Crypto Currency Prediction using Machine Learning

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ABSTRACT

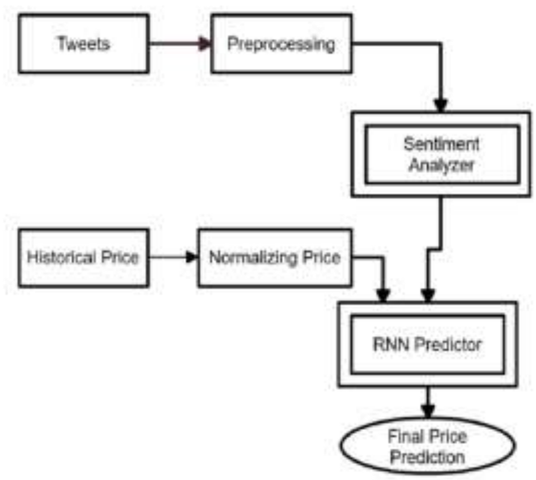
This Project describes a type of currency that exists only digitally, which operates using an encrypted online ledger to secure transactions. Due to problems with traditional currencies and investments, there has been a decrease in interest in digital currencies. However, this project aims to help predict the value of digital currencies using machine learning, specifically a type of model called LSTM. Users can access predictions for the value of Bitcoin, Ethereum, and Dogecoin.

Keywords – *LSTM Model, Bitcoin, Digital Currency*

1.INTRODUCTION

Cryptocurrencies are becoming increasingly important in the economy, and as a result, there are more news articles and social media posts about them, especially on Twitter. Like with traditional financial markets, there seems to be a connection between the sentiment expressed in media and the prices of cryptocurrency coins. Given this, the project discusses the potential value of using sentiment analysis on news headlines and tweets to predict whether a coin's price will go up or down. To do this, the system collects text data from news headlines and tweets, organizes it chronologically, and uses supervised learning algorithms to assign a label indicating whether the predicted price for each coin will go up or down. The labels are based on the majority prediction for each coin for a given day. However, it is important to note that the cryptocurrency market is highly volatile and investing in it carries significant risks. Investors need to consider several factors, such as their country's regulations, market news, expert opinions, and other factors, before making any investments.

In 2018, the price of Bitcoin has been consistently dropping, and this has caused the entire cryptocurrency market to decline. As a result, investors are interested in understanding the reasons for these downturns and how they affect the prices of digital currencies. However, for cryptocurrency traders, it doesn't matter whether prices are rising or falling as long as they can predict the direction. Investors can take advantage of this by taking a long position in cryptocurrencies before a boom period, so they can earn returns once prices increase. Alternatively, investors can short sell cryptocurrencies during a predicted bust period through margin trading, which is allowed by many cryptocurrency exchanges, to earn additional returns. Moreover, with the introduction of Bitcoin futures by the CBOE in December 2017, taking long or short positions has become easier. This financial asset allows investors to speculate on Bitcoin prices in both directions using leverage without actually holding Bitcoins. Similar strategies can also be used for other cryptocurrencies through binary options traded in offshore exchanges.



2.LITERATURE REVIEW

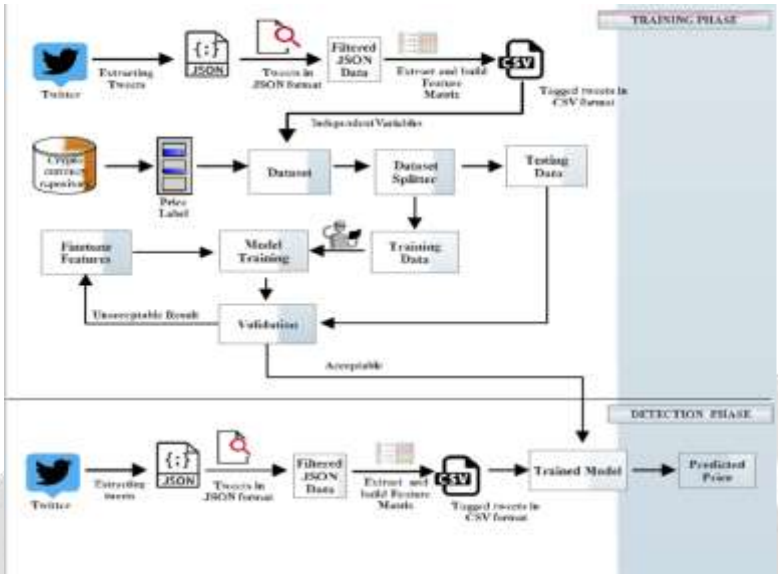
Various approaches are described for predicting future prices of financial assets. One of these approaches, known as technical analysis or charting, involves identifying patterns in past price movements to predict future prices. Autoregressive integrated moving average (ARIMA) models are also commonly used for short-term forecasting, assuming that the data exhibits consistent patterns over time with minimal outliers. However, the ARIMA method is limited by the requirement for data to exhibit stationarity, meaning the series remains relatively constant, which may not always be the case in real-world scenarios where the data fluctuate significantly and are highly volatile.

2.1 Stock Predictor

Researchers have also utilized Twitter data to analyze the relationship between Bitcoin market indicators and emotional signals expressed in Twitter posts. In one study, seasonal ARIMA models were used to estimate future fuel energy demand in Turkey over a certain period. Matta and colleagues (2015) conducted a study that examined the relationship between Google search queries and Bitcoin trading volumes, aiming to identify the impact of search frequencies on cryptocurrency markets.Previous research has predominantly concentrated on categorizing user comments in specific areas. As user comments on online communities often contain neologisms, slang, and emoticons that go beyond standard grammatical usage, C.J. Hutto and Eric Gilbert developed an algorithm known as VADER to analyze such expressions. They proposed a technique to analyze social media texts by utilizing a rule-based model.

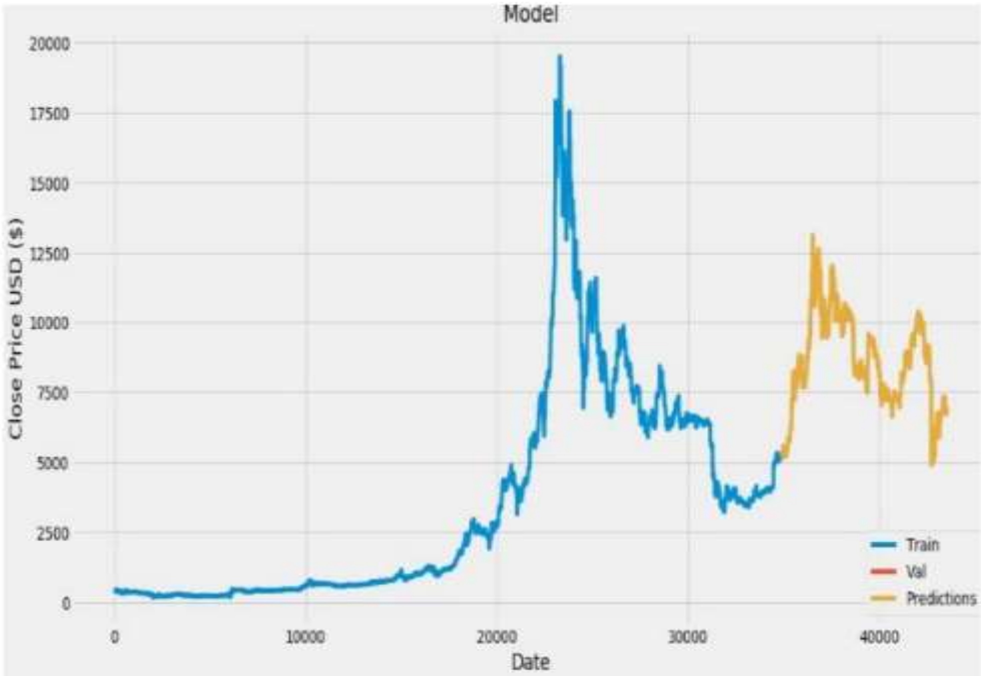
3.PROPOSED METHODOLOGY

Blockchain technology is not limited to peer-to-peer payment systems, as it offers security, privacy, and a distributed ledger that can be utilized in various applications such as internet-of-things, distributed storage systems, and healthcare. Due to the wide range of potential applications, there has been a proliferation of new blockchains and cryptocurrencies, with over 1,658 cryptocurrencies currently in existence. Cryptocurrencies are linked to the blockchain technology because they provide incentives for machines to run and validate the blockchain. As the use of blockchains grows, the use of cryptocurrencies is expected to increase as well. However, the value of cryptocurrencies is influenced by various factors and remains unclear due to its novelty as a currency and store of value. Hence, understanding the factors that drive price changes in cryptocurrencies can bring significant value.

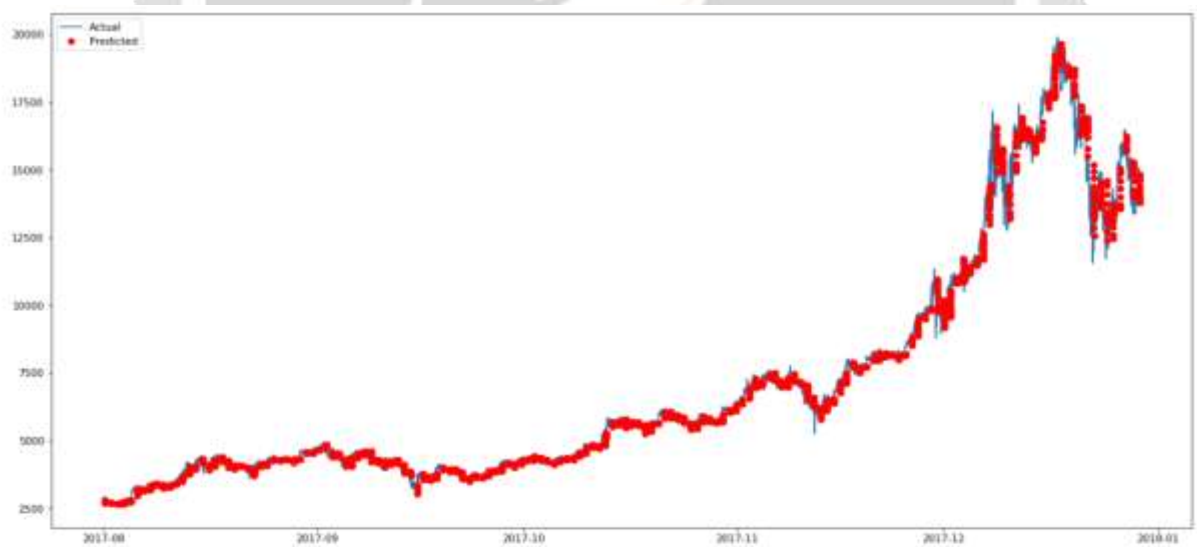


- The process of using Twitter data and cryptocurrency prices for predicting future prices involves two phases, the training phase, and the detection phase. In the training phase, Twitter data and concurrent cryptocurrency prices are collected and synchronized by converting the Twitter data in JSON format to CSV format.
- The tweets are analyzed for sentiment polarity and classified into positive, neutral, or negative tweets. The data is broken into chunks of two-hour duration, and the count of positive, neutral, and negative tweets is mapped with the corresponding average price for that duration.
- This becomes the dataset for training the model. The model is validated with the original labels of the dataset, and the training and testing process is repeated until an acceptable model is formed.
- In the detection phase, real-time tweets are fed into the model, and the model predicts the average price for the next two-hour duration.

4.RESULTS



This graph shows the Training and Testing phase of the model the curve with the blue color is the period in which the model is being trained with the historical data and after that portion of the curve we can see the predictions that the model made and we compare those prediction with rest of the historical data to get the accuracy of the model.



This graph shows the relation between the actual price of bitcoin and the model predicted price of the bitcoin i.e., we can see from the graph that the error in the predicted price is less.

5.CONCLUSION

Deep learning models, particularly LSTM, have proven to be effective in learning long-term dependencies on training data. Parallelizing machine learning algorithms on a GPU can significantly improve training performance, as demonstrated by a 70.7% improvement when training the LSTM model on a GPU compared to a CPU. These findings confirm what previous research has suggested. The positive sentiment expressed on

Twitter towards cryptocurrencies tends to remain high regardless of future price changes, and people who tweet about cryptocurrencies may have interests beyond investment opportunities, leading to biased results.

The systematic process started from data cleaning and processing, missing value, exploratory analysis and finally model building and evaluation. The best accuracy on public test data is taken into account and higher accuracy score for the given test data is implemented in the machine learning model. This application can help to find the Cryptocurrency Market Price.This project will improve that future idea of crypto currencies and it can even improve the market price of the cryptocurrency.

6.FUTURE WORK

To elaborate further, it is essential to examine the robustness of the current findings under different pricing environments. This could involve investigating the effects of changes in product pricing, market conditions, or even economic conditions on the relationship between Google Trends and tweet volumes and the outcome variable.Additionally, using more complex models such as nonlinear models or machine learning algorithms could lead to improved accuracy and predictive power of the model. These models can capture more intricate relationships between variables and identify patterns that linear models may overlook.

Furthermore, it may be worthwhile to consider additional variables that could impact the relationship between Google Trends, tweet volumes, and the outcome variable. These variables could include demographic factors, geographical factors, or even other social media platforms.Overall, future research in this area should strive to build on the current findings and investigate ways to enhance the accuracy and applicability of the model to different pricing environments and contexts

- Show the trend in cryptocurrency for 1 week.
- Automate the process and show the prediction in android application or IOS application.
- Improve the result using AI Environment.
- Add more coins and predict its market value.

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