Advanced Time Series Analysis for Cryptocurrency Investment using Machine Learning Techniques

Arnab Mitra Utsab
School of Data and Sciences
Brac University
Dhaka, Bangladesh
arnab.mitra.utsab@g.bracu.ac.bd@g.bracu.ac.bd

***Abstract*—The primary goal of this study is to determine which cryptocurrencies to invest in. A cryptocurrency is a type of digital currency that can be exchanged over a computer network. It does not rely on or require the support of any central authority, such as a government or a bank. The authors of this article proved the relationship between cryptos and market stability. To obtain more precise predictions, many data science applications were introduced. Authors have also introduced other prediction algorithms such as Holt-Winters Forecasting, Prophet for price prediction, and Lstm algorithms. Simple Moving Average was employed for growth rate analysis. The authors attempted to estimate the best possible crypto to invest in using the selected datasets in this investing marketplace.**

***Index Terms*—Cryptocurrency, Machine learning, LSTM, Moving Average, Holt Winter, Prophet Model, Data Analysis, Investment**

I. Introduction

A cryptocurrency is a digital currency that functions as a medium of exchange and relies on strong cryptography to safeguard financial transactions, limit the creation of new units, and verify asset transfers. [12] . A virtual currency that uses cryptography that functions as a medium of exchange and relies on strong cryptography to safeguard financial transactions, restrict the creation of new units, and verify asset transfers. They are based on decentralized systems that use block-chain technology, which is a distributed ledger enforced by a network of computers . In 2009, Bitcoin, the very first decentralized cryptocurrency, was released as open-source software. Around 4000 altcoins that are similar to cryptocurrencies have been released as a result of this release. The worldwide cryptocurrency market cap is USD 1.28 trillion as of May 2022.[13] Cryptocurrency price prediction can assist cryptocurrency investors in making informed investment decisions to maximize earnings, as well as policymakers and financial scholars in analyzing the behavior of cryptocurrency markets. Cryptocurrency price prediction, similar to stock price prediction, is a prevalent sort of time series problem. [3]. In this paper, we provide the crypto currency prediction method for investment by using various kinds of models of data science. Firstly, In the first part of data analysis, plotting of price, correlation between the cryptos, and relative standard deviation of market cap of all cryptos, were brought under observation to better understand the underlying patterns in our data. We also utilize Holt-Winters forecasting. The Holt-Winters method employs exponential flattening to encode a large lot of historical values, which are then used to forecast ”typical” values in the present situation. [4] Thirdly, we work on growth rate analysis by using a moving average strategy. By this method, we analysis how each crypto has performed. Since the difficulty level to generate authentic and superlative forecasting results is very high, a regression model “Prophet” has been introduced which can be intuitively readjusted by the analysts who have expertise regarding time series. This model is vigorous to missing data, outliers and provides accurate and precise results than any other forecasting models by fitting nonlinear trends. The rest of the paper is organized as follows, in section 2 discuss some related work and in section 3 we elaborate our research methodology, in the next part, we discuss the result and output, After that we conclude our work.

II. Related Words

In this section we present a brief review of the state of the art related to cryptocurrency price prediction. Previous attempts to forecast bitcoin variations used Twitter sentiment research as a proxy for future cryptocurrency demand, resulting in rising or falling prices.[1]. The authors use a stochastic neural network model to predict the price of Cryptocurrencies in this paper. Three model inputs were taken into account. Tweet sentiment was considered not to be a trustworthy signal while bitcoin values were declining, thus it was excluded. Google Trends and tweet volume were both strongly connected to pricing.They forecast bitcoin variations using Twitter sentiment research as a proxy for future cryptocurrency demand, which would result in price increases or decreases.

The author [2] present a stochastic neural network model for predicting cryptocurrency prices. The proposed method is based on the random walk theory, which is commonly used in financial markets to model stock prices. To replicate market volatility, the proposed approach introduces layer-wise randomization into the observed feature activations of neural networks.We devised a method for adaptively learning the market’s pattern. It may well be worthwhile to investigate an optimization technique for tuning the hyperparameter to find the best appropriate value. Alternate response functions can also be tested to learn the market’s reaction pattern to new data. To better imitate market volatility, these functions can be stochastic in nature.

In this study, the author discussed that [3] the challenge is accomplished with varied degrees of success by implementing a Bayesian optimized recurrent neural network (RNN) and Long Short Term Memory (LSTM) network.Deep learning models such as RNN and LSTM are clearly effective for Bitcoin prediction, with the LSTM excelling at recognising longer-term relationships. However, with such a large variance difficulty, it is difficult to translate this into outstanding validation findings. As a result, the task remains difficult. Overfitting a model and stopping it from learning are not the same thing.RNN and LSTM deep learning models are clearly useful for Bitcoin prediction, with the LSTM being better at recognizing longer-term dependencies.

However, with such a large variance difficulty, it is difficult to translate this into outstanding validation findings. As a result, the task remains difficult. Overfitting a model and stopping it from learning are not the same thing.[4] . The authors, employed a simple Neural Network technique called the Multilayer Perceptron with one hidden layer in this paper. Using more complex architecture networks, such as recurrent, self-organized, deep, and so on, could enhance prediction accuracy as well.Finally, in this study they emphasise that the development of combined Classification and Regression Tree models, as well as Neural Network models, is the long-term approach for financial time series forecasting. [5] Machine learning was contrasted against a number of ANN techniques in a Bitcoin case study.In this study, a modified Binary Auto Regressive Tree (BART) model is derived from standard regression tree models and time series data. BART combines the traditional algorithms classification and regression trees (C&RT) and ARIMA autoregressive models. they, created a short-term projection (from 5 to 30 days) using the BART model for the three most capitalised cryptocurrencies: Bitcoin, Ethereum, and Ripple. We discovered that the proposed method was more accurate than the ARIMA-ARFIMA models in forecasting cryptocurrency time series in both slow rising (falling) and transition dynamics. (change of trend).

Backpropagation neural network (BPNN), genetic algorithm neural network (GANN), genetic algorithm backpropagation neural network (GABPNN), and neuroevolution of augmenting topologies are the four ANN approaches compared in this study.[6] (NEAT). The approaches are assessed based on their accuracy and complexity. The experiment revealed that BPNN is the best technique. Another distinction is that in the stock market, NEAT outperforms BPNN, GANN, and GABPNN combined. This could be due to the same issue as before, namely that genetic algorithms are not ideal for training Bitcoin prediction models.

The author of their study [7] uses educational tools to assess the market prices of three of the most regularly traded digital currencies: Bitcoin, Digital Cash, and Ripple. This is the first step towards putting our bitcoin prediction knowledge to use. Despite the fact that the LSTM model requires more processing than non-linear pattern violence, deep learning proved to be extremely effective in anticipating the volatile character of the bitcoin market.

The goal of the paper [8] study is to extract and assess the accuracy of Bitcoin price predictions using various machine learning techniques. For comparative purposes, the experiment results are connected with both decision tree and regression models.

In the crypto-market, a machine learning-based time series analysis was used to anticipate the market price and stability of Bitcoin. This study [9] can forecast Bitcoin's future price variations. To do this, we used machine learning algorithms for time series analysis such as ARIMA, FBProphet, and XG Boosting. These models' performance was assessed using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R2 parameters. While all three techniques were tested, the results revealed that ARIMA is the best model for forecasting Bitcoin price in the crypto-market, with an RMSE score of 322.4 and an MAE score of 227.3. This research may be useful to cryptocurrency investors.

The research presented in [10] demonstrates the effectiveness of ensemble learning in improving the output of five comparable signal models. This approach yielded an annualized ratio of 80.17% and 91.35% for Sharpe, along with an annualized return of 9.62% and 5.73%, respectively, which is approximately 0.5%. The positive results of this study provide support for the notion that machine learning can offer robust methods for predicting cryptocurrency values and devising effective trading strategies, even in unfavorable market conditions.

III. Dataset

The dataset, named "Cryptocurrency historical prices" are well reserved in Kaggle and as well as in GitHub repository[14]. The information or data being referred to was obtained from a website named "Coinmarketcap," and it is freely available for usage. "Coinmarketcap" is a well-known website that offers cryptocurrency-related data such as prices, market capitalization, trading volume, and other pertinent information. dataset that contains historical price information for some of the top cryptocurrencies by market capitalization. The dataset consists of multiple CSV files, with each file containing the price history for a particular cryptocurrency.

The dataset provides daily price information for each cryptocurrency, starting from April 28, 2013. For each day, the dataset provides the following information:

1) Date: This is the date on which the price observation was made.
2) Open: This is the opening price of the cryptocurrency on the given day.
3) High: This is the highest price that the cryptocurrency reached on the given day.
4) Low: This is the lowest price that the cryptocurrency reached on the given day.
5) Close: This is the closing price of the cryptocurrency on the given day.
6) Volume: This is the volume of transactions that occurred for the cryptocurrency on the given day.

7) Market Cap: This is the market capitalization of the cryptocurrency in US dollars on the given day.

By providing this information on a daily basis, the dataset enables users to analyze the historical price trends of various cryptocurrencies, which can be useful in making investment decisions or conducting research on the cryptocurrency market.

IV. Research Methodology

A. Exploratory Data Analysis

Looking at the closing price change is very important to understand how cryptocurrencies are behaving. The author plotted the closing price of all cryptos in a single graph. But, as the crypto prices can vary significantly within months, only the most recent data of 3 months are plotted for better visualization. The question may arise as to why the authors plotted the change in closing price. Here, the "closing price" is considered the general "price" on any given day. And, considering this as the general price, it is essential to understand the fluctuations of price with each day of every cryptocurrency. This fluctuation can aid in a better understanding, when the authors will predict the price for the future using different algorithms in the latter part of our project. In figure 1, we demonstrate the daily percentage of closing price of each crypto.

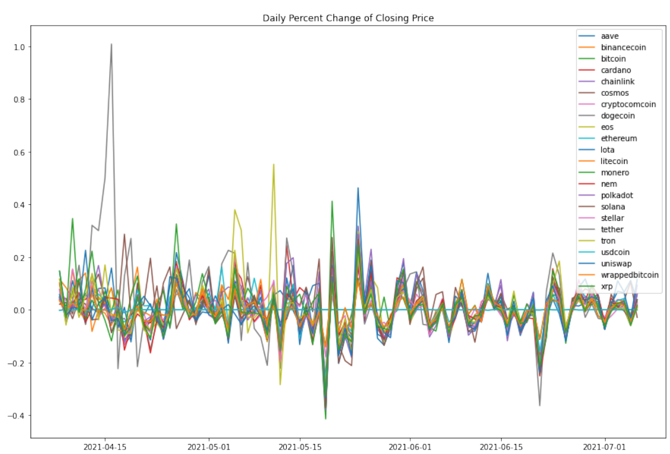

Fig. 1. Daily percent change of Closing price of each crypto

The correlation which exists between cryptos is also necessary to find out, if anyone wants to invest in some cryptos. For example, suppose a person wants to invest in crypto 'A' because it can yield a high profit. Now, say crypto 'A' has a strong positive correlation with crypto 'B'. This means that crypto 'B' will also possibly yield high profit alongside crypto 'A'. That is why knowing the crypto correlation can come in very handy while making decisions about investment. In figure 2, it demonstrated the existing correlation among the cryptos.

The code for this project is available on GitHub[1].

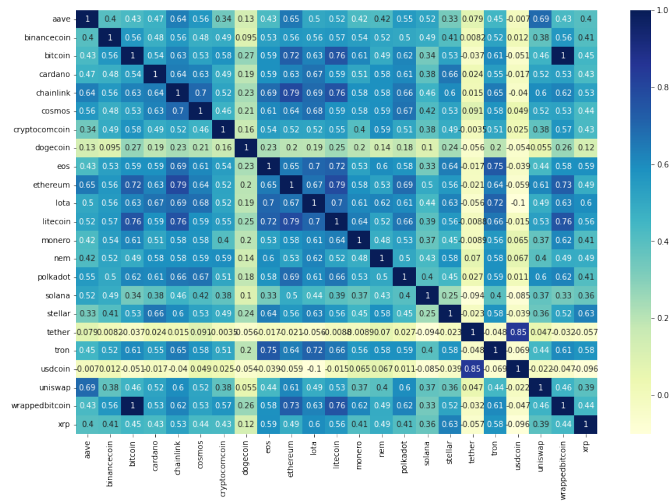

Fig. 2. The existing correlation among the cryptos

There is also "Market cap" data for each cryptocurrency. This is critical information since the stability of crypto may be readily understood by regularly watching the market cap for crypto. The exact formula for calculating market capitalization is as follows:

Market capitalization = Total circulating supply of the cryptocurrency x Current market price per unit of the cryptocurrency.

The rise and fall of this market cap can have many factors, like how many people are actively involved in this crypto, what people think about the potential of this crypto, the value of crypto according to international standards, and so on. These factors can be a very good source of gathering information about the stability and likelihood of crypto. So, the authors deemed it important to find out the stability of this market cap data for a crypto and the measurement which was taken to find out the stability is Standard deviation. Below in figure 3, is the plotting of the standard deviation of market cap data for each crypto.

B. Holt Winters Forecasting

Anomaly detection in time series is a complex problem with several practical solutions. Forecasting is one of the essential elements of Anomaly detection. Holt winters forecasting is a popular and generally straightforward technique for time series forecasting. Holt-Winters is used for modeling and predicting the behavior of a sequence of values over time—a time series. The Holt-Winters approach uses exponential smoothing to encode a large number of historical values and then utilizes them to anticipate "typical" values for the present and future. In Winter's method assumes that the time series contains a level, trend and seasonal component. Winter's exponential smoothing can be expressed as:

[1]https://github.com/Arnob-Mitra/Advanced-Time-Series-Analysis-for-Cryptocurrency-Inv

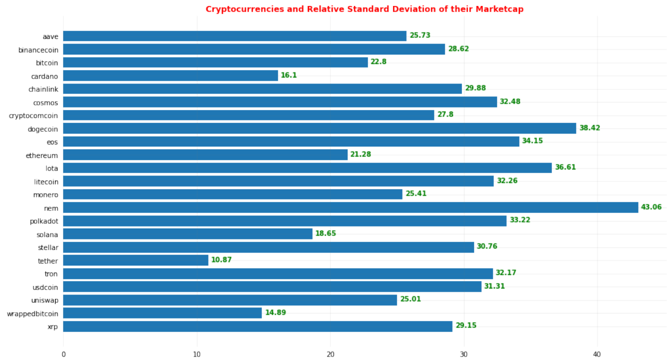

Fig. 3. Relative std. dev of market cap for each crypto

$$F_{tk} == L_t + k_{Tt} + S_{t+k-M} \tag{1}$$

Here, Lt = estimate level for time , k = number of future forecast, Tt= estimate trend in t time, St= sessional estimate at t time, M = number of sessions

In this paper the author has used this holt winters approach to predict whether in future the volume rate of the newly made cryptocurrency will increase or not. Hense, we plot the results of the seasonal decomposition. This will generate a plot with four subplots showing the original time series, the trend component, the seasonal component, and the residual component. Figure 4 displays the trend, residual, seasonal, and observed components of the data, from figure 5 to figure 8.

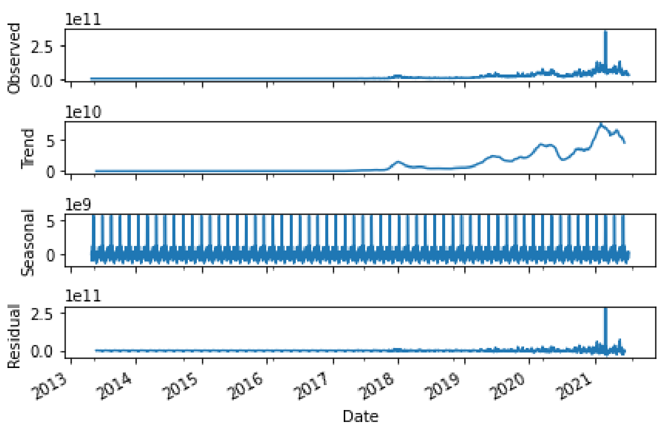

Fig. 4. Time series data frame into its trend, observed seasonal, and residual components.

Some samples using 4 different datasets are given below:

Here, we only demonstrate top 4 crypto coin's volume rate, where volume rate of coin Cardano in figure 6, coin Solana in figure 7 and coin Polkadot, demonstrated in figure 8 has been increasing, on the other hand the others are showing ups and downs. From the above figure 5, it can be seen that the volume rate of coin Aave is increasing in the future.

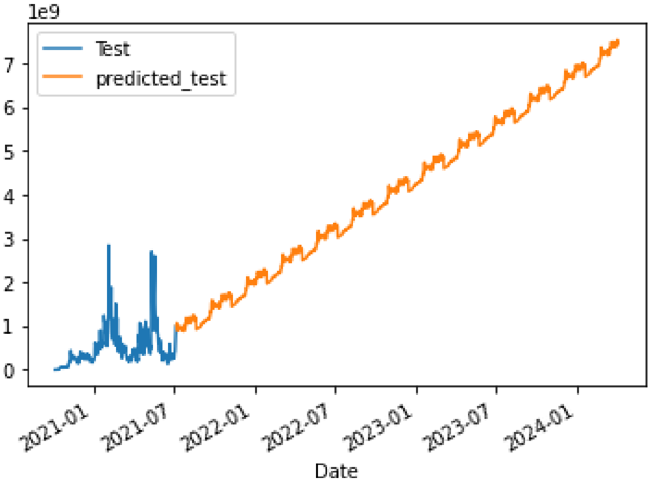

Fig. 5. coin Aave

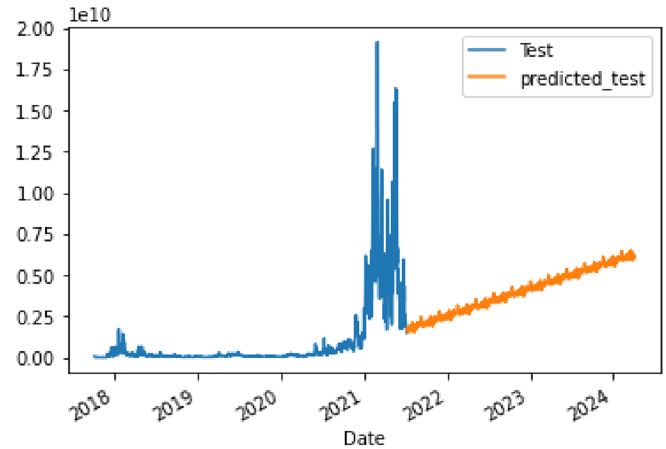

Fig. 6. coin Cardano

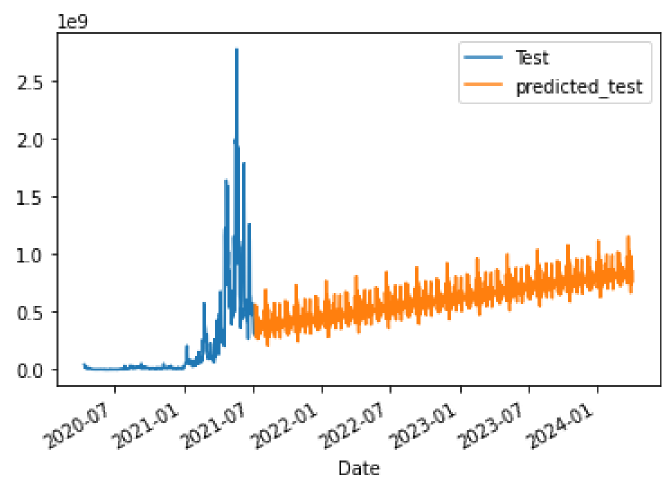

Fig. 7. coin Solana

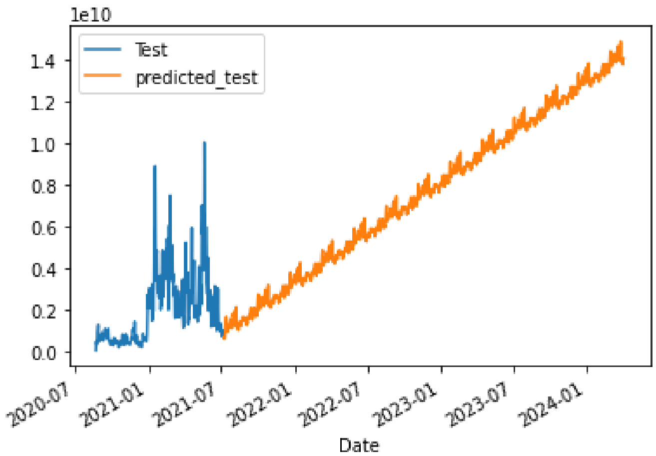

Fig. 8. coin Polkadot

C. Growth rate Analysis

Cryptocurrency is a nascent and unpredictable asset class. The market can see large fluctuations in prices in a short period of time, making future trends impossible to anticipate. Traders and investors use a range of technical indicators and data analysis tools to analyze the cryptocurrency market. Therefore, we calculates the growth rate of the Moving Average (MA) of a cryptocurrency's market price.the Moving Average strategy for 60 days has used. A moving average is a statistical computation that is used to examine data points by calculating the averages of different subsets of the entire data set. We calculate the growth rate of the 60-day moving average of the "Colse" column of each CSV file located. Then computes a 60-day moving average of the 'Close' column using the.rolling() method and saves it in a new column called 'MA60'. It also adds a new column named 'MA60 shift year' to the table, which contains the 'MA60' column shifted by 250 days. Therefore, calculates the growth rate between the 'MA60' and 'MA60 shift year' columns and stores it in a new column called 'Growth Rate'. This growth rate is calculated as the percentage difference between the 'MA60' and 'MA60 shift year' columns, which is illustrated in figure 9.

$$SimpleMovingAverage = (A_1 + A_2 + ... + A_n)/nLog \tag{2}$$

Log growth rates are frequently employed in economic modelling and empirical research. For example, in terms of year-to-year growth. The natural logarithm of the numbers in the 'Growth Rate%' column is stored in a data frame. Figure 10 indicated the Log growth rate of cryptocurrency. This is accomplished through the use of the.apply() method and a lambda function that computes the natural logarithm of each integer.

For calculating the growth rate, at first, found the moving average of 60 times of period. Then the shift year of the moving average has been deleted from the previous moving average time period. After multiplying and dividing the number by 100 growth rate can be measured. Then we find out the log growth rate from the percentage of growth rate. From the growth rate, individual growth has been assumed and then we discovered the top 5 Cryptos, showcased in figure 11 to figure 14 .

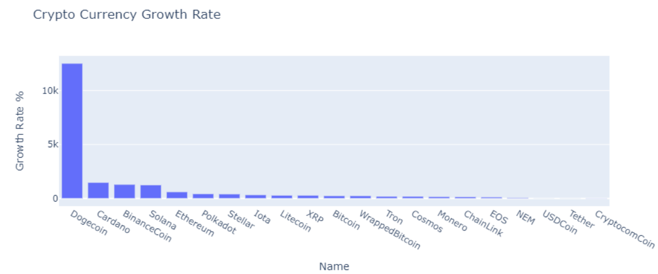

Fig. 9. Growth rate of Crypto Currency

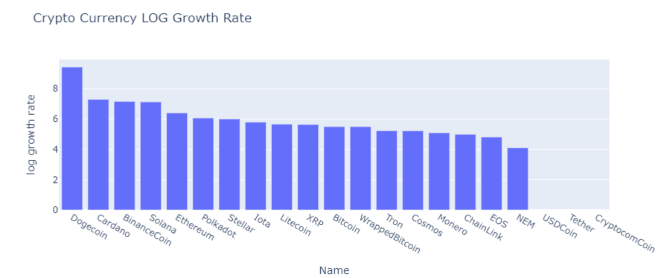

Fig. 10. Log Growth rate of Crypto Currency

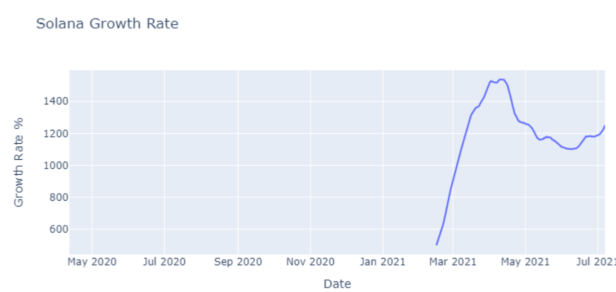

Fig. 11. Solana Growth rate

[2]

D. LSTM Model

Long Short-Term Memory networks, or LSTMs, can be used to forecast time series. For each distinct type of time series forecasting problem, there are numerous LSTM model types that can be applied. Recurrent neural networks, also known as RNNs, are a specific subtype that can learn long-term dependencies. The most efficient and well-known subset

[2]https://github.com/Arnob-Mitra/Advanced-Time-Series-Analysis-for-Cryptocurrency-Investment-using-Machine-Learning-Techniques

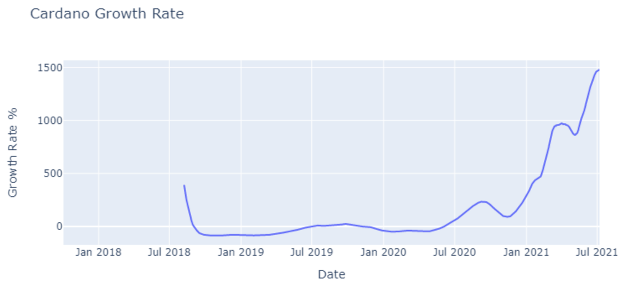

Fig. 12. Cardano Growth rate

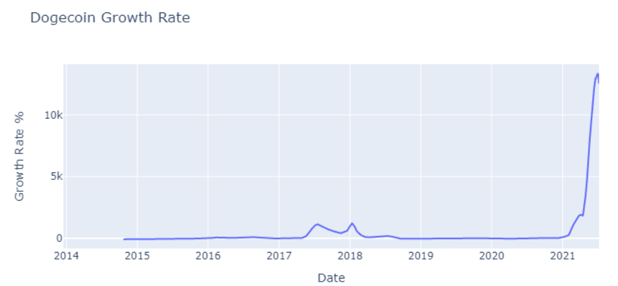

Fig. 13. Dogecoin Growth rate

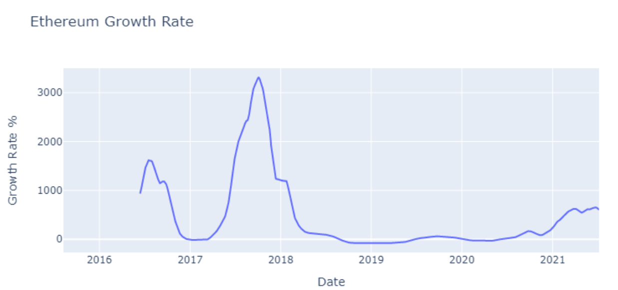

Fig. 14. Ethereum Growth rate

is LSTM, a unique kind of neural network created to address challenges involving sequence prediction or pattern recognition, among other things. [16] Therefore, the authors builds and compiles an LSTM model for time series prediction.The build Lstm function first initializes an LSTM model using the Sequential() class from Keras. Two LSTM layers are added to the model with 128 and 64 units, respectively, along with a Dense() layer with 25 units and another Dense() layer with a single output unit. The Adam optimizer, a loss function for mean squared errors, and a metric for monitoring mean squared errors during training are then added to the model.The training and validation loss over the training epochs are finally seen by calling with the hist object as input. This enables the user to assess the model's training results and determine whether overfitting is taking place.

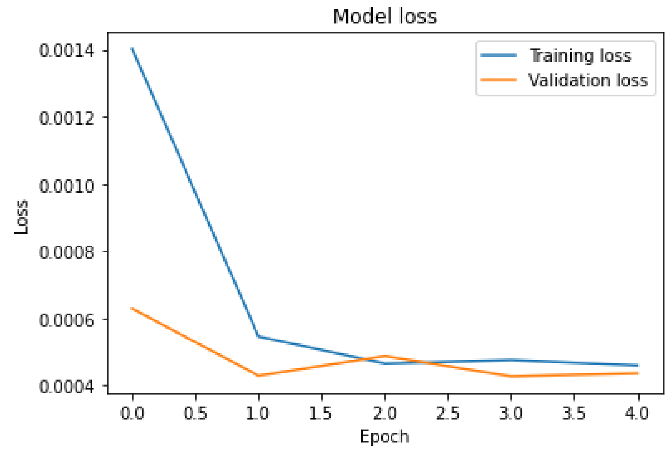

Fig. 15. Validation Loss and Training Loss

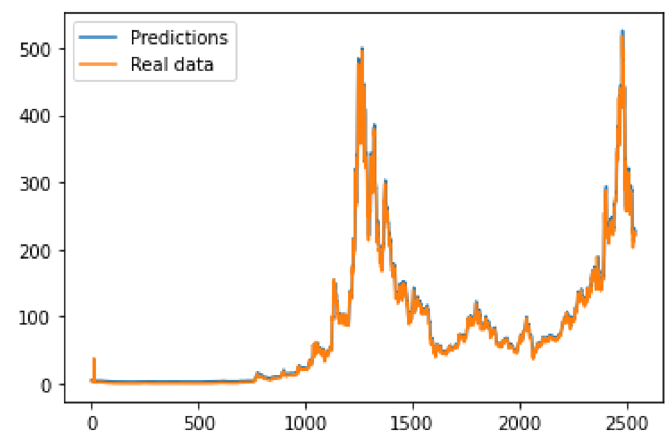

Fig. 16. Root Mean Square

E. *Prophet Model*

Forecasting is a popular data science practise. Forecasting assists individuals or organisations in setting goals, capacity planning, anomaly identification, and other tasks.[14] However, it is extremely difficult to develop dependable and high-quality forecasts since forecasting involves a wide range of time series. To address all of these issues, a modular regression model dubbed "Prophet" was devised, complete with interpretable parameters that can be intuitively readjusted by time series analysts. This forecasting model matches non-linear trends with daily seasonality, weekly seasonality, yearly seasonality, and can also account for holiday effects. In the vast majority of circumstances, Prophet outperforms all other forecasting models in terms of speed and precision.

The code for this project is available on GitHub[3].

Then, we created the Facebook Prophet package to create a time series forecast for the cryptocurrency Aave. The code first reads in a CSV file containing historical data for Aave's closing price and parses the dates. It then renames the columns

[3]https://github.com/Arnob-Mitra/Advanced-Time-Series-Analysis-for-Cryptocurrency-Inv

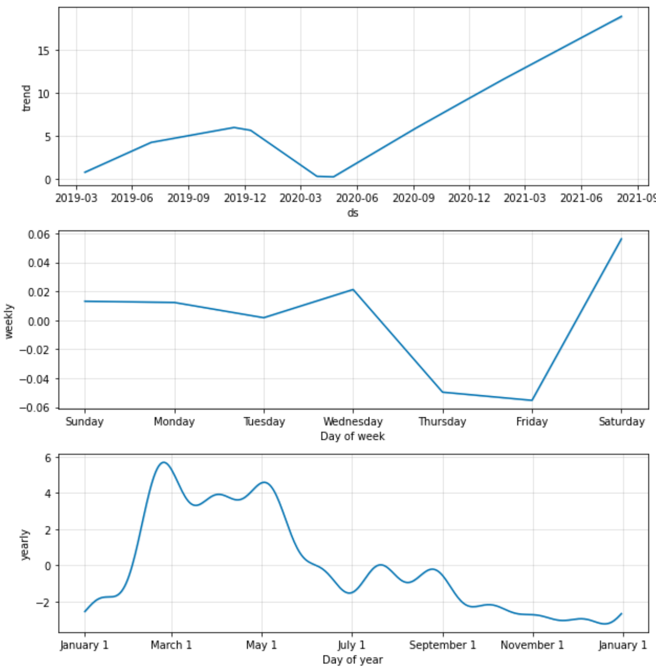

Fig. 17. coin Cosmos forecasting by Prophet Model

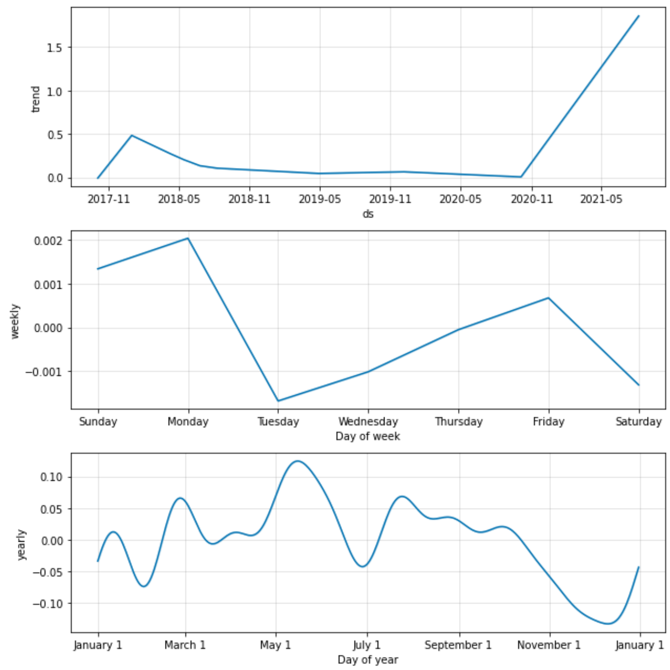

Fig. 18. coin Cardino forecasting by Prophet Model

to ”ds” and ”y” to conform to Prophet’s requirements. Therefore, we produces a plot of the forecast components using the plot components method, displaying the forecast’s trend, yearly seasonality, and weekly seasonality. We showed here some demonstrated plot in figure 17 and figure 18.

V. Result & Analysis

Initially, the authors discovered a strong positive association between the following cryptos:

1. Ethereum and Bitcoin 2. Litecoin and Bitcoin 3. Litecoin and Chain-link 4. Ethereum and Cardano 5. Ethereum and Litecoin 6. Bitcoin and Wrapped Bitcoin 7. Solana and EOS 8. Wrapped Bitcoin and Dogecoin

Now, looking at the relative standard deviation graph of the market cap for each crypto, the authors canceled out the cryptos which have relative std. dev of more than 35%. Due to this, Dogecoin, Iota, and Nem are no longer under their observation. Because these cryptos are too volatile and thus risky for investment. The authors then attempted to forecast the volume for all the cryptos in the near future. Cryptocurrencies with a low potential volume are dropped. Because of this, those cryptocurrencies will soon be off the market. These cryptocurrencies—chain-link, Monaro, stellar, wrapped Bitcoin, and XRP—are dropped in this section. The graph tells us that these cryptos will perform very poorly in terms of transactions in the future market. On the other hand, aave, cosmos, polkadot, solana, tron, and uniswap have a very high potential in terms of transactions. This means that people are more likely to transact using these coins in the upcoming days. The authors then analysed the overall growth of all cryptos. For each cryptocurrency, growth graphs are presented. This part shows that tron, polkadot, cryptocomcoin, and EOS can be avoided since their prospective growth is unsatisfactory. However, tether, USDcoin, and Solana are outperforming in terms of growth. The remaining coins are all neutral. Finally, the writers used the price forecast graph to make their final decision. At this point, aave, tether, usdcoin, and uniswap are rejected because the expected future price increase for these cryptos is insufficient. The only crypto coins that are not discarded after all calculations are bitcoin, cardano, cosmos, ethereum, litecoin, and solana. Among these, bitcoin, litecoin, and ethereum have high relationships. However, the likelihood of profit after investment for these coins is over 70%. As a result, the authors advise only investing in one of these coins. The profit likelihood for cardano and cosmos is then around 85%. As a result, the authors recommend investing in both of these cryptocurrencies. Finally, the coin Solana has the highest profit rate, which is almost 95%. As a result, the authors strongly advise investing in this currency because it has a high potential for return on investment. Figure 19, depicted this.

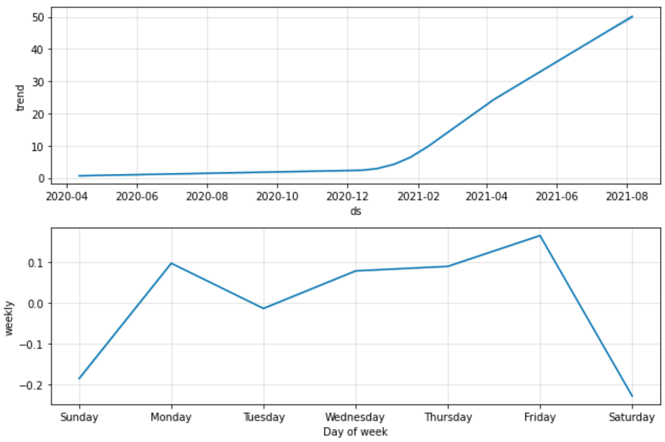

Fig. 19. coin Solana forecasting by Prophet Model

VI. Conclusion

Our work has provided us with a high-level overview of crypto analysis in investment. We use a variety of data analysis and machine learning techniques for this investigation. We carefully examined our dataset. We employed data analysis, price graphing, correlation between crypto currencies, and relative standard deviation of market cap of all crypto currencies for charting and analysis. However, we use holt winter forecasting. Detecting anomalies in time series is a difficult problem with numerous effective solutions. Following that, we examine the growth rate of each cryptocurrency. In this case, we employ the moving average, LSTM model. We employ prophet predicting to make final predictions. Based on their growth rate, the Prophet forecasting model was used to anticipate the future price of the leading crypto currencies. This model forecasts the future value of crypto currencies. According to all of the predictions and analyses, the writers strongly recommend investing in this currency because it has a significant return on investment potential.

Acknowledgment

I would like to express my sincere gratitude to my Faculty Meem Arafat Manab, BRAC University for providing invaluable guidance, encouragement, and support throughout my research work. Their extensive knowledge, insightful feedback, and unwavering dedication have been instrumental in shaping my research and enabling me to achieve my goals. I would also like to extend my heartfelt thanks to my Teaching Assistant for their invaluable assistance and support in facilitating my research work. Their dedication and commitment to helping me succeed have been greatly appreciated. I am grateful for the opportunity to work with such knowledgeable and supportive individuals, and I will always be thankful for their contributions to my academic and professional development.

The code for this project is available on GitHub[4].

[4]https://github.com/Arnob-Mitra/Advanced-Time-Series-Analysis-for-Cryptocurrency-Investment-using-Machine-Learning-Techniques

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