Bitcoin Price Prediction using Neural Network

MSc Research Project
Data Analytics

Namrata Hemraj Gawali
Student ID: x20177887

School of Computing
National College of Ireland

Supervisor: Prof.Jorge Basilio

National College of Ireland
Project Submission Sheet
School of Computing

Student Name:	Namrata Hemraj Gawali
Student ID:	x20177887
Programme:	Data Analytics
Year:	2021
Module:	MSc Research Project
Supervisor:	Prof.Jorge Basilio
Submission Due Date:	31-01-2022
Project Title:	Bitcoin Price Prediction using Neural Network
Word Count:	6032
Page Count:	23

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.

ALL internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action.

Signature:	
Date:	

PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST:

Attach a completed copy of this sheet to each project (including multiple copies).	☐
Attach a Moodle submission receipt of the online project submission, to each project (including multiple copies).	☐
You must ensure that you retain a HARD COPY of the project, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer.	☐

Assignments that are submitted to the Programme Coordinator office must be placed into the assignment box located outside the office.

Office Use Only	
Signature:	
Date:	
Penalty Applied (if applicable):	

Bitcoin Price Prediction using Neural Network

Namrata Hemraj Gawali
x20177887

Abstract

Bitcoin and other virtual currencies are becoming more popular and valuable among investors. Nowadays, these cryptocurrencies are not only are utilized for trading but they are also accepted as a mode of payment for regular transactions. Investors and distributors are becoming more interested in bitcoin as its prices fluctuate massively and returns on investment are increasing day by day. In this research, we will investigate how accurately we can predict price of bitcoin by reviewing several aspects, that affect the bitcoin price. It focuses on developing prediction model which provide reliable cryptocurrency price predictions. We considered Stock price data as an exogenous variable to build SARIMAX model. When the result of designed models were compared, it was observed that the LSTM model outperformed all SARIMA,SARIMAX and RNN model.

1 Introduction

Bitcoins is the most prominent cryptocurrency in recent years, attracting both investors and public. Investors are compelled to find a logical cause-and-effect relationship among all accessible current information to make market predictions. It has now become a worldwide thing that most people are aware of. Even though it is still a little nerdy and difficult to grasp for most consumers, banks, authorities, and a variety of businesses recognize its importance. Cryptocurrencies use cryptography to safeguard and authenticate transactions, as well as to manage the creation of new coin components. Satoshi Nakamoto developed perhaps the most well-known cryptocurrency, bitcoins, in early year 2008.

It began as decentralized "electronic payment" in year 2009. It could be transfer or received across transfer protocol channel, such as customer or a peer-to-peer. In May year 2010, one Florida programmer bought a pizza using bitcoins for first time. In late year 2017, the value of bitcoin was also around $10000. As a result, bitcoin has taken control of digital currency industry, accounting for 56.83 percent of the overall market capitalization.Furthermore, in the case of cryptocurrencies, where values are determined by several unknown factors, forecasting becomes more difficult than with traditional commodities. Figure 1 shows the various time series prediction approaches.

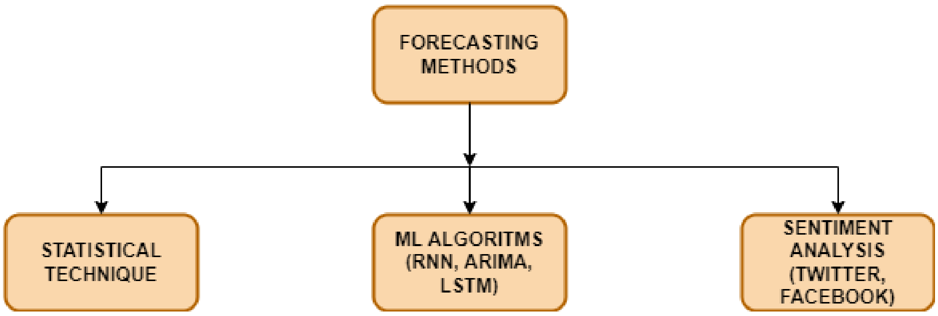

Figure 1: Time Series Forecasting Approaches

2012 was a rather was a quiet year for Bitcoins, while 2013 saw significant price increases. It started at $13.28 and hit $230 by April 8; then it saw an equally quick slowdown, falling to 68.50 dollar in July 4. Then again it dropped throughout 2014, reaching $315.21 in the beginning of 2015. Prices gradually increased throughout 2016, reaching above $900 by December 2016 year. Bitcoin's price stayed around 1,000 dollar in 2017 till mid-May, when it crossed $2,000, and afterwards jumped high $19,345.49 in December. Garcia et al. (2014) Other companies began creating cryptocurrencies to fight with Bitcoin once conventional investors, authorities, bankers, and researchers took notice

Bitcoin broke its year 2020 value record in a month in the year 2021, hitting $40,000 on January 7, 2021. As a Coin base, a cryptocurrencies exchange, came out publicly in mid-April, the prices hit fresh all-time record levels of above $60,000. It rose even higher as a result of corporate interest, reaching a high of more over $63,000 in April 2021.

1.1 Background & Motivation

Since number of people are investing in bitcoins as it is growing every single day in this digital era, there is a tremendous demand for structured and expert methods for predicting future bitcoin prices and preventing consumers from losing their money. But the reviews and prediction technique needed is not sufficient as the number continues to grow. Predictions about the price of bitcoin are extremely crucial as they are volatile. As a result, the necessity for a thorough automated approach to detect bitcoins value in future is required.

With deep learning algorithms, machine learning methods, pattern recognition, and neural networks, several attempts have been made to predict bitcoin prices in past. The goal is to develop a price forecasting model is, for investors it will be easier to understand current situation of bitcoin price and how will be affected in future.

1.2 Research Question & Objective

1.2.1 Research Question

To what extent can the designed machine learning bitcoin price prediction model provide an advantage to investors?

1.2.2 Research Objective

The objectives specified in table number 1 have been completed to answer the RQ.

Table 1: Research Objective

Objective	Description	Evaluation Metrics
1	From year 2012 to till date, a thorough analysis of the work in bitcoin price prediction model will be conducted.	-
2	The data will be processed and transformed to forecast bitcoin prices.	-
3	Model development, analysis and evaluation, results- RNN	R2, MSE,RMSE and MAE values
4	Model development, analysis and evaluation, results- LSTM	R2, MSE,RMSE and MAE values
5	Model development, analysis and evaluation, result- SARIMA	R2, MSE,RMSE and MAE values
6	Model development, analysis and evaluation, results- SARIMAX	R2, MSE,RMSE and MAE values
7	Model Comparison and Evaluation	-

2 Related Work

2.1 Analysis using Machine Learning

On everyday cryptocurrency values for 1, around 681 currencies, they put three forecasting methods to test. First is dependent on the long short-term memory rnn, while the other two are built on gradient boosting decision trees (i.e., Method 3). Under method 1, they utilized same method to forecast the rate of returns of all currencies. In second method, they constructed a separate model for every currency which leverages data from the entire market and create a forecast on that specific currency. They utilized a distinct algorithm for every currency and in last method, where the forecast is dependent on currency's prior pricing.Velankar et al. (2018) They created investment strategies depending on the various methods' forecasts and compare the results to the baseline provided by well-known a simple moving average technique.Extending the existing study to include these and few other market characteristics is a promising direction for future research. A separate but intriguing method to studying bitcoins is to estimate impact of popular perception on market behaviour, as assessed by social media footprints, in same way that it was performed for share market.]Patel et al. (2020) While it has been demonstrated that social sites footprints can be good forecasters of bitcoins and some other currency value swings, their understanding of the impact on the entire cryptocurrency market was still limited, and this is an intriguing route for further research.

The Author underlines the fact that cryptocurrencies can be used to fund terrorism. They can assist in the collection of several low donations made by unknown supporters. However, using huge sums of money in form of cryptocurrency is challenging.Teichmann

(2018) Furthermore, they are largely ineffective for financing day-to-day activity. However, they are handy for accumulating funds via the darknet is used buy weapons and explosives. As a result, they could be regarded a threat to Europe. Governments could pass legislation allowing secret remote web searches of electronic devices to eliminate this risk. This could aid in the detection of e-wallets used for funding terrorism.

The study improve current bitcoin prediction studies and forecast the value of bitcoin price by considering few characteristics.Joshila et al. (2021) After doing extensive study, they detected daily variations in cryptocurrency market by taking into account all of factors that influence its price. All data in this research was made up of distinct features from daily records from the previous few years. The support vector machine algorithm (SVM) approach is employed in this study because it provides significantly higher accuracy than earlier algorithms. This study forecasts price changes in bitcoin market for consumers so that it can simply invest it. Serafini et al. (2020)

2.2 Analysis using Deep Learning

They have assessed current developments by reviewing over 100 relevant published works in the last three years, driven by rapid growth and widespread use of deep learning methods for stock price prediction. They went over every stage of the procedure, from actual data collecting to data pre-processing to predictions model development and modelling evaluation, as well as the research progress from year 2017 to 2019.Jiang (2021) According to the author, designing a price prediction based on single source of data, such as trade data, is not a good idea because it's been extensively used in past research and outperforming existing methods would be difficult. It's a preferable notion to acquire and use variety of data sources, particularly those that haven't been thoroughly investigated in past research.

Serafini et al. (2020)They have proposed statistics plus deep-learning models for predicting the regular weighting value of bitcoin and that is the most renowned cryptocurrency stock exchange. They have used various collection of finance and sentiment characteristics to train ARIMAx plus LSTM-based RNN's model, and they found that optimal combination is formed of the solo BTC valued price as well as tweet sentiment. They investigated the predictive ability of social media sentiments, as well as analytical plus deep-learning methodologies for predicting bitcoin's future market. They examine financial and sentiment elements collected from economics and public data and illustrate how sentiment would be the most important component in determining bitcoin market prices.Aggarwal et al. (2019) The ARIMA with exogenous input parameter (ARIMAx) and recurrent neural network were two models utilized for bitcoin forecasts (RNN)as per author. Because of inclusion of researched sentiment component, both models obtain ideal outcomes on new estimates, with a value of mean squared error is less than 0.14 percent. In future scope they suggested to compare their ARIMAx model to other machine learning algorithms for market forecasting, such as CNN and GAN algorithms.

The goal of this work is to develop a model that can predict stock price movement on national stock exchange through opinion mining plus clustering method. They employed domain-specific models to estimate stocks, and from every domain, they selected a single stock with the highest capitalisation.Rajput and Bobde (2016) The method that is suggested by authors is unlike previous techniques, which took into account generic mental states or emotions and the stock price prediction model incorporates sentiments from specific subjects inside the firm or sector. Using their technique, the topics and relevant shareholder opinions are automatically collected from the postings on the message board, as well as clusters of similar types of equities being isolated from others through clustering algorithms.

2.3 Analysis using Neural Network

Any virtual currency is subjected to the analysis to detect and measure uncertainties, plus estimate their effect on outcomes using actual market value. Cryptocurrency is a type of encoded currency that is now utilized for shopping, investing, money transfers, and other purposes. %.Garg et al. (2018) Future price data is forecasted in the prediction, that was a bargain compared to prior and real - time data. Various prediction methods have been employed in past to estimate future bitcoin closing prices. The 'forecast' software is used to anticipate future data utilizing time series forecasting employing ARIMA model.

Bitcoin has risen in popularity in over the years and has become a preferred investment option for traders. Unlike equities, land or share, the rate of bitcoin fluctuates due to its own 24-hour trading time and lack of close time. Professional investors need to have a means to precisely forecast the value of bitcoin movement to avoid risk but also maximize financial gain. Moreover, many earlier studies on cryptocurrencies price forecasting have low value of accuracy and were not cross validated also they forecast relatively brief term bitcoin price.Li and Wu (2020) The basic neural network methods for predicting short - range and long-range bitcoin value changes are described in this research.Albariqi and Winarko (2020) Multilayer perceptron along with recurrent neural networks models are their baseline models. The dataset used is through bitcoin blockchain, which spans from mid-august 2010 to October end 2017, with two-day period as well as a maximum of 1300 records. From two days to 60 days, the process models created forecast both short - range and long-range price changes. The findings indicate that long period prediction outperforms short time prediction, including multilayer perception having the good accuracy when forecasting its next 2-month price movement and the recurrent neural networks having best accuracy while forecasting next 28 to 56 days price fluctuation.

3 Methodology

The CRISP - DM approach was utilized to conduct this research, that is an efficient and proven technique for the data mining studies and initiatives.

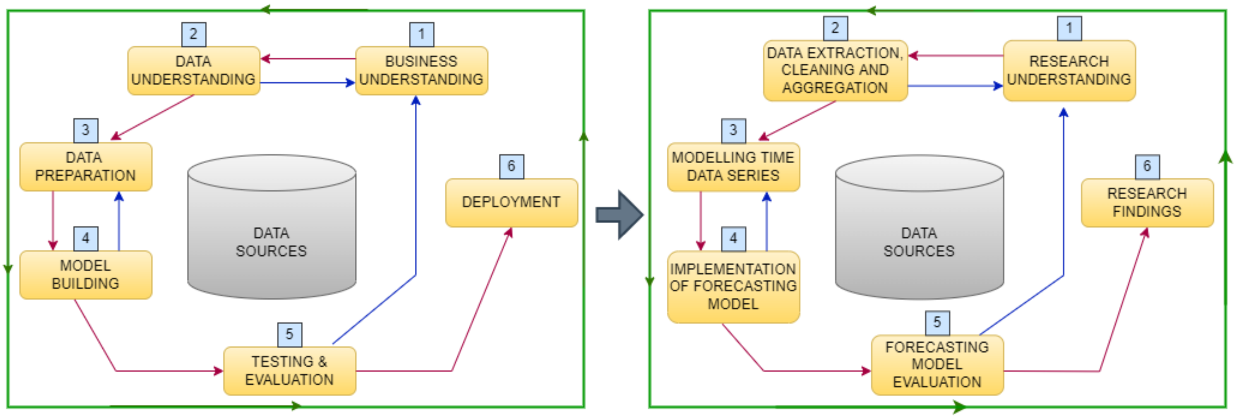

Figure 2: Crisp-DM Method for the project

The CRISP - DM -stands for cross industry standard process for data mining and is a very versatile methodology that allows you to customize it to your individual project necessities while also providing a transition plan for the whole research development process. All aspects of this process are seen in figure 2, and they are described in detail below.

3.1 Business Understanding

In the last decade there have been a numerous technological developments and advancements. But there is one technique that appeared from nowhere, that is now used in almost each industry, including banking, medical, Automobiles and so on is Bitcoins. When bitcoins were originally introduced, this technology drew a lot of attention, and has continued to grow since then. Because of it is vast bull run along with large profits on cryptocurrency investments, the previous three years were a great benefit for bitcoin traders. This has sparked a surge in interest with bitcoin investments, necessitating predictions.It was observed that accurate Bitcoin values were difficult to come by, as its prices are determined by taking requirement and supply into account.

Together with constantly rising market valuation, interest is growing due to different cryptocurrencies presently available in market, including as Ethereum, Gold and others. Currently, there are over 1500 various kinds of virtual currencies are available in the market. They now had around 170 hedge assets dedicated just to cryptocurrencies, with everyday transactions within that space exceeding $15 billion. Because of high volatile market, large market valuation, and shifting asset value, there is a lot of room for analysis and research in this area, and they will be working on accuracy of projecting cryptocurrency values.

3.2 Data Understanding

For this research, data was gathered from the websites such as financialmodelingprep and Kaggle, which allow users to obtain free virtual currency historical data. The Past data Bitcoins prices is taken from Kaggle. [1]The bitcoin data set contains more than 4 million

[1]https://www.kaggle.com/mczielinski/bitcoin-historical-data

rows which shows minute wise each bitcoin transaction. We will use weighted value in predicting the bitcoin prices because that is ratio of values to volume traded across the time horizon and also is commonly used for the financial assets. [2]

3.3 Data Preparation

The relevant historical bitcoin price dataset from year 2012 was obtained from Kaggle. To implement SARIMAX algorithm, we have shown the relationship between Bitcoins with other currencies like Stock Price, Ethereum and Gold. The Data for these factors is taken from Financialmodelling website which allow users to obtain free virtual currency data. The closed and opened prices for currencies, and higher and lower prices, the volume, plus the currencies weighted value, are among the properties retrieved, which are like those of the stock prices.The massive volatility of bitcoin prices since year 2017 shows sharp spikes.The each dataset was checked for NA and Null values.The price data was analysed to see if there were any trends or seasonality exists. It was discovered that the variance and mean of Bitcoin data changed over time.

3.4 Model Designing

The following are the 3 model's applied in this research for time-series prediction of bitcoin prices.

3.4.1 RNN Model

Apple's Siri application and Google's voice control both uses recurrent neural networks (RNNs), which is a state-of-the-art method for time series data.It is a machine learning technique that retains its input because of its internal memory, making it ideal for tackling problems requiring sequential data.This deep learning algorithms provides excellent outcomes. In this research, we'll look at how we can forecast the Bitcoin prices using data from the last nine years.Alessandretti et al. (2018)

3.4.2 LSTM Model

Long short -term memory, often known as LSTMs, are a type of Recurrent Neural Network that can learn from long term dependency. This implies that, in comparison to Recurrent neural network, they are far better at remembering data for longer periods of time.Alessandretti et al. (2018) The deep learning methodology allows the training of huge architectures, and it is more error-resistant. The LSTM model features a network that consists of numerous layers, including an input layer and output layer, having one or more hidden layers. It continues to learn throughout period and is made up of recall and forget gates which help decide the significance and quality of the data to be transferred.

3.4.3 SARIMA and SARIMAX Model

A SARIMA Model stands for seasonal autoregressive integrated moving average and is a level up from the ARIMA model that uses seasonal patterns as a basic principle.Serafini et al. (2020) It introduces three new hyper - parameters for seasonal component of time series: i.e., autoregression (AR), second is differencing (I), and third is moving average

[2] `https://financialmodelingprep.com/api/v3/`

(MA), and also an extended variable for seasonality period. SARIMAX is an extended version of SARIMA, where X is an additional variable and is the vector of exogenous factor, named SARIMAX (p,d,q) (P,D,Q)S (X). In this approach, finite differencing is utilized for making stationary data from a non-stationary one. Model recognition, parameter prediction, and diagnostics are frequently included in this model.The m variable has an impact on P, D, and Q variables. For monthly returns, an m of 12 indicates a yearlong seasonal cycle.

4 Implementation

Implementation flow for this research is depicted in Figure 3. Dataset is extracted from the FinanceModeling website API, then data pre-processing is performed, which includes data cleansing, re-sampling. The dataset is made ready for the time-series analysis. The 4 models are then created after applying the prediction algorithms. Its outcome is then reviewed for all the models using evaluation measures, and the results are compared to determine the optimum forecasting algorithm.

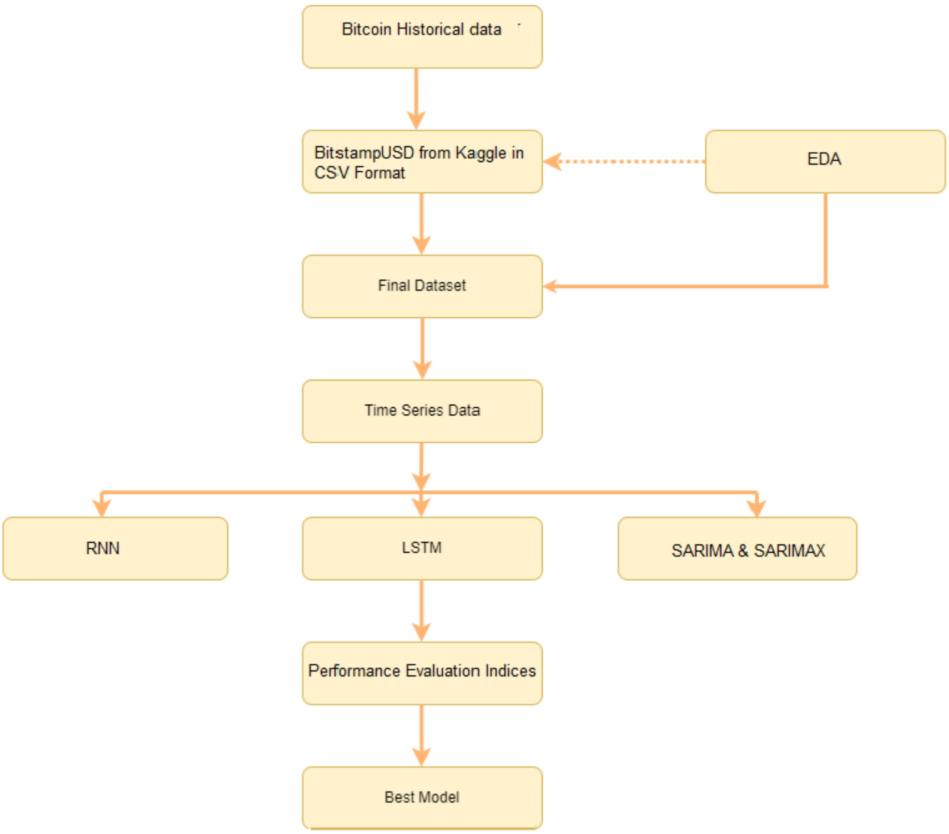

Figure 3: Project Implementation Flow

4.1 Exploratory Data Analysis

The timestamp values are shown in Unix Time form. The column timestamp with no trade or activity are stuffed with NaNs. Since the dataset contains more than 4 million records there were quite a few NaN values. There are three of the most popular Bitcoin exchanges. The historical prices from them was retrieved, Then the "Weighted Price" column was used to integrate them into the single dataframe.

The Data is checked for Null values using isna() function and there were 1243608 cords with nulll values as the timestamp for those records were absent. Created the Date colmn using Timestamps.Since this dataset is available on minute basis for each day, we have resampled it to a daily basis because the data is massively volatile and investors will consider the close price at the end of the day before investing. We have used Interpolation technique to fill in blank values as we can't afford to loose the three records whose weighted price is NaN in 2015 as it will affect the prediction model.The linear interpolation is the process of estimating a null value by finding patterns in in ascending order. In a nutshell, it calculates the approximate value in almost the same ascending sequence as the preceding values.

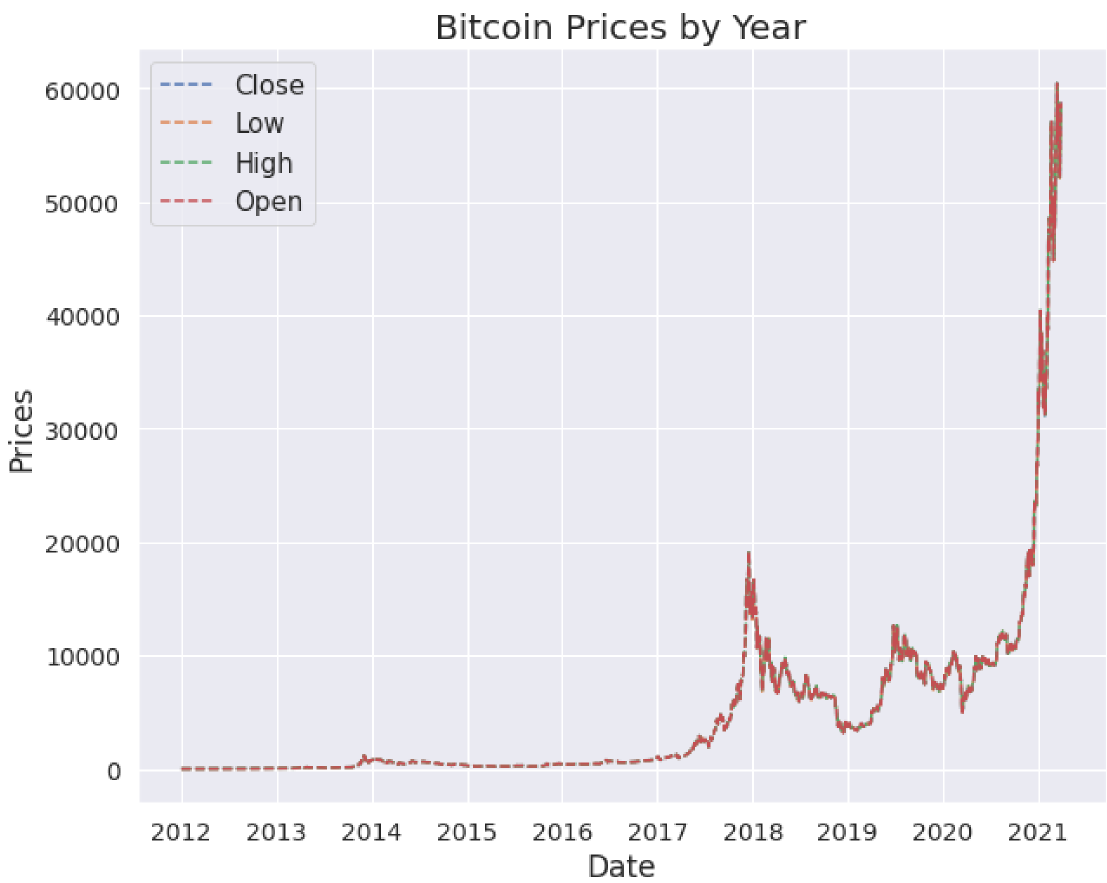

Figure 4: Growth in Bitcoin Prices over the years

Figure 4 shows the massive growth of bitcoin prices over the year. The value of Bitcoin was zero when its was first launched in 2009. Its price increased to \$.09 in July 2010. in 2011, the price surged again, reaching from \$1 towards \$29.60 by June 2011, a growth of 2,960 percent over three month. Following that, bitcoin market had a dramatic downturn, with price dropping at 2.05 dollar by mid-November.The price grew from \$4.85

until May 9 over to 13.50 dollar by August 15 in subsequent year.

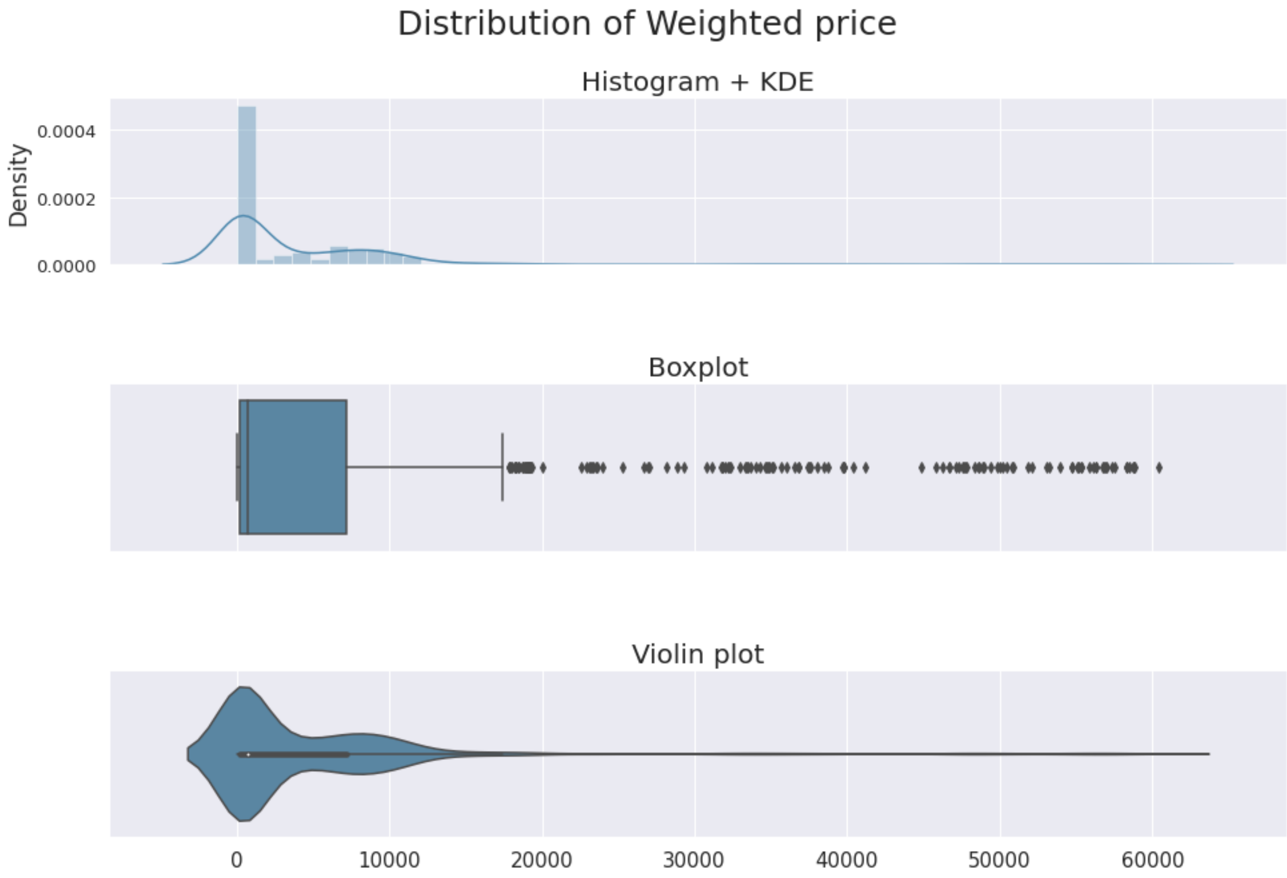

Figure 5: Distribution of Weighted Price

Figure 5 depicts the Distribution of weighted price in detailed manner with the plots. Weighted price is calculated by adding all of the values, multiplying by trade volume, and afterwards dividing by the total volume. The histogram shows the right skewed distribution in the data with the long tail to the right. Also, the plot shows bi-modal behavior with first peak in the range from 0-1000$ and second from 7000-9000$. The Box-plot and violin plot suggests that the majority of the data is concentrated from 07000$ with upper whisker till the 17000$. As the value of bitcoin was still till the beginning of year 2017 and they started growing after 2017. Thus, we can see some outliers in the data with value more than 60000$.

From the figure 6, we can illustrate that the volume of bitcoin is decreasing as the weighted price is increasing and vice versa. This is because people tend to invest more when the prices are down.

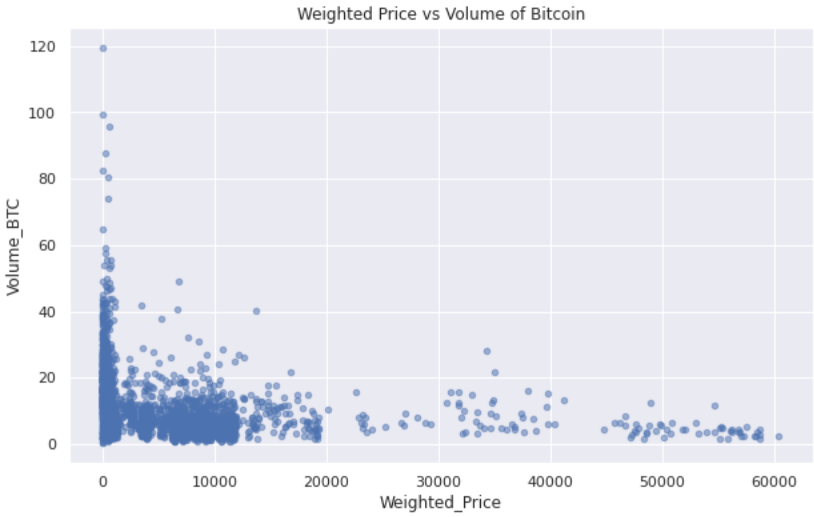

Figure 6: Weighted Price vs Volume of Bitcoin

From the figure 7, we can illustrate that the volume of currency is increase as the weighted price is increasing as these two are directly proportional to each other. Though, we can see the same behavior as the volume of bitcoin that the higher the price the lower the volume.

Figure 7: Weighted Price vs Volume of Currency

From the figure 8, we can depict that there is very less difference till 2017. But, after mod 2017 we can see the boom in the data and huge variance in the daily difference between the weighted price. In the year 2021, we can see huge fluctuations as there were announcements from the different sources about the use of bitcoin in the retail market.

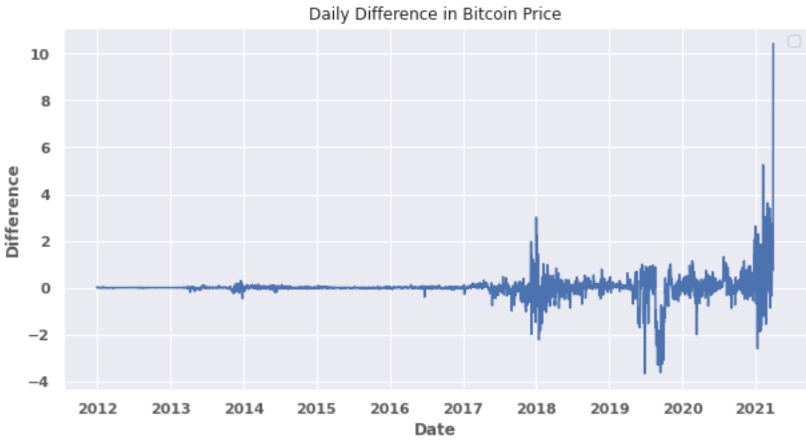

Figure 8: Daily Difference in Bitcoin Price

In the below graph, we have checked the correlation between Bitcoin, Ethereum, Gold, Forex data(EUR_USD) and Stocks. We found that the ETH and EUR_USD are less correlated with correlation index of less than 0.50, but the Gold and Stocks data are more correlated to BTC with CI of 0.65 and 0.90 respectively. Hence, we can use the **sp500** data as an exogenous variable to check its effect on the model.

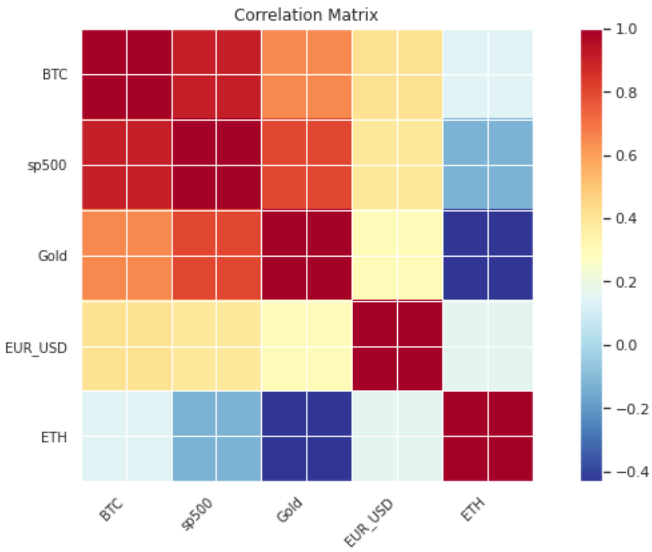

Figure 9: Correlation Matrix for Different Currencies

4.2 Recurrent Neural Network

4.2.1 Data Transformation

Before we start the model we need to split the data into 95% training and 5% testing datasets. We have applied min-max scaler function on the weighted price column so that it will contain the values between 0 and 1; 0 being the lowest and 1 being the highest. For modeling the data we need to convert it to 3D to run RNN on top of it as the input to RNN should be three-dimensional, where first dimension is the samples and a sequence is a one sample.

Figure 10: Scaled Bitcoin Weighted Price

In our case we have 3200 samples and the second dimension is the time steps. We have implemented the time-steps =10, so for a single sample it will create a sequence of 10 time-steps to predict the estimate for the 11th time. We have created such dataset by using for loop and reshape function to get the last dimension which is nothing but the number of features which in our case is only 1.

4.2.2 Model Implementation

In this study, we are implementing a four layer network with an output layer detailed as below.

First Layer: The first layer consist of 10 units which will be connected in a vertical manner for each of the inputs. We have used **ReLu activation** function which will return only positive value otherwise it will return 0 if it is negative. Also, we have set the **return_sequences** as True because it will return the 3D sequence to the next layer as input. We have added a **Dropout layer** which helps in preventing the overfitting of the data. This dropout layer sets the 20% of the input units as zero in each step. Inputs which are not dropped are scaled up by 1/(1-0.2) such that the overall input sum is unchanged.

Second Layer:
In the second layer we have increased the number of units to 50 with the ReLu activation and return_sequences as True. Also, the dropout of 20% is considered in this layer.

Third Layer:
In the third layer, we have kept everything same as second layer except the activation technique. Here, we are using the **tanh** activation which takes any real value and outputs it in the range from -1 to 1. It is very similar to sigmoid function as it has the same

S-shape and it is widely used in the time series forecasting.

Fourth Layer:
In this Simple RNN layer, the output will be 2D tensor of the shape (32, 100) where 32 is the batch size and 100 is the number of unit in the layer. We have also considered the dropout of 20 percent in this layer.

Output Layer:
This layer is responsible for the generation of the final result which is scaled bitcoin prices. It takes input from the layers before and performs calculations with the neurons to compute the output.

Model Settings:
In this model we have used **adam** optimizer as it is computationally efficient, low memory requirements and easy to implement. It is also helpful in forecasting the non-stationary data. Also, loss function used here is **mean_squared_error** which is the average of squared differences between the forecasted and real values. It is the default and preferred method in regression. Its result is always positive irrespective of the predicted and actual values.

Model fitting:
We have set the epochs=100 which means we are going to run the network with all the data 100 times. Also, the batch_size is 32 which means the number of samples processed in each cycle is 32. We have set the value as 32 because it impacts how quickly a model learns the training data and small batch sizes learn the model quickly and accurately. Lastly, we have fitted the model on the daily training dataset.

4.3 LSTM Model

4.3.1 Data Transformation

LSTM is sensitive to the scale of the data, hence we have implemented the same transformation as we did for the RNN model. Means, we have scaled the data first and then transformed it to the 3D so that we can pass it through the LSTM model.

4.3.2 Model Implementation

The Long Short-Term Memory network is a type of RNN which is trained by using Backpropagation Through Time, and overcomes the problem of vanishing gradient. In LSTM, there are memory blocks instead of neurons that are connected through the layers. The network has a visible layer with 1 input and a hidden layer with 256 LSTM block with an output layer that makes prediction for scaled weighted price. Also, we added a layer with **dropout** of 20%. By default, the sigmoid activation function is used for the LSTM blocks.

Model Settings
Here, we are using the same **adam** optimizer and loss function **mean_squared_error** for the error monitoring and optimization.

Model fitting:
We have set the epochs=100 which means we are going to run the network with all the data 100 times. Also, the batch_size is 50 which means the number of samples processed in each cycle is 50. Finally, we have fitted the model on the daily training dataset.

4.4 SARIMA and SARIMAX Model

4.4.1 Data Preparation

Stationarity:

Before sending the data to the model, it is important to check the stationarity in the model. We have applied the resampling technique to get the data by quarterly and monthly in two different datasets. Then we have checked the stationarity of the weighted price column in these two datasets along with the daily data by the help of Dicky-Fuller stationarity test. None of the datasets have shown the stationarity and hence we need to transform the data to check the stationarity. We have applied Box-cox transformation which is used to transform non-normal variables to convert into normal shape. But, still all the three dataset targets are non-stationary. Then we have checked the differencing using pandas diff function which will check the difference between the adjacent observations and it shows the stationary difference for the two datasets daily and monthly as the p-value is less than 0.05. But, the weighted price variable is still non-stationary.

Seasonal Decomposition:

Now, we are going to check the seasonal decomposition for daily and monthly data.It shows the abstract of timeseries and devide it into the core components such as Trend, Seasonality, Differentiation and Noise. Seasonality of the Time Series can be analyzed in two ways: additive or multiplicative.In additive method the difference of distinct component is calculated and added to the model however in multiplicative method as its name suggest the difference is calculated and multiplied and then added to the error component. Problems in the actual world are chaotic and noisy. The data may or may not be Additive or multiplicative. There could be an upward pattern following by a downward trend. There might be non-repeating phases combined with other seasonality components that repeat.A output object is returned by seasonal decompose() and the object includes arrays that can be used to retrieve four component of decomposition data.The mean values in the time series is called the level.The increasing or falling value in sequential data is referred to as the trend.Seasonality is the series' recurring short-term phase.The random variance in the time series is referred to as noise. We tried showing the seasonal decomposition on daily basis but since there were massive volatility the output were messed up and hence are showing it on monthly basis.

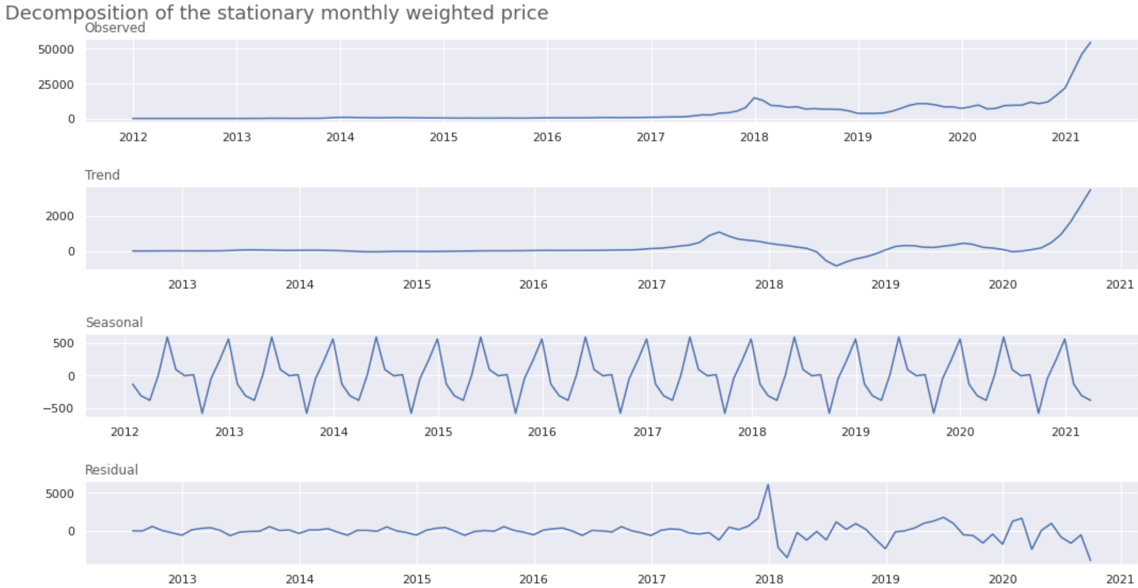

Figure 11: Decomposition of the stationary Monthly Weighted price Diff

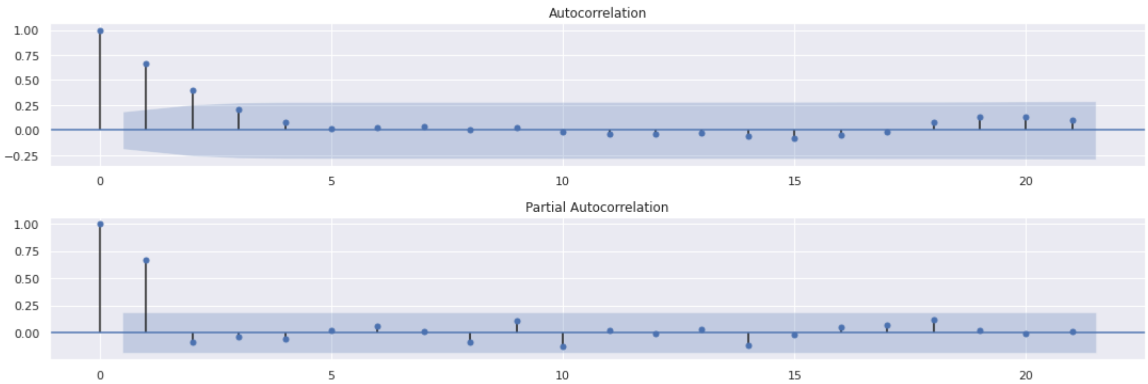

Figure 12: AutoCorrelation and Partial AutoCorrelation

The autocorrelation element shows the strength of given observed datapoint compared to previous observed datapoint, hence autocorrelation as well as partial autocorrelation factors were developed to analyse trends in the dataset of the mentioned timeseries.As illustrated in above figure the positive Correlation is visible within first to four lags.The majority of readings are observed inside blue shaded region, that is the insignificant zone, implying that seasonal elements may be present in residuals.

Bitcoin and Stocks Price Data for SARIMAX:

As we have analysed in the EDA part, we have got the maximum correlation index for the Stocks and Bitcoin. Hence, we will try to add the exogenous variable to the existing SARIMA model and re-run the model to find the difference between the two models. For this purpose, we have merged the Bitcoin daily data with the **sp500** data and resampled it for **quarterly** data. We have considered quarterly as we have applied model on monthly which is not giving the significant results. In this dataset, we have NULL values of **sp500** (Stocks) for the weekends and hence we have used **forward fill** technique considering the Stock price remains same over the weekend.

4.4.2 Model Implementation

In this model, we will iterate the model to get the optimum parameters using AIC values for PDQ and seasonal parameters(PDQ) where period is 12 months for monthly data. We got the values for PDQ and S_PDQ as (1, 1, 1) and (0, 1, 1, 12) respectively with the Lowest AIC value.

Model Settings
Here, we are using the same **adam** optimizer and loss function **mean_squared_error** for the error monitoring and optimization.

Model fitting:
We have set the epochs=100 which means we are going to run the network with all the data 100 times. Also, the batch_size is 50 which means the number of samples processed in each cycle is 50.

5 Evaluations and Forecasting

5.1 Evaluations

The effectiveness and quality of all the models are assessed once they have been implemented. The values of various Model Performance Indices such as RMSEs (Root-Mean_Square_Error), MSE (Mean_Square_Error), MAE (Mean_Absolute_Percentage) and R2 are the evaluation metrics applied. A strong R2 value, particularly within 0.7 to 1, indicates a maximum correlation between both observed and the predicted values. Weak error values indicate improved performance of the model. The outcomes for all the models were achieved and discussed thoroughly in next section.

Table 2: Evaluation Results

Metrics	R Square	MAE	MSE	RMSE
RNN	0.7360	7295.26	64133943.73	8008.36
LSTM	0.9519	2476.68	10958440.29	3310.35
SARIMA	0.4618	1541.77	35835996.92	5986.31
SARIMAX	0.6173	3408.76	24443437.62	4944.03

The RNN and LSTM model is used to estimate the value of Bitcoin over a 169-day timeframe while the SARIMA model estimates the monhtly predictions for last 6 months and SARIMAX eastimates the last two quarters. Table 2 shows the findings for each of evaluation metrics for all the models. The results of LSTM and RNN appear to be highly promising as compared to SARIMA and SARIMAX, with R2 values greater than 0.7. For LSTM, the R2 value of 0.95 indicates that it is one of the strongest model for price predictions. It implies that LSTM model gives better results and is a good fit.The values of MSE, MAE and RMSE appear to be significantly higher possibly due to the current Bitcoin price fluctuations because of several reasons which may have occurred in these figures. The prices predicted using LSTM Model are shown in below Figures and there is a slight lag between the actual price and predicted prices. As it is evident, this model performs significantly better than the other three models.

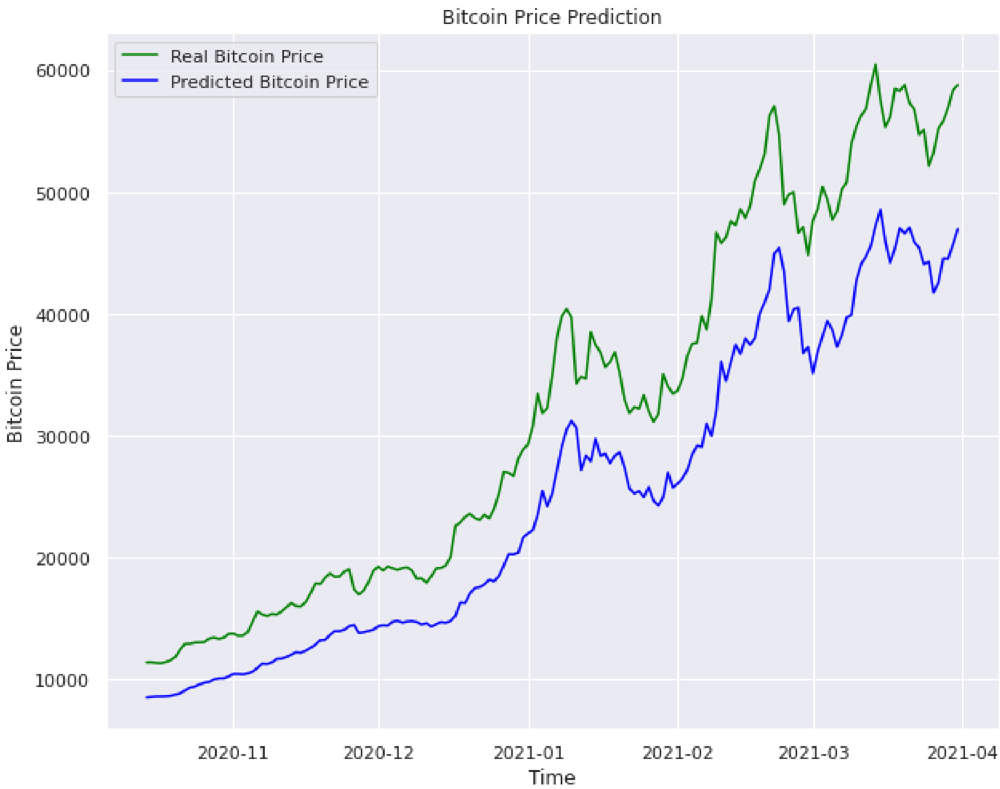

Figure 13: Model 1 - Bitcoin Price Prediction Using RNN

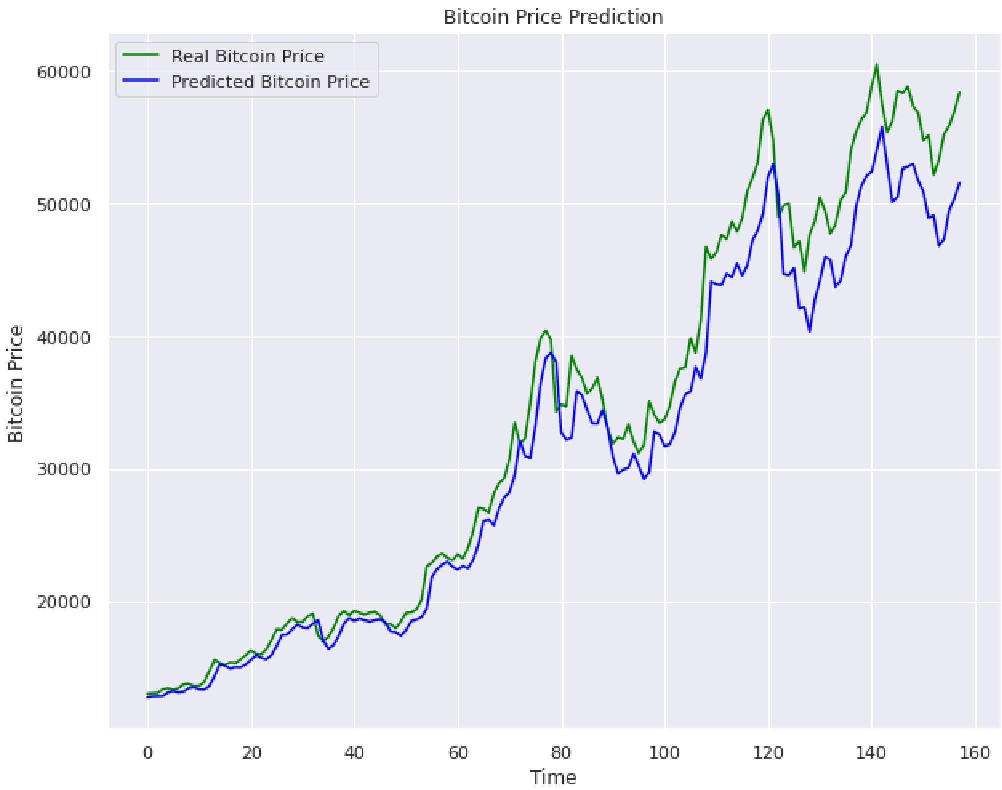

Figure 14: Model 2 - Bitcoin Price Prediction Using LSTM

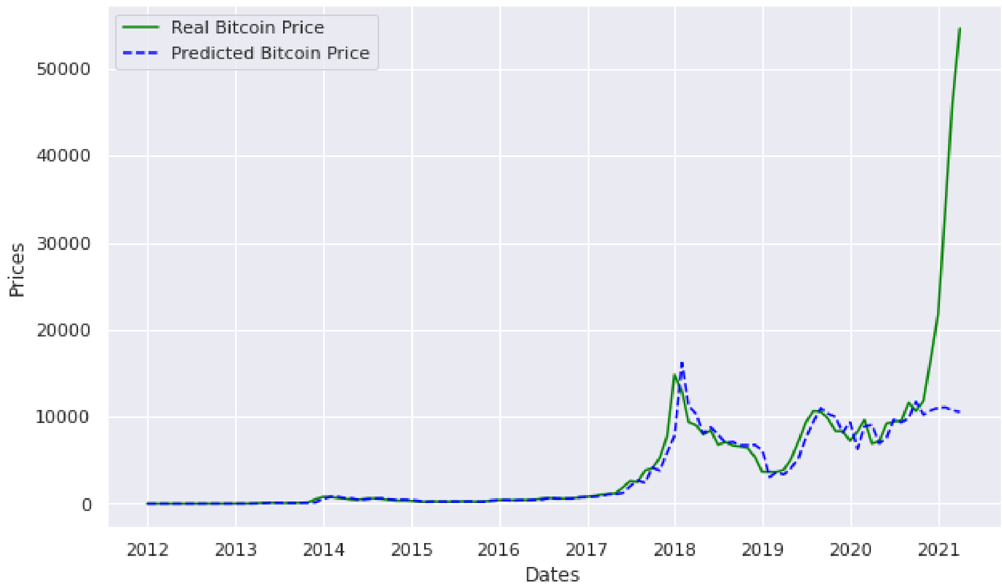

Figure 15: Model 3 - Bitcoin Monthly Price Prediction Using SARIMA

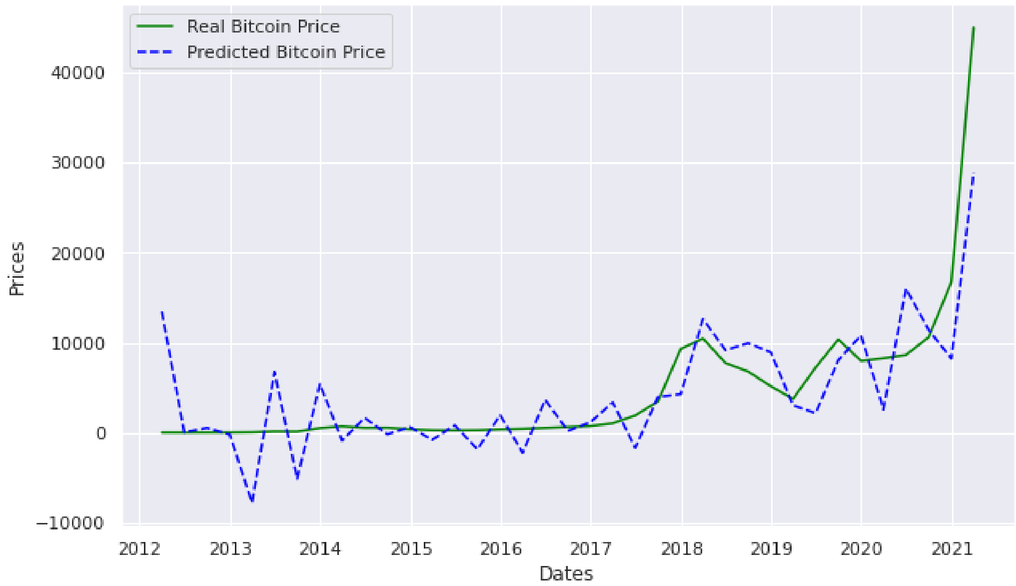

Figure 16: Model 4 - Bitcoin Quarterly Price Prediction Using SARIMAX

5.2 Forecasting

From the below forecasting graphs, we have estimated that the Bitcoin prices may reach upto 115K USD till February 2022 using the SARIMA model and 105K USD till 2022-Q1 using the SARIMAX model. It can probably be happen as the Bitcoin target till 2025 is of 500K USD as per the researchers.

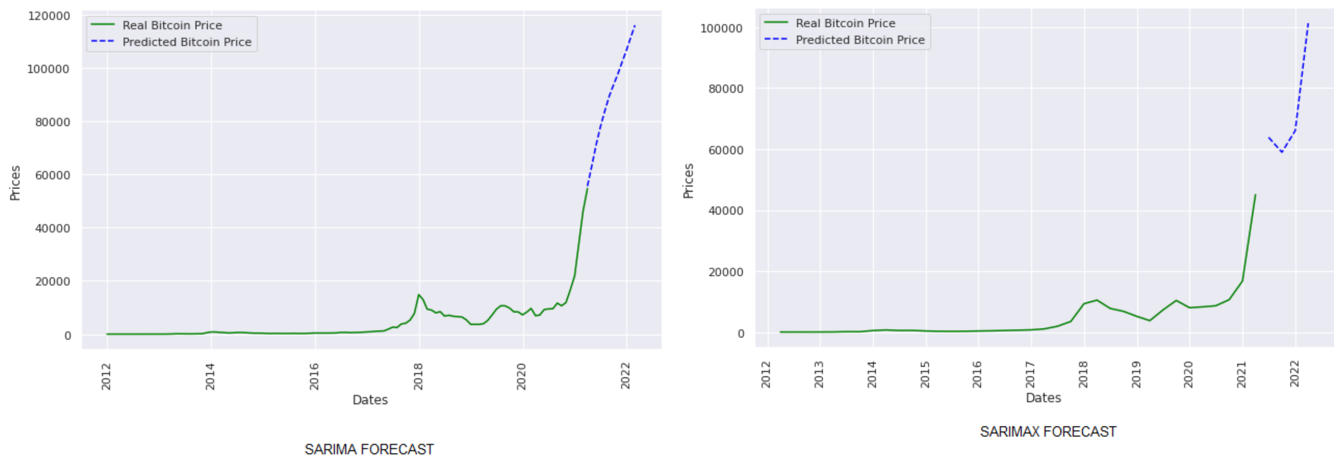

Figure 17: Bitcoin Price Forecasting Using SARIMA and SARIMAX

6 Discussion

Upcoming data is forecasted in the prediction procedure, and that is a deal compared to prior and real - time data. Various prediction methods have been employed previously to estimate future Bitcoin closing prices. Three of the created deep learning model (RNN, LSTM, SARIMA and SARIMAX) are being evaluated and compared. The major goal of this research is to evaluate the effectiveness of newly created models with other state-of-the-art algorithms that's been used to predict the price of bitcoins over the years. The obtained findings are reported Based on R2 values shown in the table. we can conclude that LSTM model beats both SARIMA and SARIMAX based on price correlation metric between observed and predicted prices.However Implementing SARIMAX model was a novel approach to predict the price of bitcoins.We took Stock Price data as an exogenous variable and based on the correlation we built the model and got R2 value of 0.61 which is avarage.

Table 3: Evaluation Results

Metrics	**R Square**	**MAE**	**MSE**	**RMSE**
RNN	0.7360	7295.26	64133943.73	8008.36
LSTM	0.9519	2476.68	10958440.29	3310.35
SARIMA	0.4618	1541.77	35835996.92	5986.31
SARIMAX	0.6173	3408.76	24443437.62	4944.03

The architecture of each of the technique is significantly distinct, as are the strategies they utilize to forecast prices. The research findings are regular and not outstanding while compared versus state of art research papers and it can be linked to two different factors. The first constraint is that certain historical bitcoin prices are examined for prediction in this study, and no other variables like mining time, COVID-19 can affect prices were considered carefully. Furthermore, the relatively large error levels could be related to the growth and drop of bitcoins price within last 2 year, since most of research evaluated and referenced uses data up until 2021 and it doesn't ignores the second big hike in the bitcoins historical price, which happened in 2019. Another thing to consider is significant disparity in transaction volumes. The Bitcoin prices are massively growing since year 2020. PayPal just stated that they will allow users and traders to purchase, sell, store, and accepts Bitcoins and other virtual currencies as payment. similarly, other companies and countries like Tesla also started accepting bitcoins as a Mode Of payment. However, it should be highlighted that RMSE levels for SARIMAX produced unexpected results, indicating that RMSE value should be improved or optimized.

7 Conclusion and Future Work

This section brings the study to a close by highlighting the most important findings and opportunities for future work in relation to research questions and objectives outlined in section 1.
The data on Bitcoin prices play a significant role. The virtual cryptocurrency used in

this research have followed a similar trend till 2017 and it started fluctuating from mid 2017 and boosted in 2021, therefore the results indicate notable variations in models' efficiency'. The results and charts show that LSTM outperforms RNN with R2 of 0.73, SARIMA and SARIMAX with R2 value of 0.41 and for SARIMA it was 0.61 respectively. it came to forecasting bitcoin prices.To summarize, of all Four models LSTM and RNN performed well, and we can be concluded that the LSTM model performed best in this study with aan R2 value of 0.95. As discussed in Discussion section we implemented SRIMAX with an exogenous variable that is stock price 500 taken from an website and got R2 value of 0.61.In Future we can do research on other factors which causes the volatility of bitcoin prices. There are some essential aspects that can be considered to improve the performance of the models. For instance, if we can reduce the fluctuation in prices by analysing external factors such as mining time, commodity prices or other virtual currencies.

Acknowledgement

As I am now completing the MSc in data analytics from the national college of Ireland with much thanks and joy. I literally have no words to express my sincere thanks to my supervisor Prof. Jorge Basilio of NCI for his support, mentor ship, and most importantly, his unwavering devotion to high academic standard and experience. I had a great time working with him and all my past NCI professors, and I'm forward to see what future hold for me. A difficult year that I could not have done without the unwavering support of people I am fortunate enough to be in my life. First and foremost, I want to express my gratitude to my Mom and friends, Vinit and Colm for their continuous encouragement and wisdom over the years.

References

Aggarwal, A., Gupta, I., Garg, N. and Goel, A. (2019). Deep learning approach to determine the impact of socio economic factors on bitcoin price prediction, *2019 Twelfth International Conference on Contemporary Computing (IC3)*, IEEE, pp. 1–5.

Albariqi, R. and Winarko, E. (2020). Prediction of bitcoin price change using neural networks, *2020 International Conference on Smart Technology and Applications (ICoSTA)*, IEEE, pp. 1–4.

Alessandretti, L., ElBahrawy, A., Aiello, L. M. and Baronchelli, A. (2018). Anticipating cryptocurrency prices using machine learning, *Complexity* **2018**.

Garcia, D., Tessone, C. J., Mavrodiev, P. and Perony, N. (2014). The digital traces of bubbles: feedback cycles between socio-economic signals in the bitcoin economy, *Journal of the Royal Society Interface* **11**(99): 20140623.

Garg, S. et al. (2018). Autoregressive integrated moving average model based prediction of bitcoin close price, *2018 International Conference on Smart Systems and Inventive Technology (ICSSIT)*, IEEE, pp. 473–478.

Jiang, W. (2021). Applications of deep learning in stock market prediction: recent progress, *Expert Systems with Applications* **184**: 115537.

Joshila, G. L., Nandini, D. U., Kalaiarasi, G. et al. (2021). Price prediction of bitcoin, *2021 5th International Conference on Trends in Electronics and Informatics (ICOEI)*, IEEE, pp. 113–116.

Li, X. and Wu, W. (2020). A blockchain transaction graph based machine learning method for bitcoin price prediction, *arXiv preprint arXiv:2008.09667* .

Patel, M. M., Tanwar, S., Gupta, R. and Kumar, N. (2020). A deep learning-based cryptocurrency price prediction scheme for financial institutions, *Journal of Information Security and Applications* **55**: 102583.

Rajput, V. and Bobde, S. (2016). Stock market prediction using hybrid approach, *2016 International Conference on Computing, Communication and Automation (ICCCA)*, IEEE, pp. 82–86.

Serafini, G., Yi, P., Zhang, Q., Brambilla, M., Wang, J., Hu, Y. and Li, B. (2020). Sentiment-driven price prediction of the bitcoin based on statistical and deep learning approaches, *2020 International Joint Conference on Neural Networks (IJCNN)*, IEEE, pp. 1–8.

Teichmann, F. M. J. (2018). Financing terrorism through cryptocurrencies–a danger for europe?, *Journal of Money Laundering Control* .

Velankar, S., Valecha, S. and Maji, S. (2018). Bitcoin price prediction using machine learning, *2018 20th International Conference on Advanced Communication Technology (ICACT)*, IEEE, pp. 144–147.