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FORECASTING AND TRADING CRYPTOCURRENCY WITH MACHINE LEARNING UNDER CHANGING MARKET CONDITIONS

1 Madhavi Indukuri
Dept. of Computer Science Engineering
K L Deemed to be University
Guntur, India
2000030583@kluniversity.in

2 G. Rohini
Dept. of Computer Science Engineering
K L Deemed to be University
Guntur, India
2000030330@kluniversity.in

3 Soumya
Dept. of Computer Science Engineering
K L Deemed to be University
Guntur, India
2000030160@kluniversity.in

4 Lohit sai
Dept. of Computer Science Engineering
K L Deemed to be University
Guntur, India
2000030545@kluniversity.in

ABSTRACT: Cryptocurrencies are peer-to-peer transaction systems that use the secure hash algorithm (SHA)-256 and message digest (MD)-5 methods to protect data transactions. Cryptocurrency values are exceedingly volatile, follow stochastic moments, and have achieved unpredictability. They are frequently used for investment and have replaced traditional forms of investment like as metals, estates, and the stock market. Their commercial prominence necessitates the creation of a strong forecasting model. However, given to its reliance on other cryptocurrencies, bitcoin price forecast is difficult. Many academics have employed machine learning and deep learning models, as well as other market sentiment-based algorithms, to forecast cryptocurrency prices. Because all cryptocurrencies belong to the same class, a rise in the price of one cryptocurrency might cause a price change for other cryptocurrencies. The emotions from tweets and other social media platforms were also used by the researchers to improve the performance of their suggested system. Motivated by this, we offer in this study a hybrid and resilient framework, DL-Gues, for cryptocurrency price prediction that takes into account its interdependence on other cryptocurrencies as well as market attitudes. For validation, we investigated Dash price prediction utilising price history and tweets of Dash, Litecoin, and Bitcoin for different loss functions. To test the applicability of DL-GuesS on additional cryptocurrencies, we inferred findings for Bitcoin-Cash price prediction using the price history and tweets of Bitcoin-Cash, Litecoin, and Bitcoin.
Keywords *– Cryptocurrency, complex systems, fusion of cryptocurrency, price prediction, VADER, sentiment analysis, deep learning, systems of systems.*

1. INTRODUCTION

A cryptocurrency is a digital type of money that was designed to be used as a regular method of transaction. To protect the confidentiality of financial transactions, it employs cryptographic methods like as SHA-256 and MD-5. In the current environment, financial transactions cannot be carried out without the participation of third-party entities such as banks, but cryptocurrency removes this need. Cryptocurrencies are now an accepted part of society. It was initially presented as Bitcoin in 2008, with the goal of replacing the whole cash exchange system with a universal digital money system [1]. To make the system transparent, safe, and dispersed, this newly developed financial system is independent of centralised financial institutions like as banks, governments, and other organisations. To maintain system integrity and consistency, methods such as proof-of-work (PoW), proof-of-stack (PoS), and other consensus algorithms were devised. When it was created, cryptocurrency exchange rates were quite low. However, due to its volatility character, its market begins to grow over time. To far, almost 4200 crypto currencies are circulating in the market, with a market valuation of $2.23 billion (till April 2021). Popular cryptocurrencies like as Bitcoin and Ethereum are the largest donors, accounting for 78% and 12% of the total [2]. This bitcoin market surge has enticed many people, investors, and businesses to invest directly or indirectly [3]. The bitcoin market surge is awkward owing to its volatility nature. Cryptocurrency values swing dramatically over time. Within a decade, the price of Bitcoin increased from $0.08 in 2010 to $64000 in April 2021 [2]. Ethereum prices grew from $0.67 in January 2018 to $2346 in April 2021, following the same pattern [2]. These patterns justify the bitcoin market's volatility. Furthermore, additional variables like as volume, mining difficulty, popularity, and the price of competing crypto coins all contribute to the volatility of cryptocurrency values.

Researchers from all around the world have utilised theories such as the efficient market hypothesis (EMH) and the alternative market hypothesis (AMH) to study bitcoin market patterns and volatility. According to the EMH theory, the prices at which cryptocurrencies are exchanged are always fair and represent all available information. Furthermore, as the difficulty of the mining challenge grows, so will the price of the related coin [4]. However, in practise, this theory does not function, and in order to solve the shortcomings of EMH, a new theory, AMH, was established with the addition of behavioural finance. Still, we may achieve nice results by using EMH like the authors of [5] do, but they are not exact.

2. LITERATURE REVIEW

A literature survey on cryptocurrency price prediction encompasses various methodologies and approaches employed by researchers to forecast the prices of cryptocurrencies, particularly focusing on Bitcoin due to its significance in the market. This survey delves into the studies conducted by researchers using different techniques ranging from stochastic neural networks to sentiment analysis and machine learning models.

Jay et al. [3] introduced the utilization of stochastic neural networks for cryptocurrency price prediction. Their work emphasizes the application of advanced neural network architectures to model the complex and volatile nature of cryptocurrency markets. By incorporating stochasticity into neural networks, they aim to capture the inherent uncertainty and randomness in cryptocurrency price movements.

Sharma [4] explored the relationship between Bitcoin mining energy costs and its price. This study investigates the impact of mining expenses on Bitcoin's valuation, shedding light on the economic factors influencing cryptocurrency markets. Understanding the cost dynamics of Bitcoin mining provides insights into its price behavior and market efficiency.

Tran and Leirvik [5] examined efficiency in cryptocurrency markets, analyzing the efficiency of various cryptocurrencies in terms of market performance and price movements. Their research contributes to understanding the efficiency hypothesis in the context of cryptocurrencies and provides insights into market dynamics and pricing efficiency.

Lamon et al. [6] proposed a methodology for cryptocurrency price prediction based on sentiment analysis of news and social media. By analyzing the sentiment expressed in news articles and social media posts related to cryptocurrencies, they aim to gauge market sentiment and its impact on price movements. This approach leverages textual data to uncover valuable insights into market sentiment dynamics.

Radityo et al. [7] investigated the prediction of Bitcoin exchange rates using artificial neural network methods. By employing artificial neural networks, they aim to capture the nonlinear relationships inherent in cryptocurrency price data. Their study contributes to the exploration of machine learning techniques for cryptocurrency price prediction and highlights the effectiveness of neural networks in modeling complex financial data.

Phaladisailoed and Numnonda [8] compared machine learning models for Bitcoin price prediction, evaluating the performance of different algorithms in forecasting cryptocurrency prices. Their research provides a comprehensive analysis of machine learning techniques and their applicability to cryptocurrency price prediction, offering insights into the strengths and limitations of various modeling approaches.

Wimalagunaratne and Poravi [9] proposed a holistic predictive model for the global cryptocurrency market. Their approach integrates multiple factors and variables to develop a comprehensive model for cryptocurrency price prediction. By considering a wide range of predictors, including market sentiment, technical indicators, and fundamental factors, their model aims to capture the multifaceted nature of cryptocurrency markets.

Hashish et al. [10] presented a hybrid model for Bitcoin price prediction, combining hidden Markov models with optimized LSTM networks. This hybrid approach leverages the strengths of both models to enhance predictive accuracy and capture complex patterns in cryptocurrency price data. By integrating different methodologies, their model offers a robust framework for cryptocurrency price forecasting.

In summary, the literature on cryptocurrency price prediction encompasses a diverse range of methodologies, including stochastic neural networks, sentiment analysis, machine learning models, and hybrid approaches. Researchers continue to explore innovative techniques to improve the accuracy and reliability of cryptocurrency price forecasts, contributing to the advancement of predictive analytics in the rapidly evolving field of cryptocurrency markets.

3. METHODOLOGY

Researchers from all around the world have utilised theories such as the efficient market hypothesis (EMH) and the alternative market hypothesis (AMH) to study bitcoin market patterns and volatility. According to the EMH theory, the prices at which cryptocurrencies are exchanged are always fair and represent all available information. Furthermore, as the difficulty of the mining challenge rises, so will the price of the related coin. However, in practise, this theory does not function, and in order to solve the shortcomings of EMH, a new theory, AMH, was established with the addition of behavioural finance. Still, we can achieve decent results by using EMH like the authors do, but it is not accurate/

Disadvantages:

1. As the difficulty of the mining challenge rises, so will the price of the related cryptocurrency.
2. We can still achieve decent results by using EMH as the authors do, but it is not correct.

Many academics have employed machine learning and deep learning models, as well as other market sentiment-based algorithms, to forecast cryptocurrency prices. Because all cryptocurrencies belong to the same class, a rise in the price of one cryptocurrency might cause a price change for other cryptocurrencies. The emotions from tweets and other social media platforms were also used by the researchers to improve the performance of their suggested system. Motivated by this, we offer in this study a hybrid and resilient framework, DL-Gues, for cryptocurrency price prediction that takes into

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account its interdependence on other cryptocurrencies as well as market attitudes.

Advantages:

1. The robustness of DLGuesS, we evaluated the performance of DL-GuesS for two distinct cryptocurrencies and compared the results.
2. In terms of forecasting bitcoin values, the suggested DL-GuesS beats existing systems. DL-GuesS.

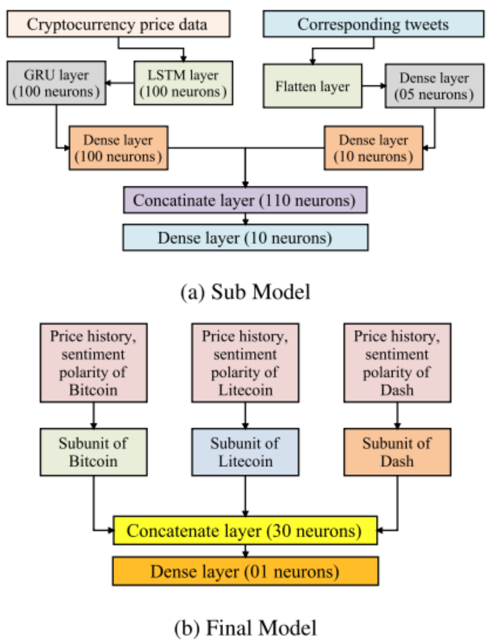

Fig.2: System architecture

MODULES:

To carry out the aforementioned project, we created the modules listed below.

- Data exploration: we will put data into the system using this module.
- Processing: we will read data for processing using this module.
- Splitting data into train and test: Using this module, data will be separated into train and test models.
- Making the model LSTM - GRU - Logistic Regression - Random Forest - Decision Tree - Support Vector Machine - MLP - Voting Classifier - (LR + RF + MLP) - ARIMA for Forecasting. Calculated algorithm accuracy.
- User signup and login: Using this module will result in registration and login.
- User input: Using this module will result in predicted input.
- Prediction: final predicted shown

4. IMPLEMENTATION

ALGORITHMS:

CNN + LSTM: A CNN-LSTM model is made up of CNN layers that extract features from input data and LSTM layers that forecast sequences. A time series is a temporal sequence of data that is primarily used for sequential data. Because it handles sequences better, LSTM is the chosen DNN algorithm. CNN is often beneficial for capturing neighbourhood information, such as in a picture.

LSTM: A deep learning architecture based on an artificial recurrent neural network, long short-term memory (LSTM) (RNN). For situations requiring sequences and time series, LSTMs offer a promising solution.

GRU: Gated recurrent units (GRUs) are a recurrent neural network gating technique established in 2014 by Kyunghyun Cho et al. The GRU functions similarly to a long short-term memory (LSTM) with a forget gate, but with fewer parameters since it lacks an output gate.

Logistic Regression: Logistic regression is a Machine Learning classification technique that predicts the likelihood of certain classes based on specified dependent variables. In summary, the logistic regression model computes the logistic of the outcome by adding the input characteristics (in most situations, there is a bias component).

Random Forest: A Random Forest Method is a supervised machine learning algorithm that is widely used in Machine Learning for Classification and Regression issues. We know that a forest is made up of many trees, and the more trees there are, the more vigorous the forest is.

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Decision tree: A decision tree is a non-parametric supervised learning technique that may be used for classification and regression applications. It has a tree structure that is hierarchical and consists of a root node, branches, internal nodes, and leaf nodes.

SVM: Support Vector Machine (SVM) is a supervised machine learning technique that may be used for both classification and regression. Though we call them regression issues, they are best suited for categorization. The SVM algorithm's goal is to identify a hyperplane in an N-dimensional space that clearly classifies the input points.

MLP: Another artificial neural network technique with several layers is the multi-layer perceptron (MLP). Although obviously linear issues may be addressed with a single perceptron, it is not well suited to non-linear applications. MLP may be used to address these difficult challenges.

Voting classifier: A voting classifier is a machine learning estimator that trains numerous base models or estimators and predicts based on the results of each base estimator. Aggregating criteria may be coupled voting decisions for each estimator output.

ARIMA: ARIMA models are commonly designated as ARIMA (p,d,q), where p represents the order of the autoregressive model, d represents the degree of differencing, and q represents the order of the moving-average model. ARIMA models employ differencing to turn a non-stationary time series into a stationary one, and then use previous data to forecast future values.

5. EXPERIMENTAL RESULTS

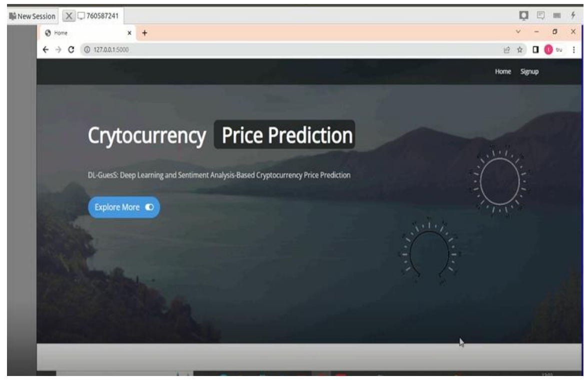

Fig.3: Home screen

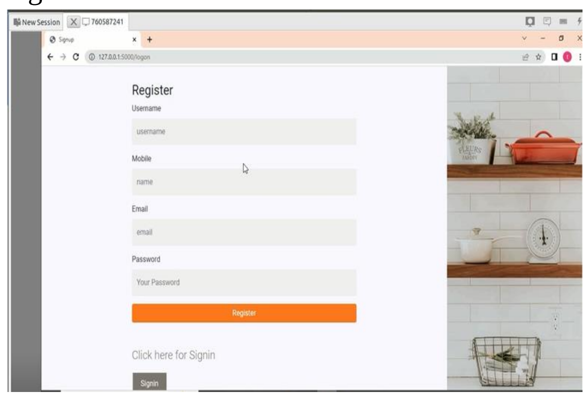

Fig.4: User registration

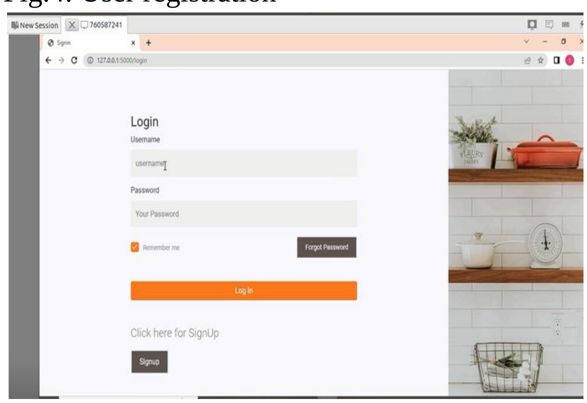

Fig.5: user login

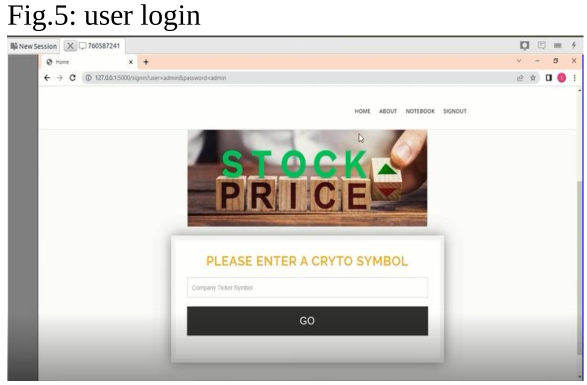

Fig.6: Main screen

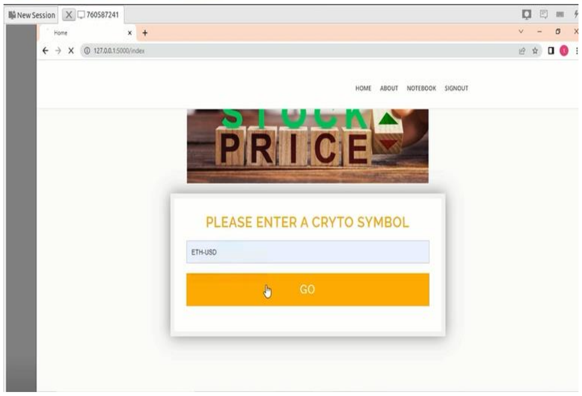

Fig.7: User input

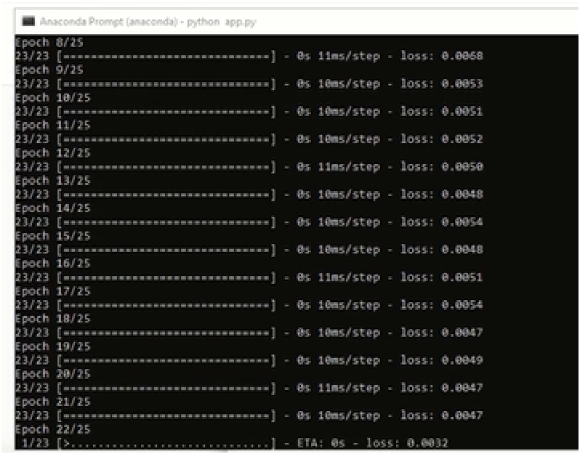

Fig.8: Prediction result

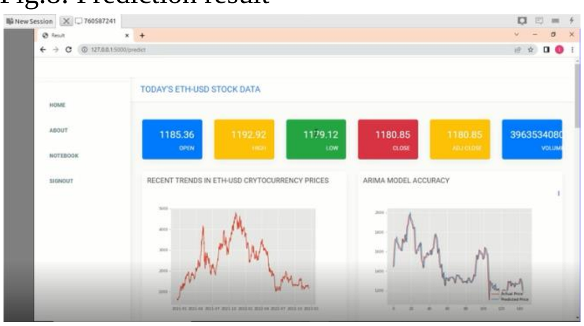

Fig.9: Stock Data

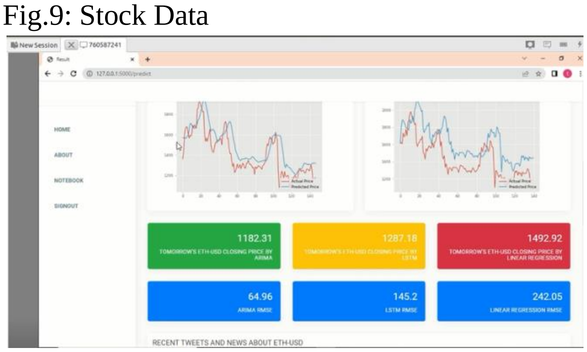

Fig.10: Stock Data

6. CONCLUSION

We examined current techniques for bitcoin price prediction in this article. Many of them are being used by fin-tech enterprises to capitalise on the benefits of bitcoin price prediction models. However, the unpredictable nature of the market and the many dependent elements make forecasting difficult. In this research, we develop a hybrid model, DL-GuesS, for bitcoin price prediction that takes into account price history and current Twitter emotions. To explain the robustness of DLGuesS, we evaluated its performance for two distinct cryptocurrencies and compared the findings, i.e., loss functions, with prior studies. In terms of forecasting bitcoin values, the suggested DL-GuesS surpasses existing algorithms. DL-GuesS.

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