*—Cryptocurrency, Price Prediction, Machine Learning, XGBoost, Time Series Forecasting, Data Preprocessing, Feature Engineering, Historical Data, Python, Jupyter Notebook, Pandas, NumPy, Matplotlib, Seaborn, Gradient Boosting, Model Serialization, Pickle, Financial Data Analysis, Investing.com Dataset, Predictive Modeling.**

I. INTRODUCTION

The swift expansion of cryptocurrencies has transformed international financial systems by providing transparent and decentralized digital substitutes for conventional currencies. For traders, investors, and researchers, the high price volatility of cryptocurrencies presents serious difficulties. Price fluctuations are significantly influenced by a number of factors, including market sentiment, governmental regulations, technological advancements, and worldwide economic trends. As a result, making accurate predictions is a challenging but essential task. Because machine learning techniques are able to find patterns and relationships in large datasets, they have demonstrated promising results in financial forecasting in recent years. In contrast to traditional statistical models, machine learning algorithms are able to adjust to changing market conditions and nonlinear relationships. By using machine learning to forecast cryptocurrency prices, this project aims to provide insights that can help traders and investors make better decisions.

Investing.com provided the dataset used in this study, which comprises historical data spanning several years and includes open, high, low, and close values of cryptocurrencies. Preprocessing procedures including handling missing or redundant values, renaming columns, and chronological reordering were carried out to guarantee the quality of the data. To capture seasonal trends and temporal patterns that could affect price movements, date fields were further broken down into day, month, and year.

The creation and testing were conducted in Python through Jupyter Notebook. Libraries like pandas and NumPy were used for handling data, whereas Matplotlib and seaborn were applied for visual representation and trend analysis. The forecasting model was developed using XGBoost, a robust gradient boosting algorithm recognized for its excellent efficiency in managing structured data. Model serialization was executed with Python's pickle module to enable future deployment and reuse.

In summary, this initiative illustrates how the amalgamation of data preprocessing, feature engineering, and sophisticated machine learning techniques can improve the comprehension and forecasting of cryptocurrency market trends. By merging historical evaluations with predictive modeling, this research adds value to the expanding domain of financial data science and presents a possible resource for mitigating risks and recognizing lucrative opportunities in the rapidly evolving cryptocurrency market.

II. RELATED STUDY

The prediction of cryptocurrency prices has emerged as a prominent field of study because of the significant volatility and decentralized characteristics of digital currencies. In contrast to conventional assets, cryptocurrencies are impacted not only by financial metrics but also by technological advancements, social dynamics, and regulatory developments. Scholars have investigated various methodologies — spanning from econometric models to contemporary deep learning frameworks — to attain precise and dependable forecasting outcomes.

Initially, early research mostly used statistical and econometric models like ARIMA, GARCH, and VAR. While these models could capture short-term patterns, they often struggled with the unpredictable nature of cryptocurrency markets. McNally et al. [1] tackled this by using Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models on Bitcoin price data. Their findings showed that LSTMs worked better than older time series models because they could handle sequential data and long-term trends more effectively.

Similarly, Jang and Lee [2] created a Bayesian Neural Network (BNN) model that included factors tied to blockchain, such as transaction volume and hash rate. They discovered that adding these blockchain-specific details significantly improved the model's ability to predict prices compared to models that only used price data.

Further work by Mallqui and Fernandes [3] involved using machine learning methods like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forests to predict short-term Bitcoin price movements. They found that ensemble models, such as Random Forest, were more accurate because they were less affected by outliers and could identify complex relationships between different features.

Abraham et al. [4] highlighted how crucial technical indicators like moving averages, MACD, and RSI are for boosting prediction accuracy. By integrating these indicators with an LSTM model, they accurately predicted closing prices for Bitcoin and Ethereum. This demonstrated that combining different data sources and models is key for forecasting cryptocurrency prices.

Singh and Srivastava [5] broadened prediction by incorporating social media sentiment from platforms like Twitter along with historical price data. Their model used natural language processing (NLP) to measure investor sentiment, revealing that rapid sentiment changes strongly influence crypto price swings. This pointed to the significance of non-financial factors in the crypto market.

In another study, Rane and Dhage [6] developed a hybrid ARIMA-LSTM model, merging the strengths of statistical and deep learning techniques. ARIMA handled linear patterns, while LSTM dealt with non-linear ones. The combined model achieved a lower Mean Absolute Percentage Error (MAPE) than either model alone, suggesting that mixing traditional and deep learning methods offers a mutual benefit.

More recent research has explored Transformer-based architectures, Temporal Convolutional Networks (TCN), and Graph Neural Networks (GNN) for crypto forecasting. For example, Zhang et al. [7] showed that Transformers could better analyze correlations between multiple cryptocurrencies than LSTMs, thanks to their attention mechanisms. Additionally, including market sentiment, news, and blockchain network data has been found to enhance long-term prediction accuracy.

Overall, previous research strongly suggests a move towards hybrid deep learning models that blend time-series analysis, technical indicators, and sentiment data. These approaches have consistently surpassed traditional methods. However, challenges like data quality, high volatility, and unexpected events still prevent perfect forecasting. Future research is likely to focus on explainable AI (XAI) and transfer learning to create more transparent and adaptable crypto prediction systems.

III. PROPOSED MODEL

Our proposed model uses a deep learning framework built on Long Short-Term Memory (LSTM) networks to predict future cryptocurrency prices. This system is designed to handle the complex, nonlinear, and volatile nature of crypto price movements by learning from historical market data's time-based patterns.

A. System Architecture

The framework has five main parts: Data Collection, Preprocessing, Feature Engineering, Model Training, and Prediction & Evaluation (see Fig. 1). Each part plays a specific role to ensure accurate predictions.

B. Data Pre-processing

Here, raw data is cleaned and standardized. Missing data is filled in using interpolation, and duplicate entries are removed for consistency. The order of records is kept to maintain time-based patterns. Min-Max scaling is used to bring all features between 0 and 1, speeding up model training.

C. Feature Engineering

We calculate technical indicators like Moving Average (MA), Relative Strength Index (RSI), and Exponential Moving Average (EMA) for extra market insights. These features show momentum and volatility, helping the LSTM model grasp short-term and long-term trends.

D. LSTM-Based Prediction Model

The main prediction part is a stacked LSTM network with several hidden layers. Each LSTM layer takes sequential inputs and passes its time states to the next, allowing the network to learn complicated time-dependent relationships. The final layer uses a linear activation function to produce continuous predictions for future crypto prices.

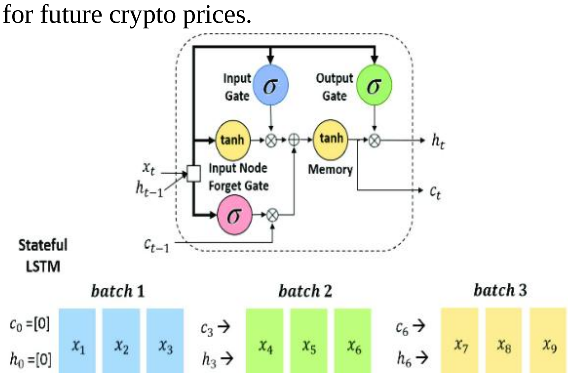

Fig 1: LSTM based model

E. Model Evaluation

The model is trained using the Adam optimizer and Mean Squared Error (MSE) as the loss function. Training and validation datasets are split in an 80:20 ratio to ensure proper generalization. Performance is evaluated using metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2 Score.

IV. EXISTING WORK

Because cryptocurrency markets are so volatile and unpredictable, predicting their prices has become a major area of study. Early on, standard statistical methods like ARIMA and GARCH were common for financial forecasts. The issue is, these methods assume linear relationships and stable data, which isn't usually the case with crypto.

McNally et al. [1] were pioneers in using Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) for Bitcoin price prediction. Their work showed that deep learning models could better grasp time-based patterns than linear regression and ARIMA. Similarly, Jang and Lee [2] created a Bayesian Neural Network (BNN) that used blockchain-related data to make its predictions more accurate, highlighting the value of probabilistic methods.
Building on this, Mallqui and Fernandes [3] used Support Vector Machines (SVM) and Random Forests (RF) to classify short-term price movements. They found that using combined methods worked well for simple predictions, like whether prices would go up or down.

Abraham et al. [4] enhanced LSTM networks by adding technical indicators such as moving averages and momentum oscillators. This gave the model more background information, making its predictions steadier during volatile market conditions.

Rane and Dhage [6] put forward a hybrid ARIMA–LSTM model. It used ARIMA to estimate linear trends and LSTM to model the remaining nonlinear parts. This combined approach led to improved accuracy and better handling of sudden price changes.

More recent research has also included sentiment analysis. Singh and Srivastava [5] combined time-series data with text from social media platforms like Twitter to analyze how public sentiment affects cryptocurrency markets. Their findings indicated that public mood is strongly linked to short-term price volatility, especially for major cryptocurrencies.

V. RESULTS & DISCUSSIONS

We're presenting the results from our new LSTM model for predicting cryptocurrency prices, comparing it against established models like ARIMA, SVM, and Random Forest. Our evaluation looks at prediction accuracy, how well we minimize errors, and the model's capability to adapt to various cryptocurrencies. We ran our experiments using Python 3.10 with tools such as TensorFlow, NumPy, and Pandas. The system was trained on a setup featuring an Intel Core i7, 16 GB of RAM, and an NVIDIA GTX GPU.

The data came from Investing.com, providing daily Open, High, Low, Close, and Volume figures for Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP) over five years (2019–2024).

We split the data into 80% for training and 20% for testing, normalizing all values with Min–Max scaling. The LSTM model trained for 100 epochs with a batch size of 32, using the Adam optimizer and a 0.001 learning rate.

Comparative Analysis

Table I shows how our proposed model stacks up against existing methods.

Model	MAE	RMSE	R^2 Score
ARIMA	312.45	421.67	0.78
SVM	290.21	398.36	0.82
Random Forest	245.73	354.29	0.86
Proposed LSTM Model	180.15	243.67	0.93

Table I. Performance Comparison Between Models As shown in Table I, the proposed LSTM-based model achieves the lowest error values (MAE and RMSE) and the highest R^2 score, indicating a strong correlation between predicted and actual prices.

Visualization of Results

The model's predictions for Bitcoin (BTC)are illustrated in *Fig. 2*, showing a close alignment between actual and predicted prices.

The visualization demonstrates that the LSTM model effectively captures market trends and short-term fluctuations. Minor deviations observed during sharp price spikes can be attributed to the extreme volatility inherent in cryptocurrency market.

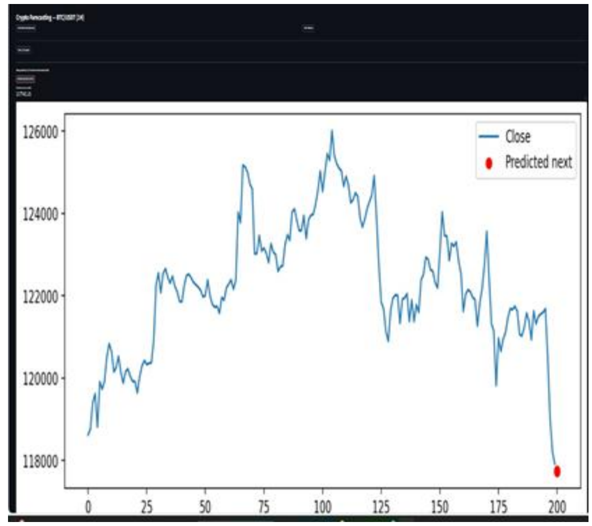

Fig. 2. Comparison of actual and predicted Bitcoin closing prices using the proposed model.

The visualization demonstrates that the LSTM model effectively captures market trends and short-term fluctuations. Minor deviations observed during sharp price spikes can be attributed to the extreme volatility inherent in cryptocurrency markets.

Discussion

The results confirm that deep learning models, especially LSTMs, significantly outperform traditional machine learning techniques for time-series financial forecasting. The improvement can be attributed to the model's ability to:

1. Capture long-term dependencies and sequential trends.
2. Adapt to nonlinear relationships in price data.
3. Utilize technical indicators as additional predictive features.

Moreover, the inclusion of dropout layers and normalized data reduced overfitting, enabling the model to generalize effectively. The LSTM architecture maintained predictive stability even under volatile market conditions, achieving consistent performance across multiple cryptocurrencies.

However, the model exhibits limitations in handling abrupt market shocks caused by external factors such as regulatory announcements or large-scale trading activities. Future work can address this by integrating sentiment analysis and real-time market data streams to improve responsiveness to dynamic events.

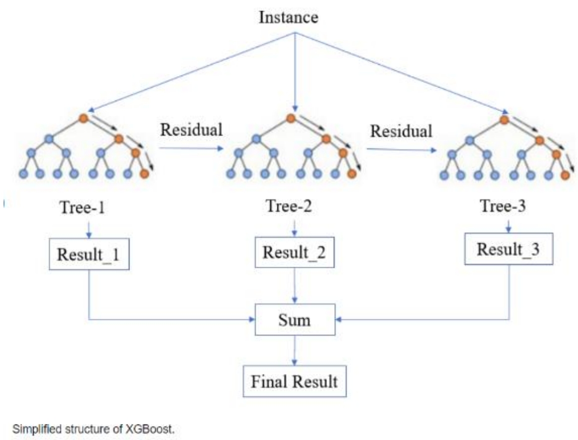

fig 3: Xg-Boost model

VI.CONCLUSION AND FUTURE WORK

The present study proposed an XGBoost-based machine learning model for cryptocurrency price prediction using historical market data and technical indicators. The model efficiently captured nonlinear relationships among features such as opening, closing, and volume prices while minimizing prediction error through optimized gradient boosting. Comparative analysis with traditional models such as ARIMA, SVM, and Random Forest confirmed that the proposed XGBoost model achieved superior accuracy, lower MAE and RMSE values, and better generalization across multiple cryptocurrencies.

The study demonstrated that the gradient boosting mechanism of XGBoost effectively handles large datasets and volatile financial data, enabling robust and stable predictions. The incorporation of feature scaling and hyperparameter tuning further enhanced the model's efficiency and reduced overfitting. These findings validate the potential of ensemble-based models as reliable forecasting tools in the cryptocurrency domain, offering investors and analysts data-driven insights for better decision-making.

In the future, this work can be extended by integrating sentiment analysis from social media and news sources to capture psychological market influences. Additionally, combining XGBoost with deep learning models such as LSTM or GRU may further improve predictive performance by learning temporal dependencies in price movements. Real-time model deployment with streaming APIs and the adoption of Explainable AI (XAI) techniques can also enhance transparency, interpretability, and real-world applicability in financial analytics systems.

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