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Bitcoin Price Prediction using Deep Learning and Machine Learning Techniques

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ABSTRACT: The most contentious advancement in the contemporary global economy has been the quick rise of digital currency, particularly cryptocurrencies, over the past ten years. Investors are quite confused as a result of the very volatile market and swings in the price of bitcoin. In this study, a unique deep learning technique for prediction model creation is proposed. Deep learning algorithms have the potential to learn from extensive previous data and accurately forecast future pricing. The aforementioned issue falls under time series forecasting issues. Models addressing time series prediction issues include Long Short-Term Memory, Gated Recurrent Units, and Convolutional Neural Networks. The degree of accuracy of various models is evaluated, and the model with the highest accuracy is chosen.

KEYWORDS: Deep Learning, Recurrent Neural Network, Random Forest, Long Short-Term Memory, Elastic Net

I. INTRODUCTION

An electronic exchange instrument called cryptocurrency employs cryptographic operations to carry out financial transactions. Cryptocurrencies use blockchain technology to provide transparency, decentralization, and immutability. The most well-known cryptocurrency is Bitcoin, which was developed in 2009 by an unidentified individual or group going by name of Satoshi Nakamoto and reached its highest value on December 16, 2017, rising to about \$20,000. 1512 alternative cryptocurrencies, including Ethereum and Litecoin, were developed in the previous 10 years, demonstrating the market's emergence and rapid expansion. Bitcoin is now the most popular cryptocurrency in the world, and its use has been steadily increasing over time. However, due to their extreme volatility, Bitcoin values are particularly hard to forecast. In order to help Bitcoin investors make large gains, it is crucial to design an accurate prediction tool that uses intricate and advanced mathematical formulae.

Similar to stock price prediction, the forecast of the price of Bitcoin may be seen as a standard time series issue. Traditional time-series models, such as the well-known ARIMA, have been used to forecast the price and movement of cryptocurrencies. Despite this, the exponential growth in research and the quick development of digital technology results in an increase in the volume, scope, and complexity of data. Therefore, unlike Deep Neural



Networks, which are likely the most appropriate and effective method to address these issues, these models are unable to capture the non-linearity of samples in the training set. Deep Neural Networks (DNNs) are powerful and modern machine learning techniques that have been used in a variety of fields, including drug design, bioinformatics, medical image analysis, speech recognition, computer vision, audio recognition, and natural language processing, social network filtering, and machine translation. DNNs, or deep neural networks, are more particularly very complicated non-linear systems that are composed of artificial neural networks with numerous layers separating the input and output layers and are intended to simulate complex non-linear connections. Due to recent advances in their teaching methodology, their popularity has increased dramatically over the past ten years. Implementing deep learning models that have recently been suggested in the literature for predicting Bitcoin price based on time series data, hyperparameter tweaking, optimization, and potential enhancement is the goal and the innovation. The data set to be utilized will come from the Kaggle database's historical Bitcoin data.

II. LITERATURE REVIEW

In the year 2009, Satoshi Nakamoto published "Bitcoin: A Peer-to-Peer Electronic Cash System." In 2009, a trustless decentralized system, whose transactions are documented in an open ledger known as the Blockchain, served as the foundation for the first digital and decentralized money. To stop double-spending and verification, a mechanism was suggested.

Y. Yao, J. Yi, S. Zhai, Y. Lin, T. K. G. Zhang, and L. Y. Lee published "Predictive project of cryptocurrency price using deep learning" in 2018. The recurrent neural network (RNN) and the long short-term memory (LSTM), which are efficient learning models for training data with the LSTM being better at recognizing longer-term associations, are used in this paper to propose a novel method to predict cryptocurrency price by taking into account various factors such as market cap, volume, circulating supply, and maximum supply. The suggested method is put into practice in Python and tested on benchmark datasets.

S. Yogeshwaran, M. J. Kaur, and P. Maheshwari's "Project-based learning - forecasting bitcoin prices using deep learning" was published in 2019. In order to foster student creativity and place an emphasis on real-world, open-ended projects, this article explores the structure and delivery of project-based learning in computer science engineering as a major project. The technology that might aid humankind in predicting future occurrences is the most well-liked. More people are looking to invest in the digital market as a result of the advent of the crypto digital era. This enables us to develop a model that can forecast cryptocurrencies, particularly Bitcoin. A variety of machine learning strategies and techniques can be used to achieve this.

F. Tschorsch and B. Scheuermann published "Bitcoin and beyond: a technical assessment on decentralized digital currencies" in 2016. Blockchain technology, for example, was greatly affected by Bitcoin, which transformed the world of digital money. Significant scientific attention was also generated by this. The authors of this survey roll up and organize the varied findings and ideas for further investigation. They describe the foundational elements of the Bitcoin protocol. By talking about previous contributions and outcomes, they also investigate the design domain.

In the year 1996, I. Kaastra and M. Boyd published "Designing a Neural Network for Forecasting Financial and Economic Time Series." The use of neural networks in finance for tasks including pattern recognition, classification, and time series forecasting has significantly risen in recent years. The design process still includes a lot of trial and error due to the enormous number of parameters that must be chosen in order to create a neural network forecasting model. In order to anticipate economic time series data, this project offers a useful introduction to neural network architecture. An eight-step process for creating a neural network forecasting model is described, along with tradeoffs in parameter selection, some typical mistakes, and areas of practitioner dispute.



In the year 1988, H. White published "Economic Prediction Using Neural Networks: The Case of IBM Daily Stock Returns." The goal of this project is to identify and interpret nonlinear regularities in asset price movements using neural network modeling and learning approaches. The case of IBM common stock daily returns is the author's main emphasis. Dealing with the key characteristics of economic data shows the importance of statistical inference and necessitates changes to conventional learning methods that could be advantageous in other situations.

By S. Velankar, S. Valecha, and S. Maji in the year 2018: "Bitcoin price forecast using machine learning" The authors of this project make an effort to precisely anticipate the price of bitcoin while taking into account a number of factors that influence its value. A key first step is to recognize daily market patterns while learning about the best conditions for the Bitcoin price. The data set included several aspects of the Bitcoin pricing and payment network throughout a three-year period that were daily recorded. Predict the sign of the daily price change with the greatest degree of accuracy using the information at your disposal.

By V. Derbentsev, N. Datsenko, O. Stepanenko, and V. Bezkorovainyi in the year 2019: "Forecasting cryptocurrency prices time series using machine learning technique" This project outlines the development of a machine learning-based short-term cryptocurrency price forecasting algorithm. The Binary Auto-Regressive Tree (BART) modified model was created using the time series data and conventional regression tree models. Classification and regression trees (C&RT), a well-known method, and autoregressive models (ARMA) are combined in BART.

E. Mahendra, H. Madan, S. Gupta, and S. V. Singh's "Bitcoin Price Prediction Using Deep Learning and Real-Time Deployment" for the year 2020 The creation of a prediction model utilizing a deep learning approach is proposed as a unique technique in this project. Given that the deep learning model takes into account the non-linear character of pricing, the suggested technique was more accurate than the machine learning models utilized for prediction.

III. PROBLEM STATEMENT

The most complicated cryptocurrency, with a value that varies every second, is bitcoin. Bitcoin's price has been fluctuating wildly recently, which is difficult for any investor given the surge of attention it has received and all the ramifications it has for both new and established enterprises. For any human to thoroughly research and evaluate the Bitcoin market before investing is practically impossible. Due to their decentralized nature and lack of government backing, cryptocurrencies like bitcoin and others present both opportunities and risks for investors. Therefore, unlike the stock market, its price might not change depending on variables determined by a centralized body. Bitcoin investment is more difficult and less lucrative.

IV. PROPOSED SOLUTION

In order to anticipate the daily price of bitcoin, the suggested solution takes into account deep learning-based LSTM (Long Short-Term Memory), Elastic net, and Random Forest prediction models. These models discover and assess pertinent information on their own to forecast the daily price of bitcoin. We can evaluate the accuracy of the model is much more accurate for the future fulfillment of our aim after applying models for bitcoin prediction, and we can then choose the proper parameters to acquire a higher performance.

V. SYSTEM DESIGN

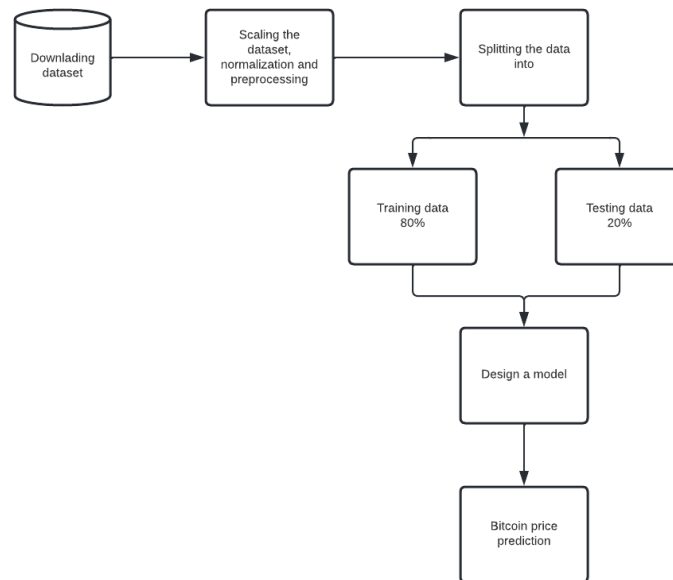


Fig. 1. System Architecture Diagram

The system architecture consists of the following steps:

- Collecting datasets appropriate for the project.
- Preprocessing the data for better results.
- Splitting them into training and testing data.
- Designing different machine learning and deep learning models for prediction.
- Predict price using different models and choose the model with the highest accuracy.

VI. METHODOLOGY

The methodology proposed involves the following steps:

- Collect the required image dataset and perform the pre-processing of collected data in order to remove null values, and normalize and scale data as required by the model.
- Once the preprocessing is done, the data is divided into training data and testing data.
- The training data is used to train the model in all aspects and testing data tests the trained model so that it gives the correct result.
- This methodology comprises Long Short-Term Memory, Elastic net, and Random forest models.
- Each model is trained and tested individually for the collected dataset based on which the model giving better accuracy is identified.
- At last, the model predicts the price of bitcoin on the day user inputs for prediction.

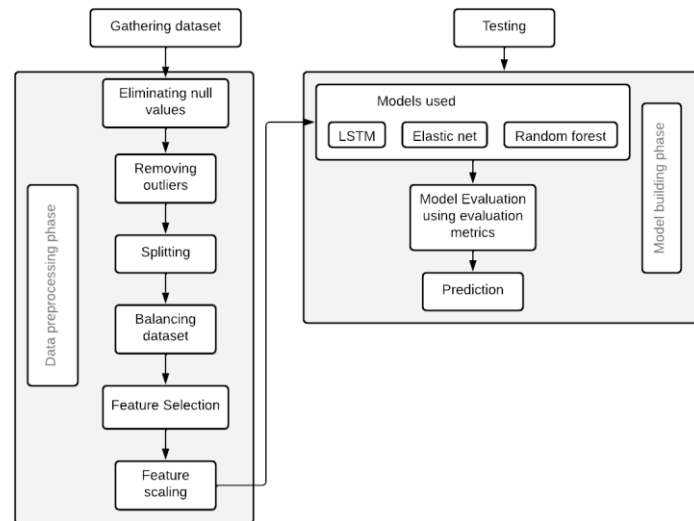


Fig. 2. Methodology Diagram

PSEUDO CODE

LSTM

FUNCTION LSTM_MODEL(X)

```

weights ← DEFINE WEIGHTS
biases ← DEFINE BIASES
x ← RESHAPE(x, shape < [PIXEL_X, PIXEL_Y, SLICE_COUNT])
conv1 ← RELU_ACTIVATION_FUNC(CONV3D(x, weights[0]) + biases[0])
conv1 ← DROPOUT(0.5)
conv1 ← MAX_POOL3D(conv1)
conv2 ← RELU_ACTIVATION_FUNC(CONV3D(conv1, weights[1]) + biases[1])
conv2 ← DROPOUT(0.5)
conv2 ← MAX_POOL3D(conv2)
fully_connect ← RESHAPE(conv2, INVERSE(weights[2]))
fully_connect ← RELU_ACTIVATION_FUNC(fully_connect * weights[2] + biases[2])
fully_connect ← DROPOUT(0.8)

output ← fully_connect * weights[3] + biases[3]

```

RETURN output
END FUNCTION

Elastic net

1. Initialise weights $w_0, w_1, \dots, w_k$ from standard normal distribution with zero mean and standard derivation
2. for epoch in $1, \dots, e$ do
3. for each (x, y) belongs to do
4. $y < w_0$
5. if $(y > 1 \text{ and } y = 1) \text{ or } (y < -1 \text{ and } y = -1)$ then
6. continue

```

7. w0 < w0-2(y-y)
8. for i in 1...k do
9. end for
10. end for
11. return w0, w1, ..., wk
    
```

Random forest

```

FUNCTION RANDOM_FOREST(X)
    model ← RANDOM_FOREST()
    X_train, X_test, y_train, y_test ← TRAIN_TEST_SPLIT()
    FIT_MODEL
    y_pred ← PREDICT(X_test)
    test_score ← MEAN_SQUARED_ERROR(y_test and y_pred)
    RETURN y_pred and test_score
END FUNCTION
    
```

VI. RESULTS AND DISCUSSION

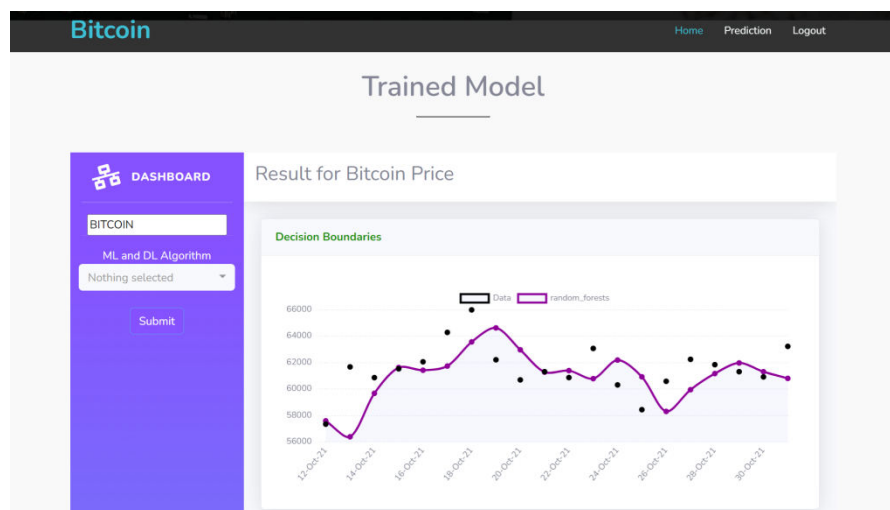


fig. 3. The trained model with a graph for predicted and actual values

VII. CONCLUSION

The project shows that the Long Short-Term Memory model outperforms Elastic net and Random forest in terms of accuracy. This project only compares models using the features open, close, high, and low; as a consequence, the outcome may be different if we were to also take other aspects into account. Data sets cannot be the main basis for predicting because the cryptocurrency market is unpredictable and affected by social media and other outside variables. As technology develops, additional data may be gathered, examined, and used, improving the outcomes of this experiment.

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