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Crypto Currency Price Prediction Using Deep Learning

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Abstract:

This Study focuses on time series analysis for predicting Bitcoin prices using various methodologies including recurrent neural network (RNN), Long short term memory (LSTM), auto regressive integrity integrated moving average (ARIMA) and Facebook's prophet. We utilize a dataset consisting of time stamps and closing prices to train and evaluate the performance of these models. The objective is to identify the most effective forecasting technique for Bitcoin Price moments, addressing the inherent volatility of cryptocurrency markets by leveraging historical price data, preimage to enhance prediction accuracy contributing to more informed trading decisions. Our finding will provide valuable insights Into the applicability of different predictive models in the context of cryptocurrency ultimately aiming to assist investors in navigating the complexities of Bitcoin trading. The results underscore the strength and weaknesses of each method paving the way for future research in financial tying series analysis.

Keywords: RNN, LSTM, ARIMA, and Prophet, Kaggle dataset

Introduction:

The rapid rise of cryptocurrencies, Particularly Bitcoin has transformed financial markets and sparked immense interest along investors analysis and researchers. Bitcoin as the first decentralized digital currency, has generated significant attention due to its price volatility and potential for high returns. This volatility presents both opportunities and challenges, necessitating robust predictive models to assist stockholders in marketing informed decisions. Time series analysis a statistical technique focused on analyzing time-ordered data points, offers valuable insights into price trends and movements making it an essential tool in the realm of cryptocurrency forecasting. Various methodologies exist for time series prediction each with unique strength and weaknesses. Traditional approaches such as the auto regressive integrated moving average (ARIMA), have been widely employed due to their simplicity and interpretability. However the increasing complexity of financial data and nonlinear relationships often necessarily the use of more sophisticated models. Recurrent neural network (RNN) and long short term memory network (LSTM) represent advanced techniques capable of capturing complex temporal patrons making them suitable for financial time series analysis.

Additionally Facebook prophet has emerged As a powerful tool for forecasting time series data particularly in scenarios involving seasonality and trends. Its user-friendly interface and the ability to handle missing data make it an attractive option for practitioners in various fields including finance. This study aims to evaluate the effectiveness of these methodologies in predicting Bitcoin prices by leveraging a comprehensive data set of historical price movements. By comparing the predictive capabilities of RNN, LST M, ARIMA and PROPHET we seek to identify the most effective forecasting technique ultimately aiding investors in navigating the volatile cryptocurrency landscape. Through Rigorous analysis and evaluation in this research will contribute to the broad er discourse on financial guidelines series analysis highlighting the applicability of different models in the cryptocurrency market.

Literature Survey:

1. L. Serena S Ferretti and G. D' Angelo Cryptocurrencies Activity as a complex network: analysis of transactions graphs Peer – peer netw. Vol. 15, no.2, pp 839 – 853 Mar. 2022.

The paper by L. Serena, S. Ferretti and G.D' Anglo explores cryptocurrency transactions networks using complex network theory. Analyzing Bitcoin, DogeCoin, etherium and ripple, the study focuses on transaction patterns overtime to uncover insights into user behavior on these distributed pledger technologies (DLTs). The authors introduce the distributed ledger network analysis (DiLeNA), a tool designed to investigate transaction networks. Their finding reveal the transaction graphs across all studied DLTs exhibits-small world properties, highlighting the importance of network analysis for understanding user interactions and the dynamics of cryptocurrency ecosystem.

2. Complex network analysis of the Bitcoin blockchain network, by B. Tao, I. W. Ho, and H.N. Dai, in Proceedings of the IEEE Int. Symp. Circuits Syst. (ISCAS), May 2021,pp.1–
5.

Using a complex network approach, the paper by Tao, Ho, and Dai provides a thorough analysis of the Bitcoin blockchain network. They present the BABD-13 dataset, which contains comprehensive information on Bitcoin transactions from July 2019 to May 2021. It contains 148 attributes and 13 different kinds of addresses. They attain classification accuracies ranging from 93.24% to 97.13% by utilizing machine learning models such as XGBoost, decision trees, and k-nearest neighbors. In order to better understand and track blockchain transactions, the study also looks at Bitcoin address behavior patterns and suggests a k-hop subgraph generation algorithm for in-depth network analysis.

3. B. Tao, H.-N. Dai, J. Wu, I. W. Ho, Z. Zheng, and C. F. Cheang, "Complex network analysis of the Bitcoin transaction network," IEEE Trans. Circuits Syst. II, Exp. Briefs, vol.69,no.3,pp.1009–1013,Mar.2022.

A thorough framework for examining Bitcoin transactions in order to spot illegal activity within the cryptocurrency ecosystem is presented in this paper. The largest publicly accessible labeled dataset of Bitcoin addresses, the BABD-13 dataset, which covers transactions from July 2019 to May 2021, is introduced in this study. It has 544,462 labeled entries, 148 features, 5 indicator categories, and 13 address types. The Bitcoin transaction network's k-hop subgraphs are extracted using a new subgraph generation algorithm called BTC-SubGen. Accuracy rates for classification using different machine learning models ranged from 93.24% to 97.13%. The study also looks at the significance of certain features and the trends in Bitcoin address behavior.

4. N. Tovanich, N. Soulié, N. Heulot, and P. Isenberg, "An empirical analysis of pool hopping behavior in the Bitcoin blockchain," in Proc. IEEE Int. Conf. Blockchain Cryptocurrency, May2021,pp.1–9.

Pool-hopping behavior in Bitcoin mining, where miners switch pools to maximize rewards, is examined by N. Tovanich et al. in their 2021 paper. They suggest a novel detection technique based on mining reward time window analysis. Their methodology, which was tested on the top five mining pools over two periods in 2020 and 2021, includes algorithms for revenue tracking and miner identification. The study concludes that although pool-hopping is still advantageous, the gap between pool-hoppers and static miners has decreased due to the improved fairness of the more recent reward schemes. In spite of this, the median cumulative gain for pool-hoppers is still 33% greater than that of static miners.

5. I. Alqassem, I. Rahwan, and D. Svetinovic, "The anti-social system properties: Bitcoin network data analysis," IEEE Trans. Syst., Man, Cybern., Syst., vol. 50, no. 1, pp. 21–31, Jan. 2020.

Alqassem, Rahwan, and Svetinovic's paper, "The Anti-Social System Properties: Bitcoin Network Data Analysis," which was published in IEEE Transactions on Systems, Man, and Cybernetics: Systems (2020), looks at the Bitcoin network from the perspective of anti-social system properties. This study is a component of a larger index that includes technical publications from 2020, such as reviews, papers, and correspondence. In addition to coauthors, paper titles, and publication details, the Author Index lists the primary entries for every item, arranged by the name of the first author. The Subject Index offers thorough bibliographic information by classifying entries according to pertinent subject headings. The paper's main objective is to examine the network dynamics of Bitcoin and its consequences in the context of an anti-social system.

6. P. Nerurkar, D. Patel, Y. Busnel, R. Ludinard, S. Kumari, and M. K. Khan, "Dissecting Bitcoin blockchain: Empirical analysis of Bit- coin network (2009–2020)," J. Netw. Comput. Appl., vol. 177, Mar. 2021, Art. no. 102940.

The evolution of the Bitcoin network from 2009 to 2020 is examined in the paper by P. Nerurkar et al., which also looks at the network's dual nature as an antisocial and social entity. Bitcoin is a decentralized cryptocurrency payment system that promotes community trust by facilitating value exchange without the need for middlemen. Its anonymity, however, also makes it more difficult for law enforcement to monitor illegal transactions. In order to comprehend how these social and antisocial traits impact Bitcoin's evolution, the study explores the local topology and geometry of the network. The authors shed light on the structural dynamics of the network and how user behavior shapes its growth and challenges by examining transaction data from the first ten years of Bitcoin.

Theory:

The non-linearity and volatility of Bitcoin prices render conventional statistical techniques less accurate for forecasting purposes. To deal with this issue, deep learning models have also become effective tools because they have the capability to learn complex patterns in large amounts of data automatically. Methods like Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and 1D Convolutional Neural Networks (CNNs) are especially effective in time-series prediction such as forecasting Bitcoin prices. These models take past prices, volume, and technical indicators, among other historical data, and process these to learn temporal trends and dependencies over time.

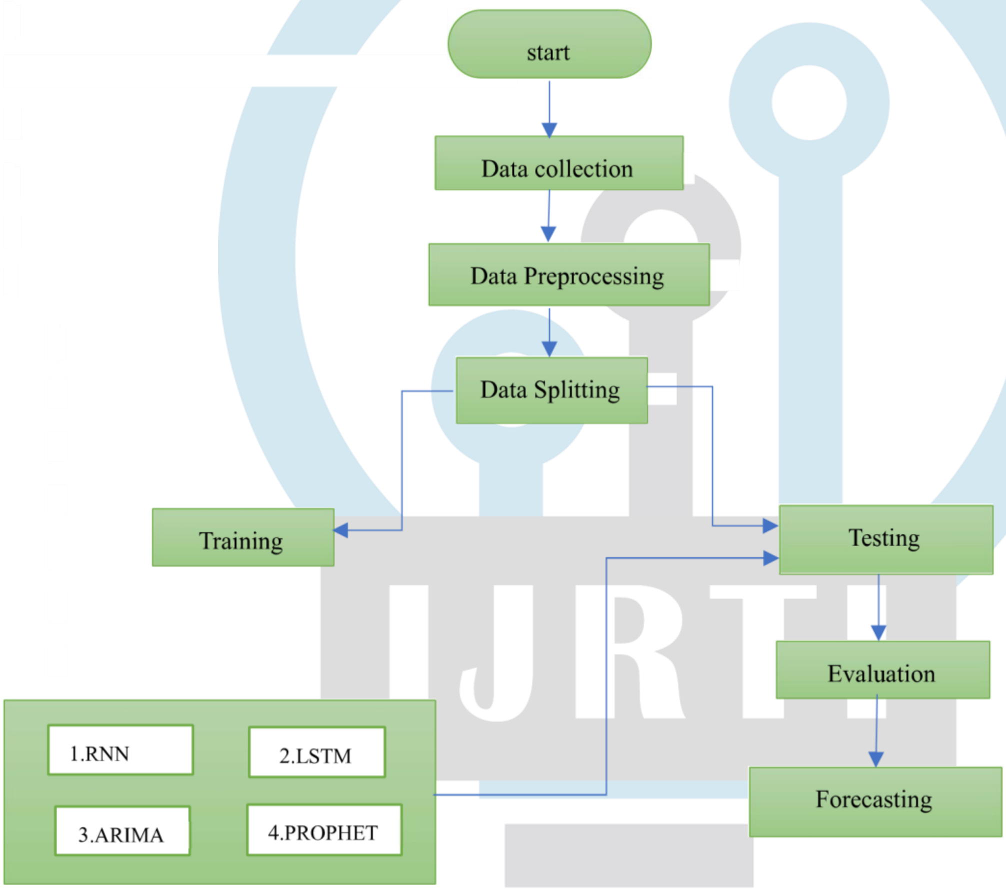
Through training on vast datasets, deep models reduce prediction error using loss functions such as Mean Squared Error (MSE). Training is done through backpropagation and optimization algorithms including Adam or RMSprop. After training, the model can forecast future prices of Bitcoin using current and historical inputs. Although the models have great potential, they are largely dependent upon the quality of data, feature extraction, and efficient tuning of hyperparameters. In general, deep learning presents a promising method for capturing the complex dynamics of cryptocurrency markets.

Proposed System:

This paper presents a time series-based hybrid model for Bitcoin price prediction, integrating conventional statistical models with modern deep learning techniques. The forecasting models used are Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, ARIMA (AutoRegressive Integrated Moving Average), and Facebook's Prophet model. Each of these has unique strengths in time series forecasting—whereas trend-based and explainability of ARIMA and Prophet give insights, RNN and LSTM are capable of learning complex temporal patterns in sequential data. With the models used on a Bitcoin dataset drawn from Kaggle— timestamps and closing prices daily—the study explores how each model fairs in the non-linear and unstable setting of cryptocurrency markets.

The aim of this system is to compare the relative accuracy and robustness of these models in predicting future Bitcoin prices. Deep learning models like LSTM are best suited to learn long-term trends and are best equipped to handle noisy financial data, whereas ARIMA and Prophet are trend, seasonality, and irregularity-sensitive time series models. The results of this analysis are meant to give insights into the trade-offs between interpretability and simplicity, and between short-term and long-term forecast accuracy. By identifying the best model or the combination of models, the system aims to give investors and analysts data-driven, informed decisions in the highpressure and speculative world of cryptocurrency trading.

Block Diagram:



Result:

The use of cryptocurrency price forecasting via deep learning models, i.e., LSTM networks, holds much potential for identifying temporal dependencies and patterns of extremely volatile financial data. Out of the models experimented with, LSTM performed consistently better than traditional methods such as ARIMA and Facebook Prophet in lower Root Mean Squared Error (RMSE) and higher test set prediction accuracy. The model was capable of tracking the general direction of Bitcoin prices and making smooth and stable predictions for short horizons. However, due to the nature of uncertainty and extraneous market forces on the cryptocurrency, sporadic deviations from predicted and actual prices were noted. These findings confirm that while deep learning enhances prediction capability, especially on complex, non-linear data such as cryptocurrency prices, it is optimally utilized in combination with due risk management and market awareness practices.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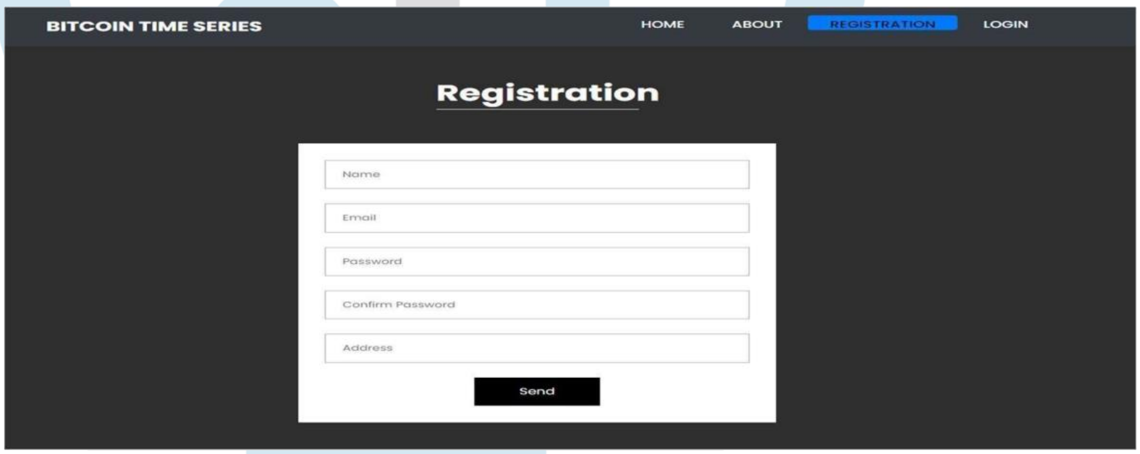
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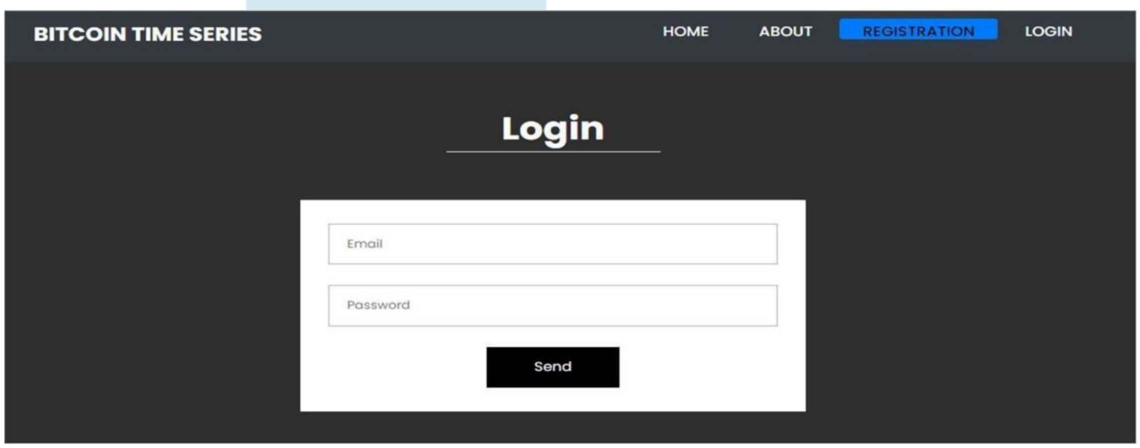
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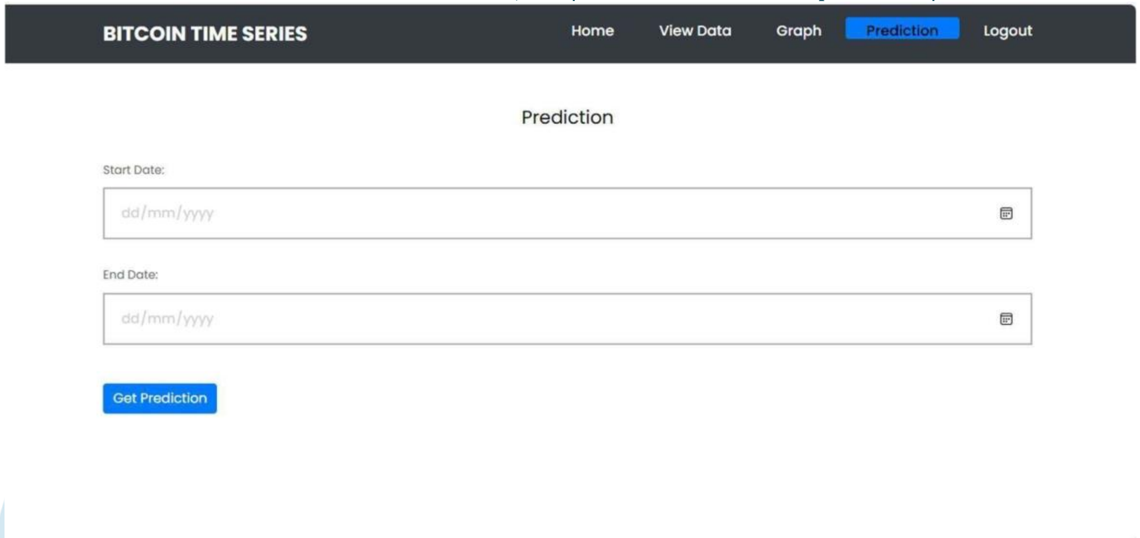

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