Crypto Forecast: Unveiling DL – GuesS for Precise Cryptocurrency Price Prediction

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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 A cryptocurrency price prediction that takes into account its interdependence on other cryptocurrencies as well as market attitudes. For validation, we investigated Dash price prediction utilizing 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

Cryptocurrency is a digital currency designed for transactions using cryptographic methods like SHA-256 and MD5 to ensure secure transactions. Unlike traditional financial systems that require third-party intermediaries like banks, cryptocurrency eliminates this need. First introduced as Bitcoin in 2008, it aimed to replace the traditional cash exchange system with a decentralized digital currency. This system operates independently of centralized institutions like banks and governments, using consensus algorithms like Proof-of-Work (PoW) and Proof-of-Stake (PoS) for integrity and transparency. Initially, cryptocurrency values were low but have grown significantly due to market volatility. By April 2021, around 4200 cryptocurrencies were circulating with a market valuation of $2.23 billion, dominated by Bitcoin and Ethereum, contributing 78% and 12%, respectively. The rapid growth and volatility of the market have attracted investors, with Bitcoin rising from $0.08 in 2010 to $64,000 in 2021 and Ethereum increasing from $0.67 in 2018 to $2346 in 2021. Factors such as trading volume, mining difficulty, popularity, and competing cryptocurrencies drive this volatility.

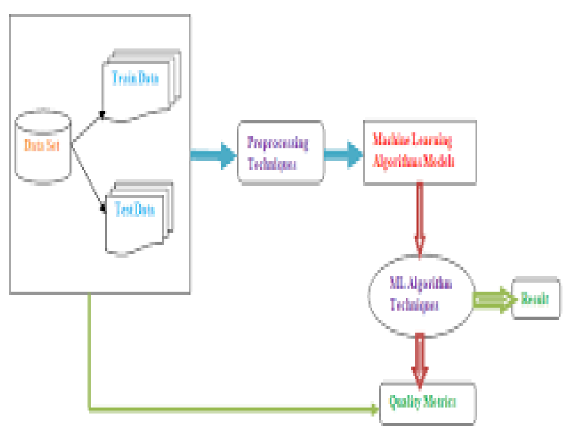

Fig.1: Example figure

Researchers worldwide have applied theories like the Efficient Market Hypothesis (EMH) and the Adaptive Market Hypothesis (AMH) to analyze cryptocurrency market trends and volatility. EMH suggests that cryptocurrency prices are always fair, reflecting all available information, and that as mining difficulty increases, so does the coin's price. However, this theory is flawed in practice. To address these limitations, AMH was developed, incorporating behavioural finance. While EMH can still produce useful, though not fully accurate, results as shown by authors in [5], it remains limited in explaining the market dynamics.

2. LITERATURE REVIEW

Stochastic neural networks for cryptocurrency price prediction:
The rise of blockchain technology has led to increased use of cryptocurrencies. However, due to their high volatility and unstable market, cryptocurrencies are not widely viewed as investment opportunities. Traditional deterministic methods for cryptocurrency price prediction are often unsuitable for real-time forecasting. To address these issues, we propose a stochastic neural network model based on random walk theory, commonly used in financial markets to simulate stock prices. This approach incorporates layer-wise randomization in neural networks to account for market volatility and includes a strategy for learning market response patterns. We trained Multi-Layer Perceptron (MLP) and Long Short-Term Memory (LSTM) models for Bitcoin, Ethereum, and Litecoin, with results showing that our model outperforms deterministic approaches.

Efficiency in the markets of crypto-currencies
We show that market efficiency in the five major cryptocurrencies fluctuates significantly over time. Before 2017, Bitcoin markets were mostly inefficient, consistent with existing studies. However, from 2017 to 2019, they became more efficient, differing from recent research. This difference may be due to our larger sample size and the more rigorous efficiency measure we used. Overall, Litecoin is the most efficient cryptocurrency, while Ripple is the least efficient.
Cryptocurrency price prediction using news and social media sentiment
Bitcoin was introduced through a document anonymously published under the pseudonym Satoshi Nakamoto. Its success led to the creation of numerous other cryptocurrencies, driven by market volatility and profit-seeking interest. Twitter is a key platform for cryptocurrency enthusiasts to share and learn news and ideas. This study explores the potential of Twitter sentiment analysis to predict cryptocurrency price changes. Tweets and price data for seven major cryptocurrencies were collected and analyzed using VADER sentiment analysis. Time-series stationarity was assessed using ADF and KPSS tests, followed by Granger Causality testing. While price changes influence sentiment for Bitcoin, Cardano, XRP, and Doge, Ethereum and Polkadot show predictability based on bullishness ratios. Price returns were further analyzed using Vector Autoregression (VAR), with highly accurate predictions for Ethereum (99.67%) and Polkadot (99.17%).

Prediction of Bitcoin exchange rate to American dollar using artificial neural network methods
Cryptocurrency trading has become a popular investment option, with the market being compared to forex and stock markets. However, due to its high volatility, a prediction tool is needed to guide investors. Artificial Neural Network (ANN) methods, commonly used for stock and forex predictions, have not been extensively studied for cryptocurrencies. This study explores several ANN methods to predict Bitcoin’s next-day closing value. The methods evaluated include Backpropagation Neural Network (BPNN), Genetic Algorithm Neural Network (GANN), Genetic Algorithm Backpropagation Neural Network (GABPNN), and Neuro-Evolution of Augmenting Topologies (NEAT). These approaches are assessed for accuracy and complexity. Results show that BPNN is the most effective, with a MAPE of 1.998 ± 0.038% and a training time of 347 ± 63 seconds.

Machine learning models comparison for bitcoin price prediction
Bitcoin has become the most valuable cryptocurrency, but its price volatility makes accurate prediction difficult. This study aims to identify the most efficient model for predicting Bitcoin prices using various machine learning techniques. Multiple regression models were tested using scikit-learn and Keras

libraries on 1-minute interval trade data from the Bitcoin exchange bitstamp, covering the period from January 1, 2012, to January 8, 2018. The top results showed a Mean Squared Error (MSE) as low as 0.00002 and an R-Square (R^2) as high as 99.2%.

3. METHODOLOGY

Researchers worldwide have applied the Efficient Market Hypothesis (EMH) and Adaptive Market Hypothesis (AMH) to analyze Bitcoin market trends and volatility. EMH suggests that cryptocurrency prices are always fair and reflect all available information, with prices increasing as mining difficulty rises. However, this theory is impractical in real-world scenarios. To address EMH's limitations, AMH was developed, incorporating behavioral finance. While EMH can still yield reasonable results, as shown by some studies, it is not fully accurate.

Disadvantages:
1. As mining difficulty increases, cryptocurrency prices generally rise.
2. While EMH can yield reasonable results, it is not fully accurate.

Many researchers have employed machine learning, deep learning models, and sentiment-based algorithms to predict cryptocurrency prices. Since cryptocurrencies belong to the same class, a price change in one can influence others. Researchers have also leveraged sentiments from tweets and social media to enhance their models. Inspired by this, we propose a hybrid and resilient framework, DL-Gues, for cryptocurrency price prediction, considering the interdependence among cryptocurrencies and market sentiment.

Advantages:
1. DL-GuesS was tested on two different cryptocurrencies, demonstrating its robustness.
2. DL-GuesS outperforms existing systems in predicting Bitcoin prices.

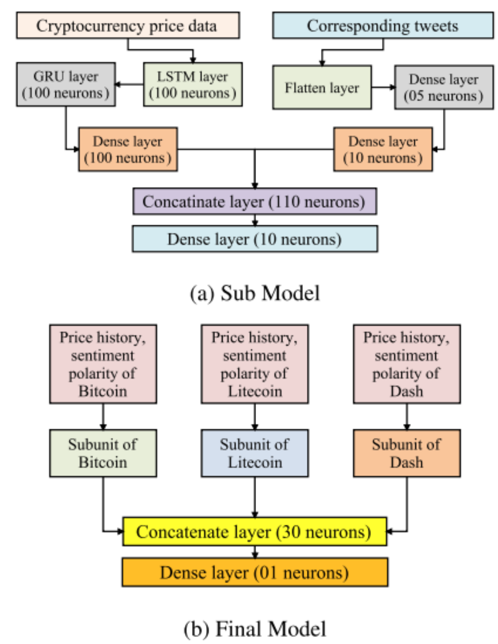

Fig.2: System architecture

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 neighborhood 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.

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

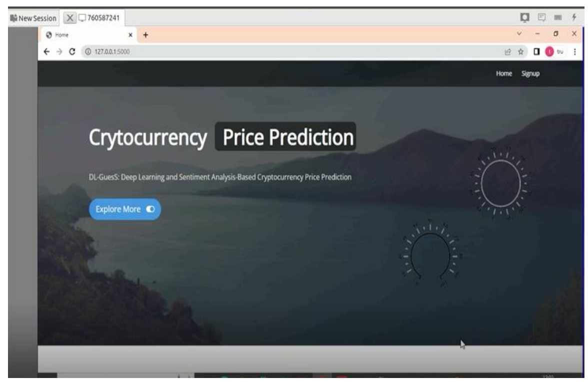

Fig.3: Home screen

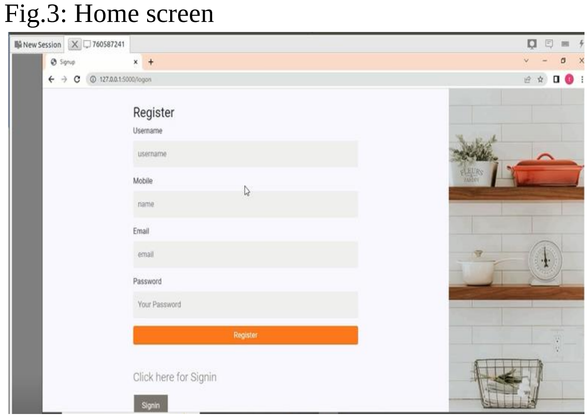

Fig.4: User registration

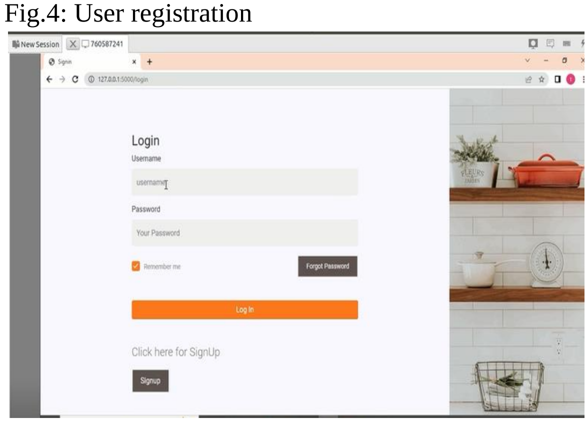

Fig.5: user login

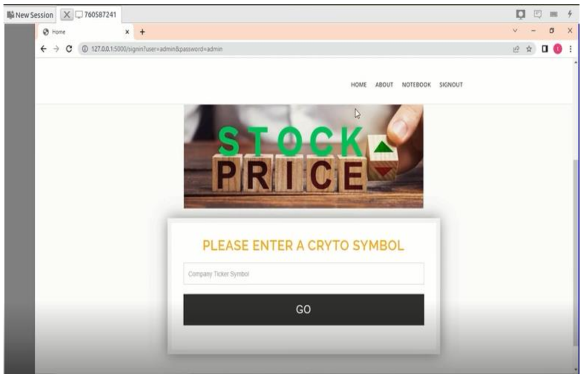

Fig.6: Main screen

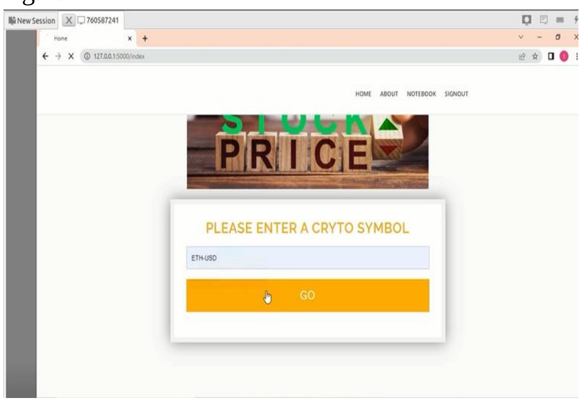

Fig.7: User input

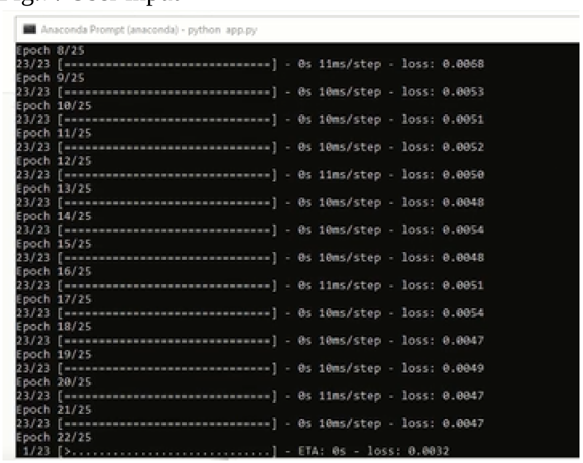

Fig.8: Prediction result

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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