School of Computer Science and Engineering

May 2021

Digital Assignment Report
on
Cryptocurrency Time Series Analysis

Submitted

as part of "Domain Specific Predictive Analytics" (CSE6021) theory course assement

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To

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Chapter 1

PROBLEM STATEMENT

To do a comparative study of blockchain networks and develop a time series based cryptocurrency visualization system to predict the future values.

The inquiry we look to answer is the accompanying one: How is the expectation accuracy of a set estimating for the Cryptocurrency influenced by the various time series forecasting models.

Chapter 2

INTRODUCTION

In recent years, there have been a few distinct trends in research on financial time series analysis: an increase in the diversity of topics covered, with richer and stronger connections with other disciplines; a focus on increasingly complex models; and a renewed focus on the role of computational techniques. All of these trends should be viewed as a response to the fast-evolving demands of financial analysis, which provide scholars and practitioners with new issues on a regular basis.

Time series are created by the prices of commodities or investments. For decades, several financial time series have been documented and researched. All financial market transactions are now recorded, resulting in a massive quantity of data available, either for free on the Internet or for a fee. Practitioners and theoreticians alike are interested in financial time-series analysis for drawing conclusions and forecasts. Furthermore, the stochastic uncertainties inherent in financial time-series, as well as the theory required to cope with them, make the subject particularly

appealing to statisticians and physicists. In financial aspects nowadays blockchain is the most trending topic. A blockchain is a digital log of transactions that is copied and distributed throughout the blockchain's complete network of computer systems. Each block on the chain comprises a number of transactions, and whenever a new transaction happens on the blockchain, a record of that transaction is added to the ledger of each participant.

Due to its extensive application areas and significant influence, financial time series forecasting is without a doubt the top option of computational intelligence for finance researchers from academia and the financial sector. Successful financial time series data prediction has long piqued the curiosity of the finance sector.

This article attempts to address this need by comparing a large number of various point and density forecasting models for three main cryptocurrencies: Bitcoin, Ripple, and Ethereum. We contrast univariate autoregressive models with univariate linear regression models using a large number of crypto–predictors. Commodity prices, other financial assets such as stock and bond prices, volatility indexes to proxy market attitudes, and a few other financial assets are among the predictors. This paper mainly takes the Cryptocurrency market data, Stock market OHCL data obtained via Yahoo finance as input and shows the Price fluctuations of assets affected by the value of an initial amount over a specified period of time and Portfolio time series view, and summary table as an output. Also, these statistics will provide a state-of-the-art picture for financial time series forecasting research. Simultaneously, it will highlight regions that are currently mature, as well as prospective or fresh areas where there is still space for progress. This paper will cover what has been accomplished via academic and industry successes, as well as expectations for what may be required in the future. It underlines the areas where more study is needed.

Chapter 3

OBJECTIVE

1) The major goal of this work is to use a data science technique to identify a partial

connection between the price fluctuation in the financial market

2) To visualize historical cryptocurrency market data, performance comparison

3) To predict cryptocurrency price using various time series methodologies

4) To give the result of a bitcoin forecast from the Yahoo Finance stock market.

5) To estimate the price for the future days using the data split to train and test.

Chapter 4

LITERATURE SURVEY

Sr.no	Year & Reference	Title	Authors	Key concepts
1	IEEE 2020	“Monitoring Financial Stability Based on Prediction of Cryptocurrencies Price Using Intelligent Algorithm”	Siti Saadah, Ahmad Whafa A.A	Forecasting bitcoin, Ethereum, and XRP using three intelligent algorithms: K-Nearest Neighbours (KNN), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM)
2	IEEE 2019	“A LSTM-Method for Bitcoin Price Prediction: A Case Study Yahoo Finance Stock Market”	Ferdiansyah, Siti Hajar Othman, Raja Zahilah Raja Md Radzi, Deris Stiawan, Yoppy Sazaki, Usman Ependi	LSTM is can't good enough to make the decision to invest in bitcoin
3	IEEE 2019	”Stochastic Neural Networks for Cryptocurrency Price Prediction”	PATEL JAY, VASU KALARIYA, PUSHPENDRA PARMAR, SUDEEP TANWAR, NEERAJ KUMAR, AND MAMOUN ALAZAB5	This paper used the approach which is based on the random walk theory. Mostly used in financial markets for modeling stock prices.The proposed model initiates

				layer-wise arbitrariness into the noticed element initiations of neural organizations to reenact market unpredictability
4	IEEE 2019	”Impact Analysis of Additional Input Parameters on Neural Network Cryptocurrency Price Prediction”	Anton Misnik, Siarhei Krutalevich, Siarhei Prakapenka, Peter Borovykh, Max Vasiliev	This investigation shows critical improvement of neural network predictions because of the consideration of a more extensive choice of pertinent information focuses. They have applied neural networks to approximate the price of Bitcoin (BTC).
5	IEEE 2018	”BitExTract: Interactive Visualization for Extracting Bitcoin Exchange Intelligence”	Xuanwu Yue, Xinhuan Shu, Xinyu Zhu, Xinnan Du, Zheqing Yu, Dimitrio Papadopoulos, and Siyuan Liu	Two big targeted issues are characterized, namely, exchange selection preference for participants and exchange network evolution, thanks to close collaboration with domain experts. To address these issues, BitExTract is

				incorporated, this highly immersive simulation framework, in the exploration process.

Chapter 5

DESIGN

Abstract Model:

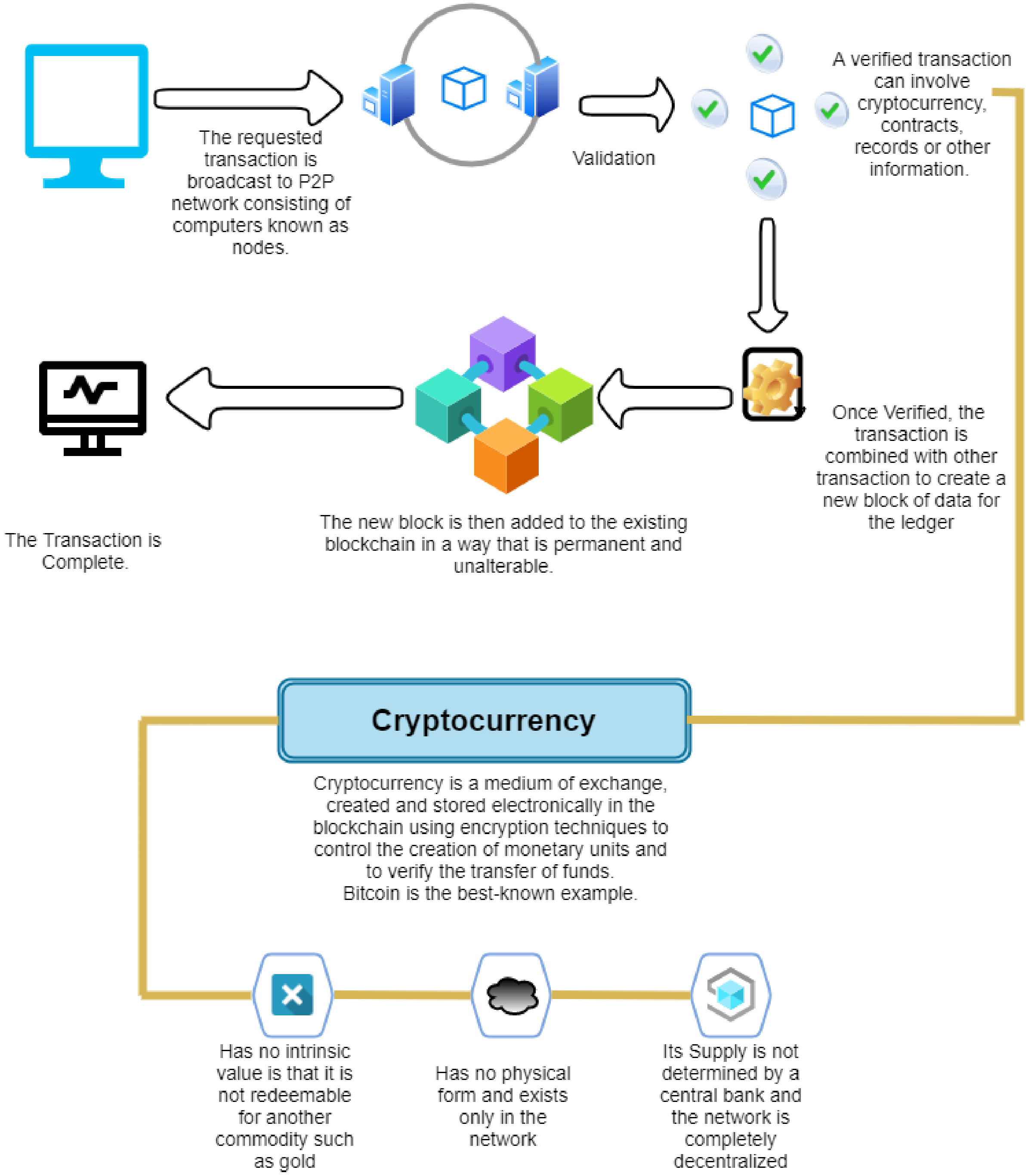

Figure 1. Abstract Model on How Cryptocurrency Works.

System Architecture:

Time series analysis is a type of analysis of data used to check the behavior of data over a period of time. The data is collected over time sequentially by the ts() function along with some parameters. It helps in analyzing the pattern of the data over a graph.

Data:

- Cryptocurrency historical data (2010-2021)

- Stock market OHCL data from Yahoo Finance: Consisting of 51 Crypto-assets and 6230 Financial-assets.
  The features are as follows: Symbol, Name of the company, Last sale amount, Market Capitalization, year of IPO, Sector of industry (Technology, Healthcare, etc), Industry (Computer Software, Medical Instruments, etc), Summary Quote

- Cryptocurrency data from CoinMetrics: the hourly data of given cryptocurrency between selected dates.
- Google Trends data form Tiingo: cryptocurrency google trends based on geological location.

- Cryptocurrency Market Capitalization form CoinMarketCap

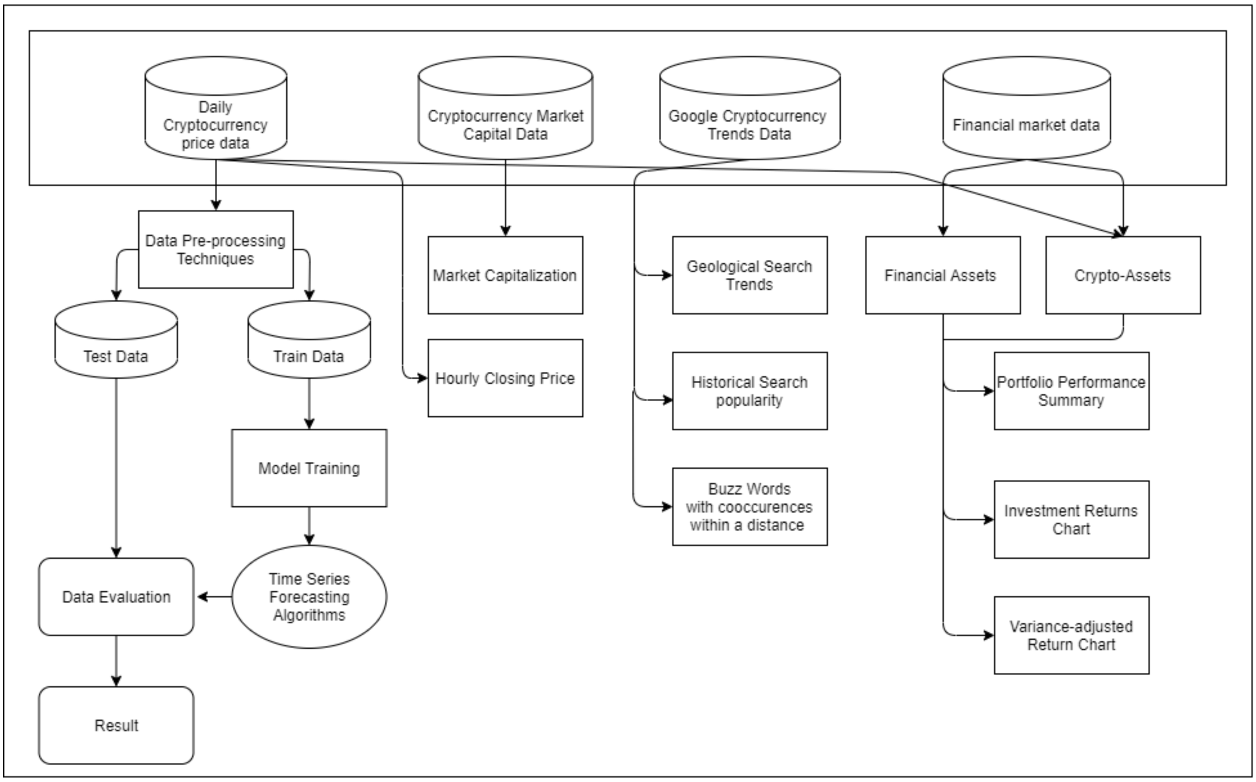

Figure 2. System architecture

1) Cryptocurrency Market Analysis
    a. Hourly Closing Price of a given cryptocurrency, between a range of dates
    b. Historical trading prices
    c. Comparison between Cryptocurrency Market Capital and Historical Market Cap

2) Cryptocurrency data exploration
    a. Google search trends geologically spread
    b. Frequently occurring buzz words

3) Cryptocurrency price prediction

Time Series Forecasting: Time series forecasting is an interaction of foreseeing future qualities with the assistance of some measurable instruments and techniques utilized on an informational collection with authentic information. A portion of the uses of time series forecasting are:

- Predicting stock costs
- Forecast climate
- Forecast the deals of an item

Using following time series forecasting models to predict selected cryptocurrency price:
    a. Arima
    b. SVM
    c. Neural Network
    d. Hybrid Model
    e. Prophet

4) Cryptocurrency and Financial Market Analysis
In the event that a person had M measure of cash to contribute over the long haul time frame T, what might have been the better venture as decided by different measurements: Financial Asset A or Financial Asset B?"
To figure out what measurements may be of most prominent significance to your specific inquiry, think about the accompanying:

1. Imagine a scenario where the person cares about the total benefit that he makes : Provided that this is true, at that point consider the straightforward portfolio execution measurements.

2. Imagine a scenario in which the person cares about relative additions and misfortunes : Assuming this is the case, at that point think about the pace of return rate.

3. Imagine a scenario in which I care about the compromise that exists between resource execution and the danger/instability related with holding that resource : Assuming this is the case, at that point consider the variance-adjusted rate of return.

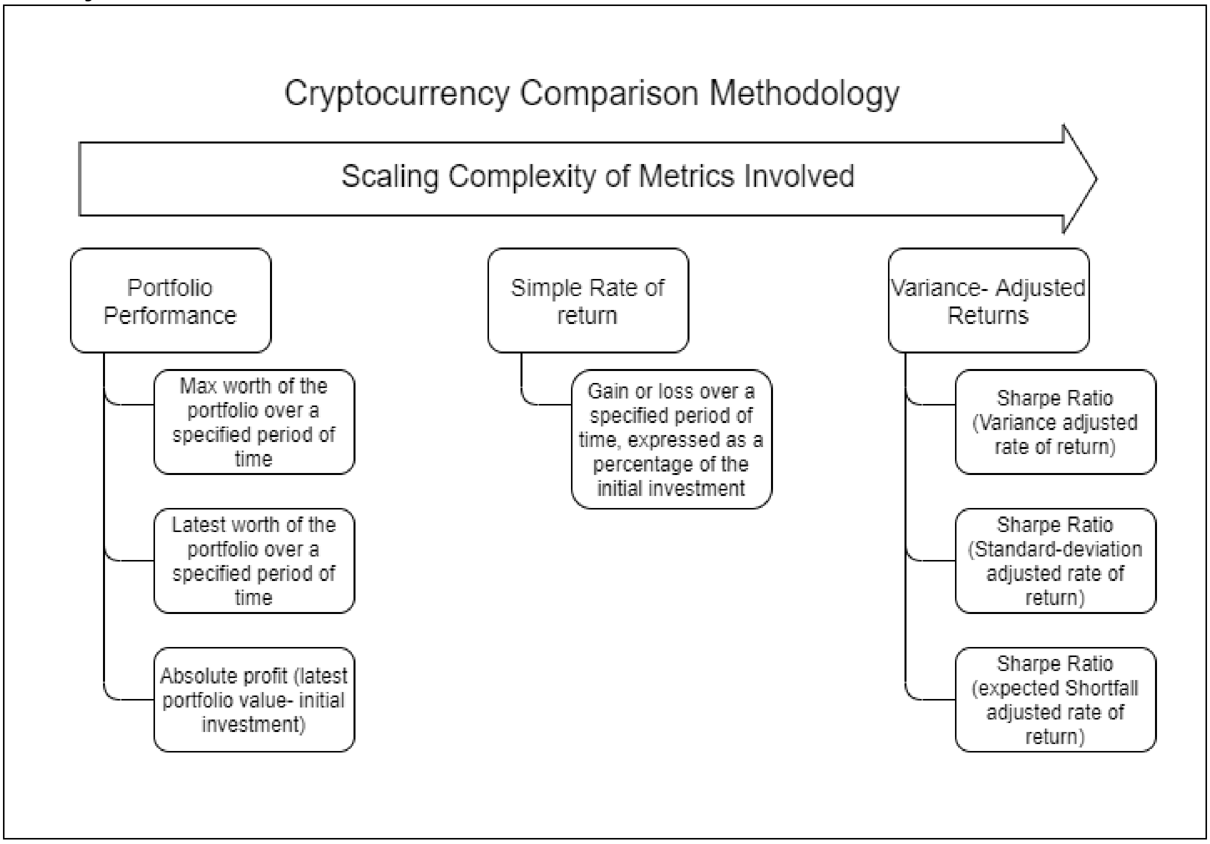

Figure 3. Financial Asset Comparison Methodology

CHAPTER 6

METHODOLOGIES

Data preprocessing:
The data consists of following columns Sr. No, Name, Symbol, Date, High, Low, Open, Close, Volume, Market cap. For the purpose of prediction four features will be used as follows, date: date of observation, open: opening price on the given day, high: highest price on the given day, low: lowest price on the given day, close: closing price on the given day, volume: volume of transactions on the given day, and market cap: market capitalization in USD. Each required column seems to have null values we will have to remove those we can remove null values by removing the row directly but this method will affect time series as some days will be missing if we delete those rows. Deleting rows is not a good option. To maintain mean value of column, replace null with mean.
The data can be divided into training and testing dataset based on the percentage provided by the user at runtime, and it can be changes throughout as per the user.

Implementing the following models to forecast time series :

1) <u>ARIMA</u>

There are numerous procedures used to forecast the time series object over the plot diagram however the ARIMA model is the most generally utilized methodology out of them.

ARIMA represents Autoregressive Integrated Moving Average and is determined by three request boundaries: (p, d, q).

AR(p) Autoregression: A relapse model that uses the reliant connection between a current perception and perceptions over a past period. An auto-regressive (AR(p)) part alludes to the utilization of past qualities in the relapse condition for the time series.

I(d) Integration: Uses differencing of perceptions (taking away a perception from perception at the past time step) to make the time series fixed. Differencing includes the deduction of the current values of an arrangement with its past qualities d number of times.

MA(q) Moving Average: A model that utilizes the reliance between a perception and a remaining mistake from a moving normal model applied to slacked perceptions. A moving average segment portrays the mistake of the model as a blend of past error terms. The request q addresses the quantity of terms to be remembered for the model.

2) Standard Vector Machine (SVM)

The SVM guides the information of input space into a high dimensional element space, to address numerous troublesome issues that cannot be addressed by the linear strategy in the original sample space. Contrasted with the neural network calculation, SVM has more straightforward preparing measure and better speculation ability. SVM likewise can be utilized in field of time arrangement forecast.

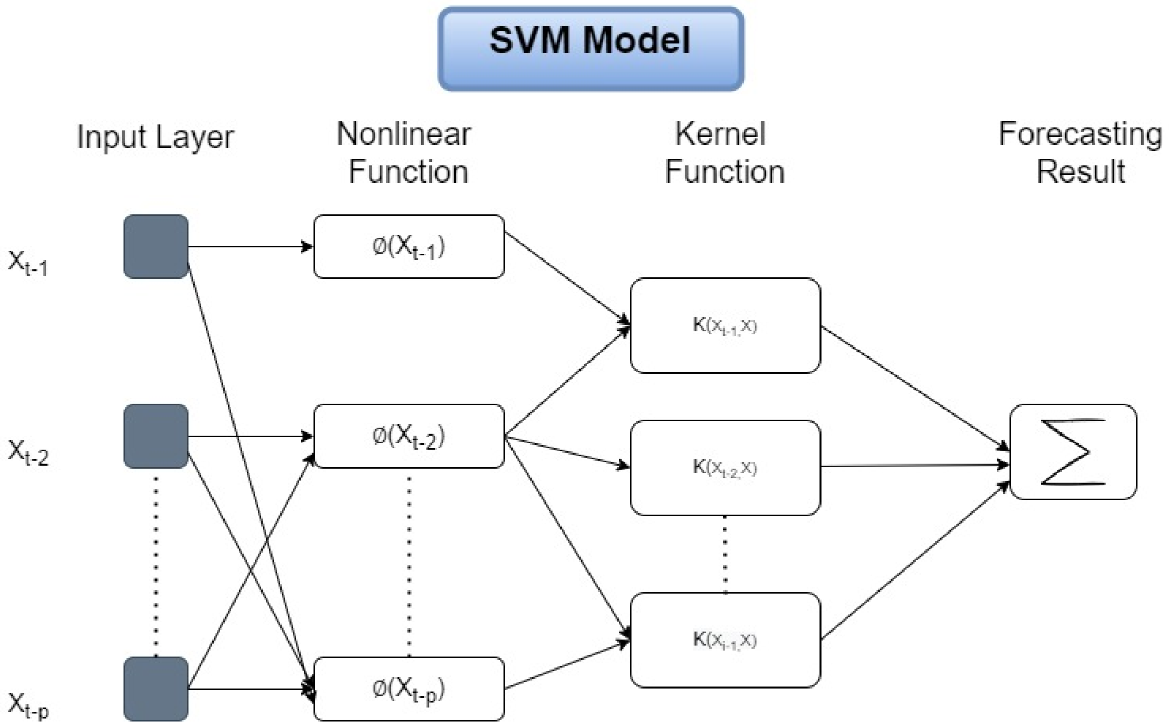

Figure 4. SVM working

3) Neural Networks

Neural Networks for time series models have been investigated in the literature[] and have shown great predictive capabilities. This spurs us to investigate neural networks for forecasting the cryptocurrency data. The neural network that we will utilize the feed-forward neural network with a variable number of nodes.

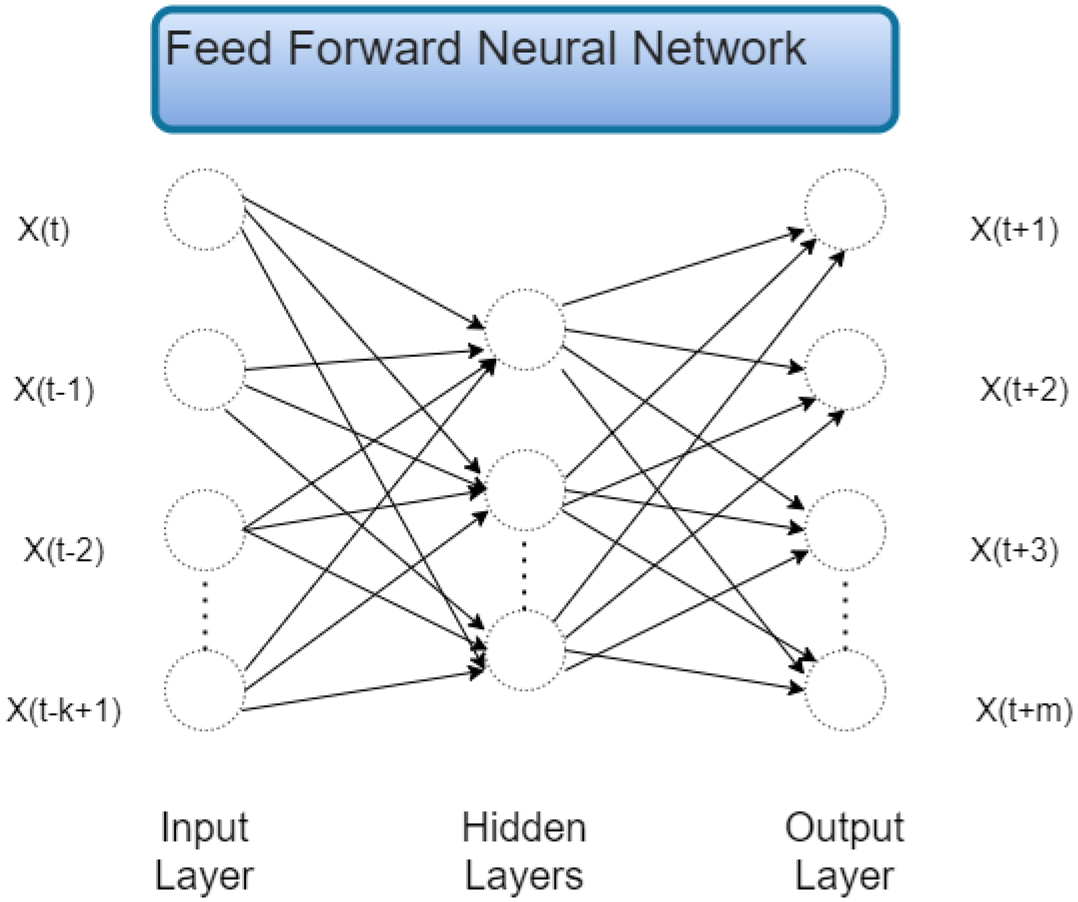

Figure 5. Feed Forward Neural Network

4) Hybrid Model

Hybrid ARIMA-support vector machine model. Cryptocurrency market data is given as contribution to the SVM model use kernel function as polynomial with degree and coefficient, to anticipate the future quantities of the given digital currency.

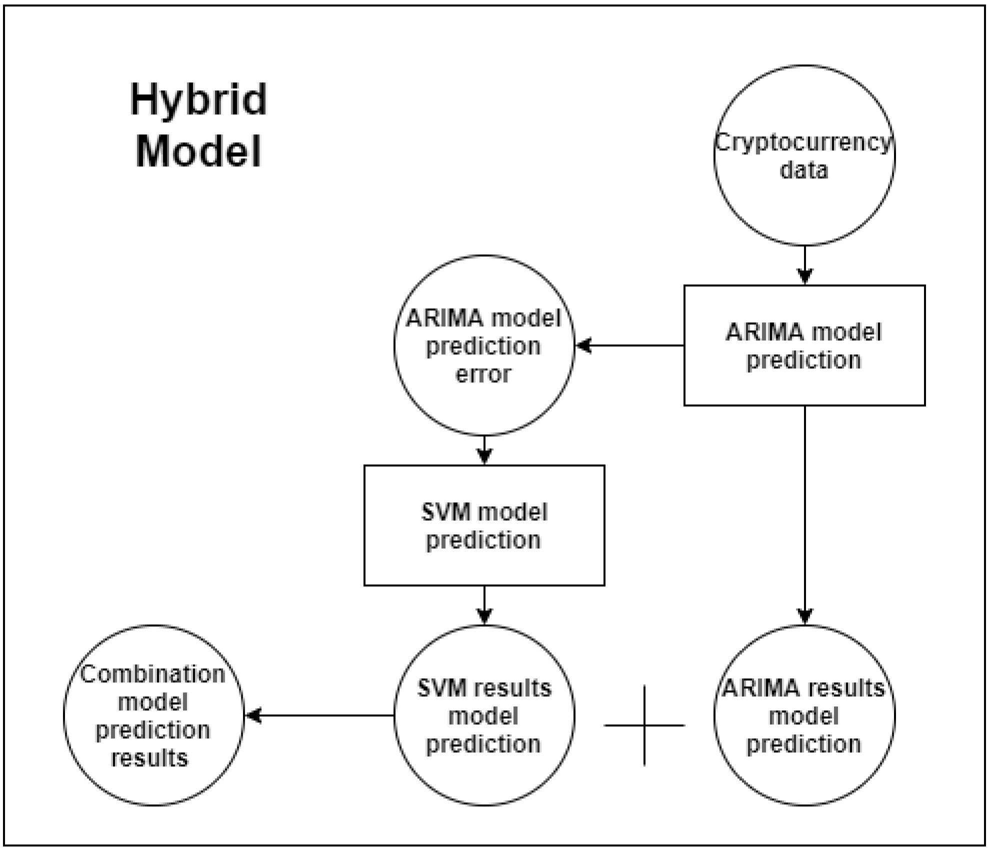

Figure 6. Hybrid Model working

For hybrid model, we propose two models in this exploration and they are comprised of linear model and non-linear functions and used to gauge the linear and non-linear requests.
In this part, the ARIMA is utilized to foresee the linear values of future worth. At that point, the residuals acquired from the ARIMA are entered to SVM as the dataset.
The equation for the hybrid model can be shown as follows:

$$y = \hat{L} + \hat{N} + \varepsilon$$
$$Where, y\ is\ the\ actual\ value, \hat{L}\ is\ the\ linear\ value,$$
$$\hat{N}\ is\ the\ non-linear\ value, \varepsilon\ is\ white\ noise$$

The conduct of digital currency costs cannot effectively be caught. Consequently, a mixture procedure that has both linear and non-linear displaying capacities is a decent option at anticipating digital currency costs. Both the ARIMA and the SVMs models have various capacities to catch information attributes in linear or non-linear spaces, so the cross breed model proposed in this investigation is made out of the ARIMA and the SVMs components. Along these lines, the hybrid model can display linear and non-linear examples with improved generally speaking estimating execution.

5) Prophet

The Prophet library is an open-source library designed for making forecasts for univariate time series datasets. It is easy to use and designed to automatically find a good set of hyperparameters for the model in an effort to make skillful forecasts for data with trends and seasonal structure by default.

The Prophet utilizes a decomposable time series model with three principle model parts: trend (i.e pattern), seasonality (i.e irregularity), and holidays (i.e occasions). They are joined in the accompanying equation:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon t$$

- $g(t)$: piecewise linear or logistic growth curve for demonstrating non-periodic changes in time arrangement
- $s(t)$: periodic changes (for example week by week/yearly irregularity)
- $h(t)$: impacts of holidays (given) with sporadic timetables
- εt: error term represents any uncommon changes not obliged by the model

Using time as a regressor, Prophet is attempting to fit a few linear and non-linear elements of time as parts. Prophet is outlining the forecasting problem as a curve fitting activity as opposed to taking a gander at the time based reliance of every perception inside a period arrangement.

Metrics:

Forecast errors:

A forecast "error" is the contrast between a noticed worth and its forecast. Here "error" doesn't mean a misstep, it implies the erratic piece of a perception. It very well may be
composed as

$$e_{T+h} = y_{T+h} - \hat{y}_{T+h|T} \text{ ,}$$

$$\text{where the training data is } \{y_1, \dots, y_T\} \text{ and}$$
$$\text{the test data is } \{y_{T+1}, y_{T+2}, \dots\}$$

Note that the forecast errors are not quite the same as residuals in two departments. In the first place, residuals are determined on the training set while forecast errors are determined on the test set. Second, residuals depend on one-venture forecasts while forecast errors can include multi-step estimates.

We can gauge forecast exactness by summing up the figure blunders in an unexpected way.

Scale-dependent errors

The forecast errors are on a similar scale as the information. Exactness estimates that depend just on e_t are accordingly scale-dependent and can't be utilized to make correlations between arrangement that include various units.

The two most ordinarily utilized scale-dependent measures based on the absolute errors or squared errors:

$$Mean\ absolute\ error: MAE = mean(|e_t|),$$
$$Root\ mean\ squared\ error: RMSE = \sqrt{mean(e_t^2)}$$

When contrasting forecasting techniques applied with a solitary time arrangement, or to a few time arrangement with similar units, the MAE is mainstream as it is not difficult to both comprehend and register. A forecast technique that limits the MAE will prompt figures of the middle, while limiting the RMSE will prompt estimates of the mean. Therefore, the RMSE is additionally broadly utilized, in spite of being more hard to decipher.

Percentage errors

The rate of error is given by$p_t = 100 \frac{e_t}{y_t}$. Error rates enjoy the benefit of being unit-free, as are oftentimes used to look at forecast exhibitions between informational collections. The most usually utilized measure is:

$$Mean\ absolute\ percentage\ error: MAPE = meqan(|p_t|)$$

Measures dependent on percentage errors have the drawback of being endless or vague if yt=0yt=0 for any tt in the time of revenue, and having outrageous qualities if any ytyt is near nothing. Another issue with error rate that is frequently ignored is that they expect the unit of estimation has a significant zero. For instance, a rate mistake has neither rhyme nor reason when estimating the precision of temperature figures on either the Fahrenheit or Celsius scales, since temperature has a subjective zero point.

The two metrics that we will use for our project are

1. The root mean squared error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{N}}$$

$$i = variable\ i, N = number\ of\ non - missing\ data\ points,$$

$$x_i = actual\ observations, \hat{x}_i = estimated\ time\ series$$

2. The mean absolute percentage error (MAPE)

$$MAPE = \frac{100}{N} \times \sum_{i=1}^{N} \left| \frac{x_i - \hat{x}_i}{x_i} \right|$$

Where:

1. x_i are the actual observations time series
2. $\hat{x}_i$ are the estimated or forecasted time series
3. N is the number of non-missing data points

CHAPTER 7

RESULTS

i. Cryptocurrency Market Analysis

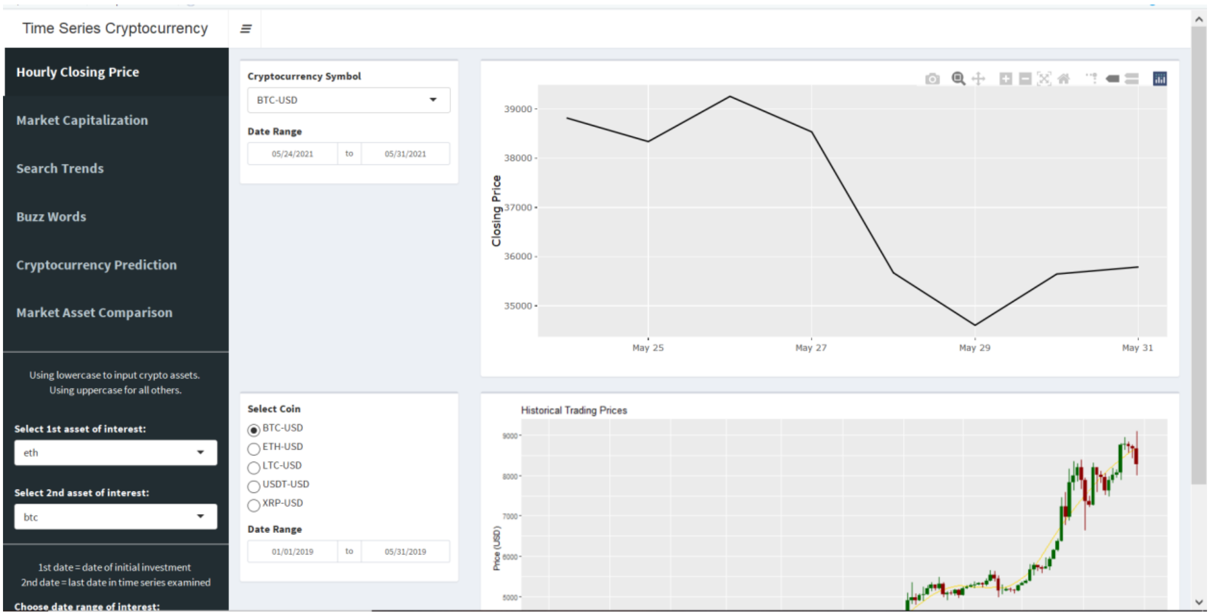

Figure 7. Hourly Closing Price

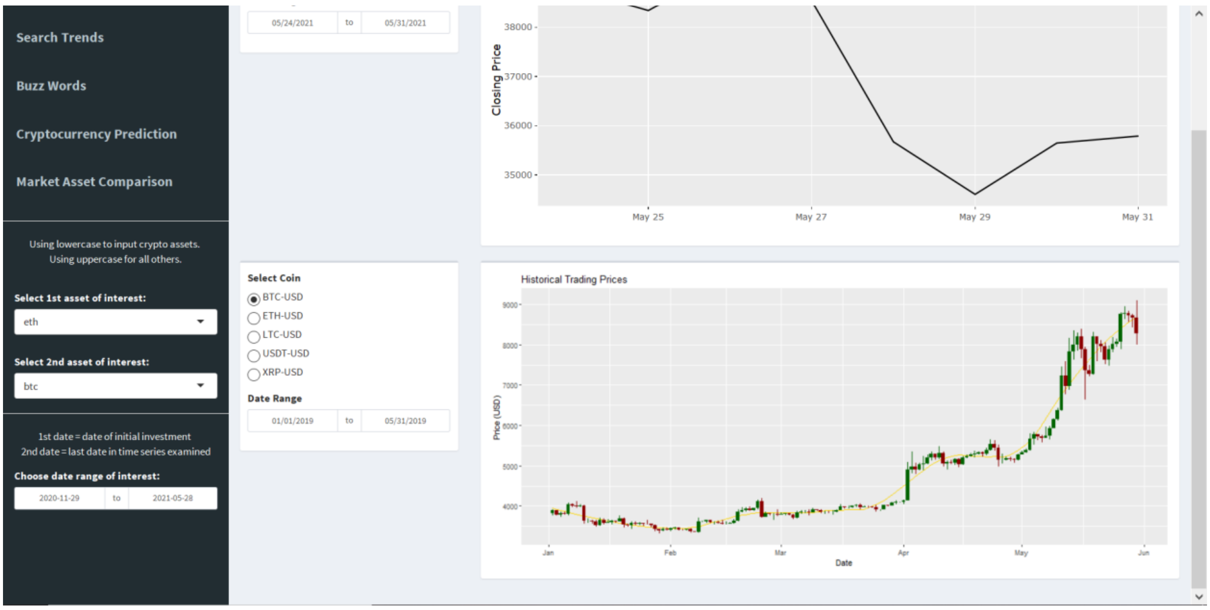

Figure 8. Historical Trading Prices

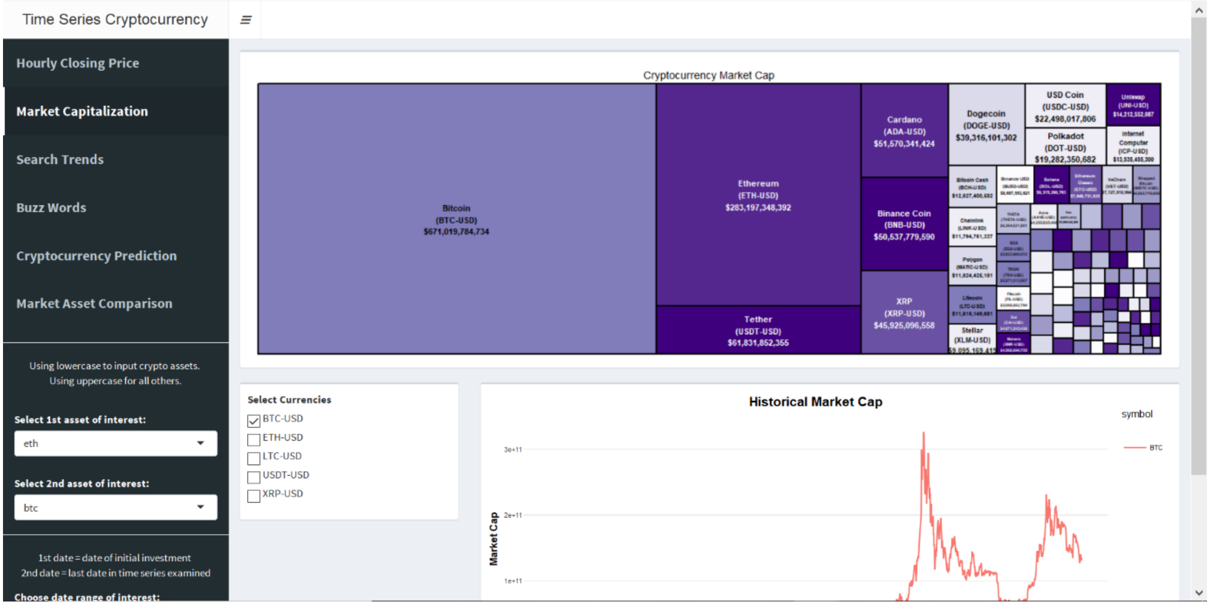

Figure 9. Hierarchical Tree map of Cryptocurrency market cap

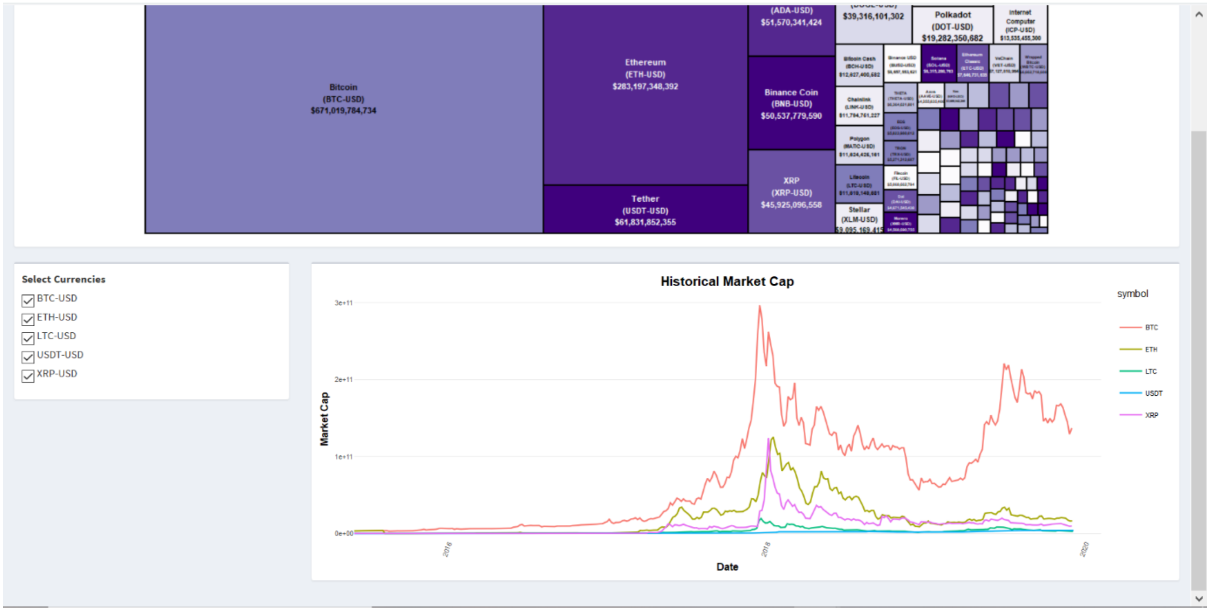

Figure 10. Historical Market Cap

ii. Cryptocurrency data exploration

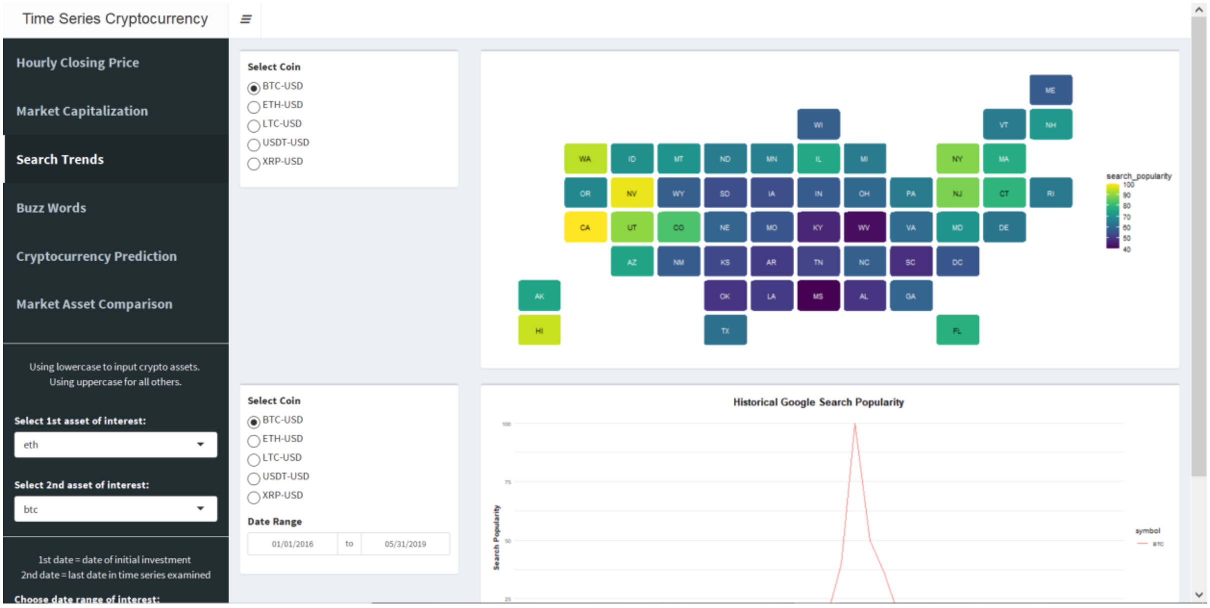

Figure 11. Search trends displayed geologically across USA

Figure 12. Historical Google Search Popularity

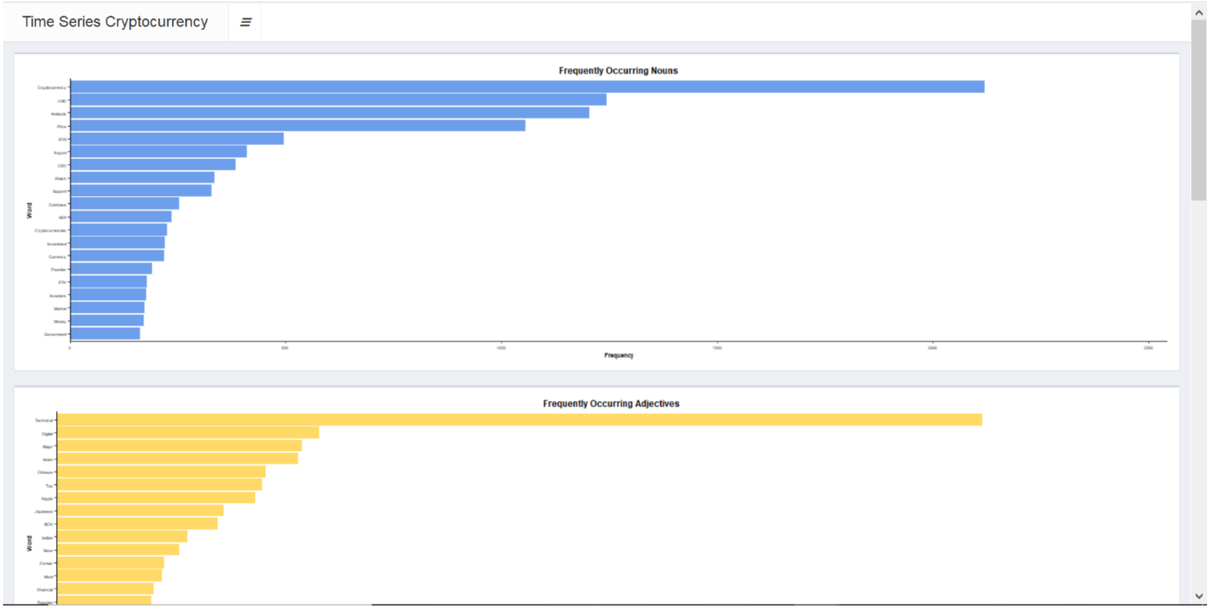

Figure 13. Frequently occurring Nouns and Adjectives

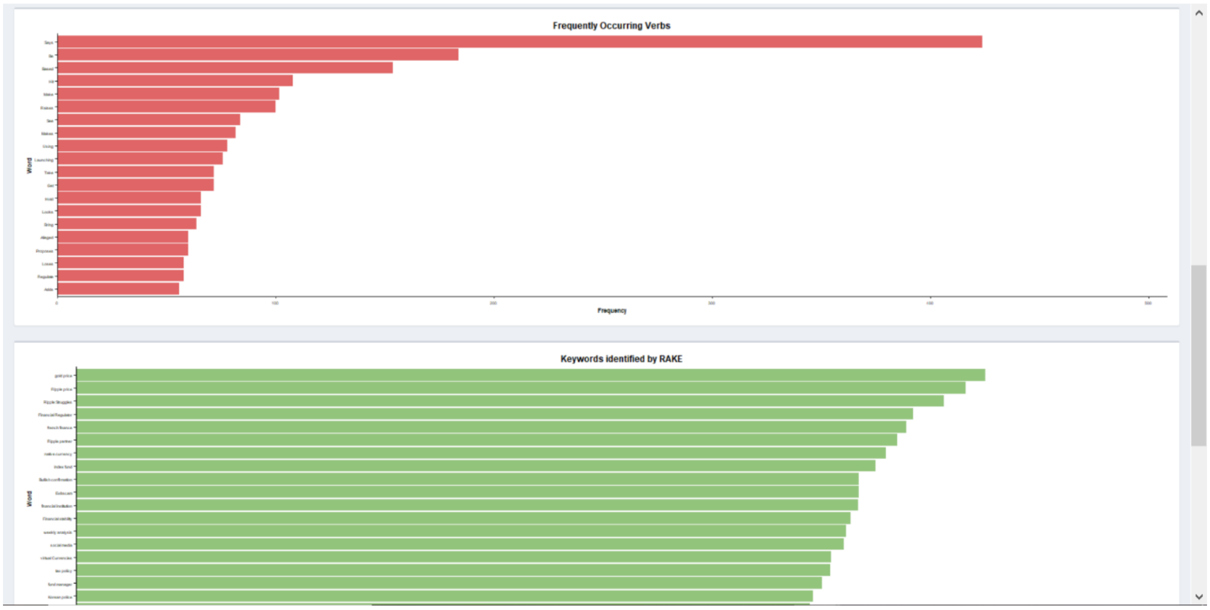

Figure 14. Frequently occurring Verbs

Figure 15. Co-occurrence within 3 words distance

iii. Cryptocurrency Price prediction

Since the resultant dashboard allows the user to select the variables at run-time, there are various options available, such as,

The cryptocurrency: Bitcoin, Ethereum, Ripple, Litecoin, MIOTA, Dogecoin, and Monero

The price variable: close, open, high, and low

The time series forecast model: Arima, SVM, Neural Network, Hybrid Model, and Prophet

Train data percentage: ranging from 10-99

Step size: ranging from 2-30

Figure 16. Cryptocurrency price plot

Figure 17. Decomposition plot

Figure 18. Seasonality plot

Figure 19. Prediction plot

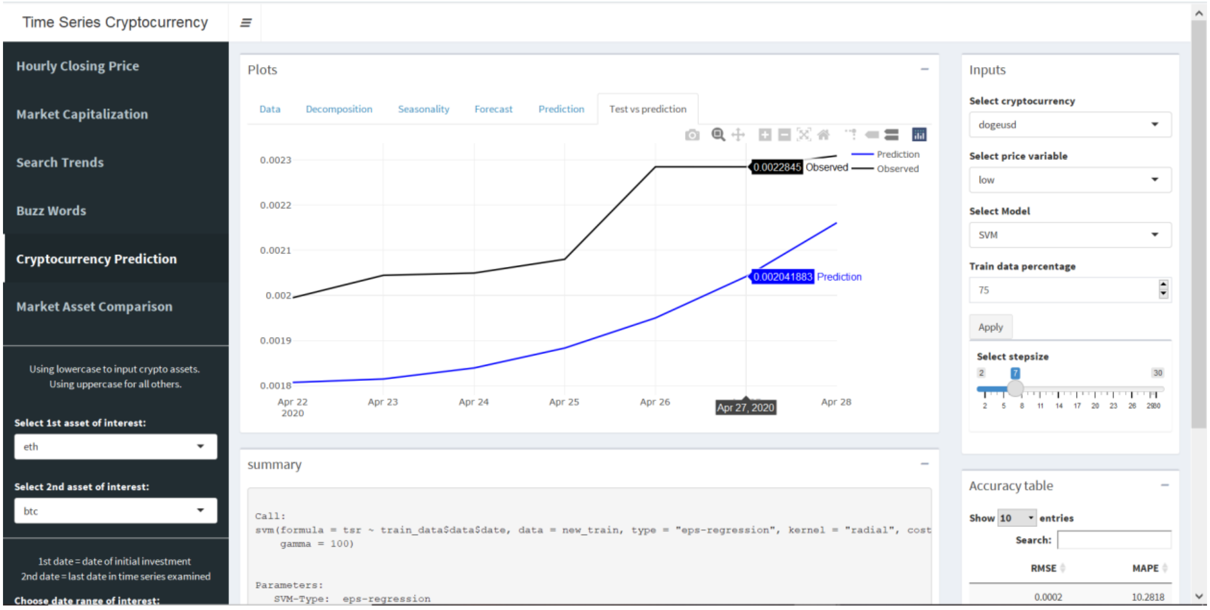

Figure 20. Test Vs. Prediction plot

<u>Case 1</u>: Cryptocurrency: Bitcoin, Price Variable: “close

The summary of all cases is as follows:

Price variable= “close”	RMSE		MAPE	
	Train Set	Test Set	Train Set	Test Set
1) Arima	192.7388	448.7907	*3.1492	11.909
2) SVM	-	*338.2793	-	*9.1781
3) Neural Network	*78.2347	817.4305	6.0427	20.862
4) Hybrid Model	109.8086	570.5272	3.1999	15.1349
5) Prophet	-	8927.8433	-	253.3062

The models in the order of best performance to worst performance is given as follows:

a. SVM
b. Arima
c. Hybrid model
d. Neural Network
e. Prophet

<u>Case 2</u>: Cryptocurrency: Bitcoin, Price Variable: "open"

The summary of all cases is as follows:

Price variable= "open"	RMSE		MAPE	
	Train Set	Test Set	Train Set	Test Set
1) Arima	196.7465	461.4949	*3.2598	12.0308
2) SVM	-	*339.613	-	*9.0183
3) Neural Network	*79.7731	790.7462	4.3587	18.0984
4) Hybrid Model	107.3906	618.4537	3.314	15.9156
5) Prophet	-	9041.4399	-	252.421

The models in the order of best performance to worst performance is given as follows:

a. SVM

b. Arima
c. Hybrid Model
d. Neural Network
e. Prophet

Case 3: Cryptocurrency: Bitcoin, Price Variable: “high”

The summary of all cases is as follows:

Price variable= “high”	RMSE		MAPE	
	Train Set	Test Set	Train Set	Test Set
1) Arima	153.2272	306.7561	2.9689	7.2462
2) SVM	-	*265.5501	-	*6.9581
3) Neural Network	*75.6552	570.5636	*2.535	14.348
4) Hybrid Model	119.502	369.961	3.8743	8.8476
5) Prophet	-	9301.3248	-	248.0601

The models in the order of best performance to worst performance is given as follows:

a. SVM
b. Arima
c. Hybrid Model
d. Neural Network
e. Prophet

<u>Case 4</u>: Cryptocurrency: Bitcoin, Price Variable: "low"

The summary of all cases is as follows:

Price variable= "low"	RMSE		MAPE	
	Train Set	Test Set	Train Set	Test Set
1) Arima	170.9975	381.0475	3.5817	10.4363
2) SVM	-	235.3433	-	6.2787
3) Neural Network	72.9491	*182.3019	4.8948	*4.0919
4) Hybrid Model	112.1139	568.7279	4.0603	16.0934
5) Prophet	-	8327.9982	-	247.3806

The models in the order of best performance to worst performance is given as follows:

a. Neural Network (Best Case lowest RMSE and MAPE of all cases)
b. SVM
c. Arima
d. Hybrid Model
e. Prophet

Since, SVM performed best comparatively, applying SVM to all the cryptocurrencies. The resultant summary table is as follows:

SVM	RMSE	MAPE

"low"	Test	Test
Bitcoin	235.3433	6.2787
Ethereum	7.9196	*5.3265
Ripple	0.0232	8.9779
Litecoin	4.3211	9.3711
MIOTA	0.0374	15.4568
Dogecoin	*0.0002	10.2818
Monero	7.1207	11.1527

The lowest RMSE is for Dogecoin with 0.0002 and lowest MAPE is resulted for Ethereum with 5.3265. Hence, it shows SVM is more likely to give an accurate result for Dogecoin and Ethereum as compared with other coins.

Analysing Neural Network performance applying to all the cryptocurrencies. The resultant summary table is as follows:

Neural Network	RMSE	MAPE
"low"	Test Set	Test Set
Bitcoin	211.9123	5.1252
Ethereum	11.1277	6.3156
Ripple	0.0339	14.6822
Litecoin	3.1739	6.2733
MIOTA	0.008	*2.3644
Dogecoin	*0.0001	3.4784
Monero	2.2116	3.6813

The lowest RMSE is for Dogecoin with 0.0001 and lowest MAPE is resulted for MIOTA with 2.3644. Hence, it shows Neural Network is more likely to give an accurate result for Dogecoin and MIOTA as compared with other coins.

iv. Financial Market data analysis

The return rate segment (screen capture beneath) is completely instinctive: it is essentially a period arrangement graph of the profits for the picked asset over the period indicated.

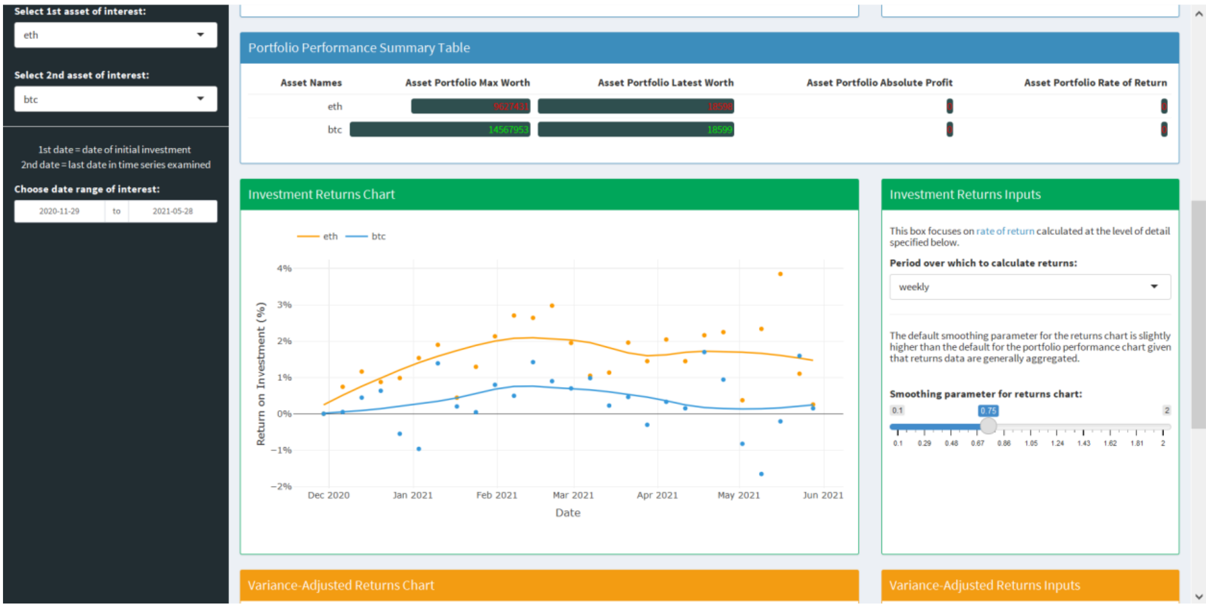

Figure 21. Investment Returns Chart

The variance-adjusted return area (screen capture beneath) is a marginally more muddled extra arrangement of measurements intended to enhance the base return rate.

The boundary that permits the client to choose the period over which to figure pace of get back (from the part above) likewise influences the fluctuation changed returns area, as the three assortments of Sharpe Ratio are determined throughout that equivalent time-frame. One should be cautious while picking the Risk Free Rate, since that rate ought to be picked comparative with the time span chose.

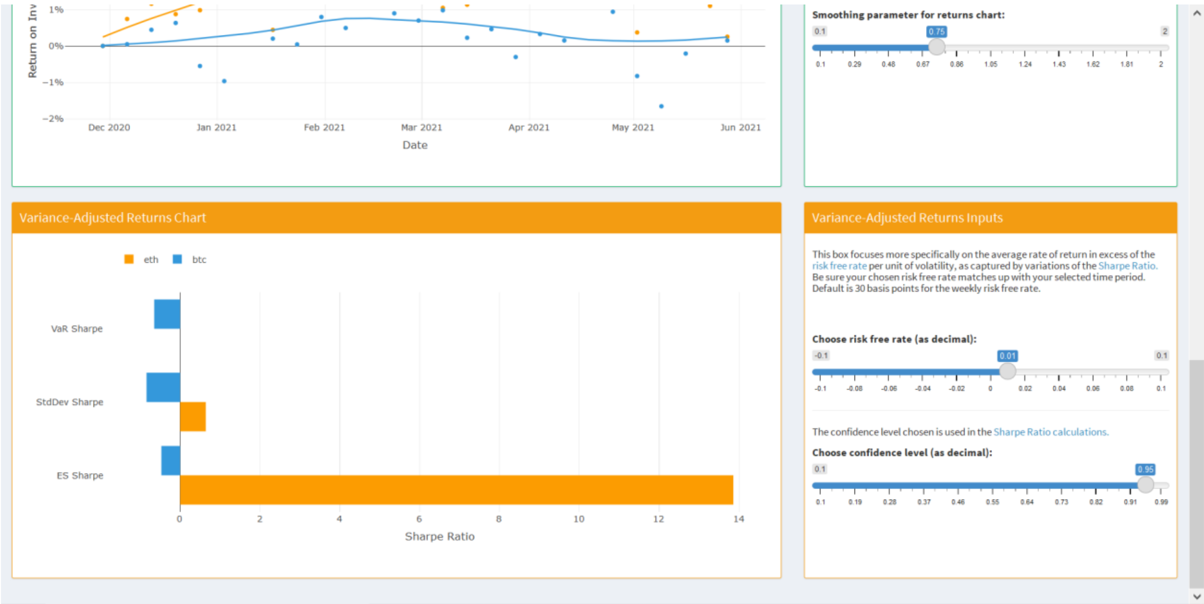

Figure 22. Variance Adjusted Returns Chart

CHAPTER 8

CONCLUSION

The overall best results were obtained by using price variable as “low” or “high”, on the other hand the scores for “open” and “close” are comparatively higher, hence, in this case are not a good fit for prediction. The best case scenario is when Price variable is taken as “open” and Neural Network model is applied resulting in the lowest RMSE and MAPE of all cases combined, as 182.3019 and 4.0919 respectively, for test data. Overall SVM performs comparatively better than other models, and Prophet performs the worst in all the cases.

In future scope, other models such as a hybrid model using Neural Networks and SVM can be used for better performance. A novel technique can be developed to consider a combination of price variables for prediction.

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