CRYPTO CURRENCY PRICE PREDICTION USING DEEP LEARNING

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for the degree of
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Certificate

This is to certify that the project entitled Crypto Currency Price Prediction Using Deep Learning is a bonafide work of **Shivprakash Vishwakarma(Roll No. 58), Afzal Siddique(Roll No. 49), Swaraj Kondlekar(Roll No. 33)** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of Undergraduate in **DEPARTMENT OF INFORMATION TECHNOLOGY.**

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This mini project report is entitled **Crypto Currency Price Prediction using Deep Learning** by **Shivprakash Vishwakarma(Roll No: 58), Afzla Siddique(Roll No:49), Swaraj Kondlekar(Roll No: 33)** is approved for the degree of **DEPARTMENT OF INFORMATION TECHNOLOGY.**

Examiners

1.

2.

Date:

Place:

Declaration

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data /fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which havethus not been properly cited or from whom proper permission has not been taken when needed.

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Date:

Abstract

The decentralization of cryptocurrencies has greatly reduced the level of central control over them, impacting international relations and trade. Further, wide fluctuations in crypto Currency price indicate an urgent need for an accurate way to forecast this price. This project proposes a method to predict crypto Currency price by considering various factors such as market cap, volume, circulating supply, and maximum supply based on deep learning techniques such as the recurrent neural network (RNN) and the long short-term memory (LSTM),which are effective learning models for training data, with the LSTM being better at recognizing longer-term associations.

Acknowledgement

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ABBREVIATIONS:

ARIMA: Autoregressive integrated moving average

LSTM: Long-Short Term Memory

RNN: Recurrent Neural Networks

Chapter 1

INTRODUCTION

1.1 Introduction

Crypto Currency, is a decentralized digital or virtual Currency. Use of cryptography for security makes it difficult to counterfeit. Cryptocurrencies started to gain attention in 2013 and since then witnessed a significant number of transactions and hence price fluctuations. The crypto Currency market is just similar to Crypto Currency market. It has gained public attention and so effective prediction of price movement of crypto Currency will aid public to invest profitably in the system. This project tries to predict the price of Cryptocurrencies like Bitcoin. Deep learning techniques were implemented and the use of Long ShortTerm Memory (LSTM) network proved very efficient in predicting the prices of digital currencies.

1.2 Objectives

1. To implement LSTM model which will be train on available historical data.

2. To forecast the price of Crypto Currency(Bitcoin).

3. To integrate this model in order to develop simple system through which user can interact and perform predictions as per his requirements i.e no. of days for which he/she want to predict the future price of bitcoin.

4. To provide insights of data in graphical format such as bar charts,line chart, comparison between predicted vs actual, accuracy of prediction etc.

1.3 Purpose, Scope & Applicability

1.3.1 Purpose

The Cryptocurrencies like Bitcoin are influenced by many uncertainties factor such as political issue, the economic issue at impacted to local or global levels. To interpretation key of success, factor to providing accurate predictions is complicated work. For the market, we can analyze with any techniques such as technical indicator, price movements, and market technical analysis. To solve the problem regarding the fluctuations there's a need automation tool for prediction to help investors decide for bitcoin or other crypto Currency market investment. Nowadays the automation tools are usually used in common Crypto Currency market predictions, and we can do the same works and strategy on this domain cryptocurrencies.

The purpose of this study is to predict the price of Bitcoin and changes therein using the LSTM model and to build a system which will help common people, investors or business analyst to invest in digital currencies as bitcoin by predicting their future values and to visualize and analyse the pattern of digital currencies .

1.3.2 Scope

Dataset Includes Historical bitcoin market data at 1-min intervals for select bitcoin exchanges where trading takes place. It consists time period of Jan 2012 to September 2020, with minute to minute updates of OHLC (Open, High, Low, Close), Volume in BTC and indicated Currency, and weighted bitcoin price.

Now that our data has been converted into the desired format, let's take a look at its various columns for further analysis.

- The **Open and Close** columns indicate the opening and closing price on a particular day.
- The **High and Low** columns provide the highest and the lowest price on a particular day, respectively.
- The **Volume** column tells us the total volume of traded on a particular day.

- The **Weighted price** is a trading benchmark used by traders that gives the weighted price a security has traded at throughout the day, based on both volume and price. It is important because it provides traders with insight into both the trend and value of a security. To read more about how Weighted price is calculated.

Visualising the Time Series data

```
bitstamp.set_index("Timestamp").Weighted_Price.plot(figsize=(14,7), title="Bitcoin Weighte
d Price")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f78a194b7d0>
```

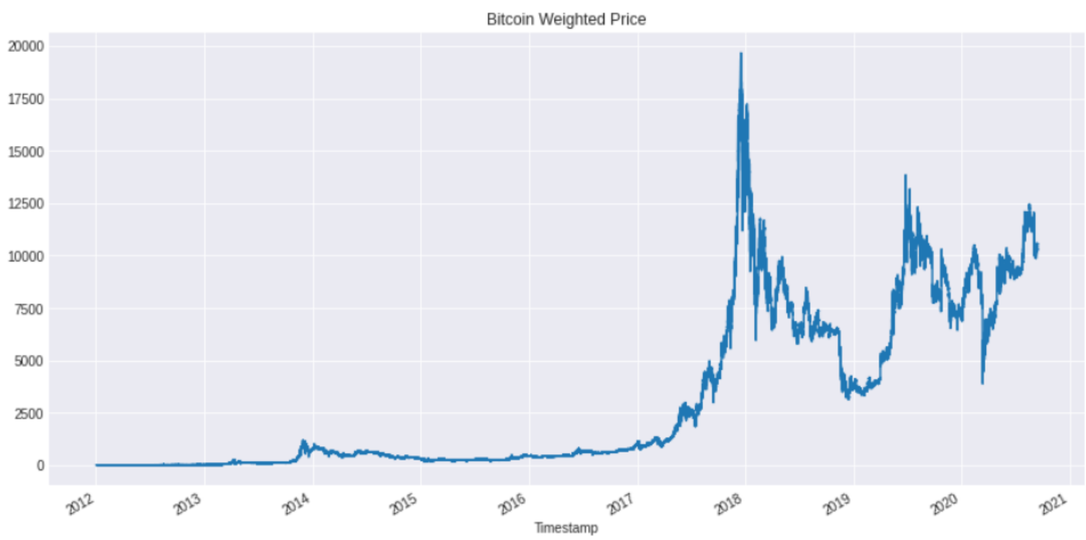


FIG.1 TIMESTAMP

Handling Missing Values in Time-series Data

Imputations Techniques for non-Time Series Problems

Imputation refers to replacing missing data with substituted values. There are a lot of ways in which the missing values can be imputed depending upon the nature of the problem and data. Depending upon the nature of the problem, imputation techniques can be broadly they can be classified as follows:

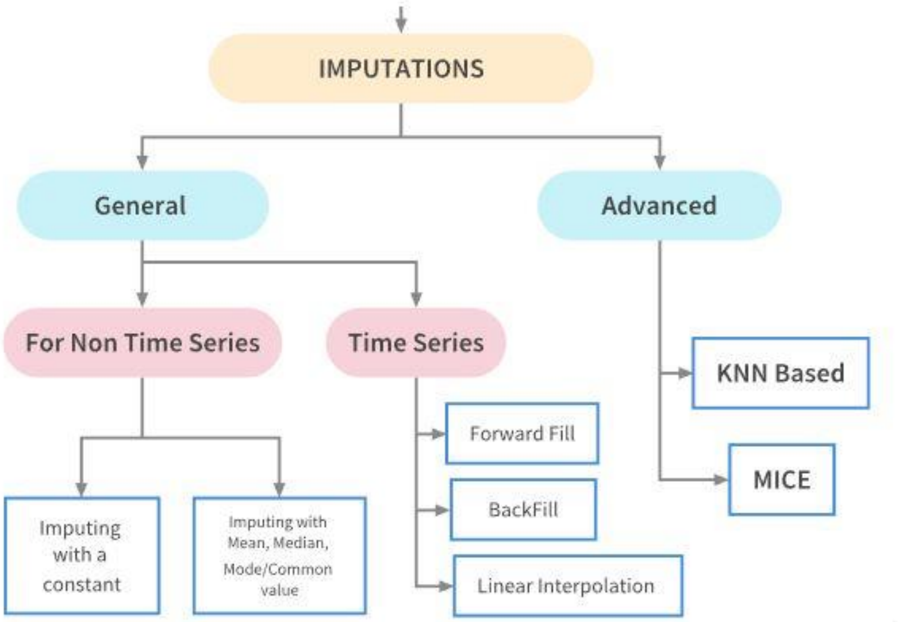


FIG.2 IMPUTATION

```
a['interp'] = a['Weighted_Price'].interpolate()   # Imputation using interpolation
```

Exploratory Data Analysis

Visualizing the weighted price using markers

When working with time-series data, a lot can be revealed through visualizing it. It is possible to add markers in the plot to help emphasize the specific observations or specific events in the time series.

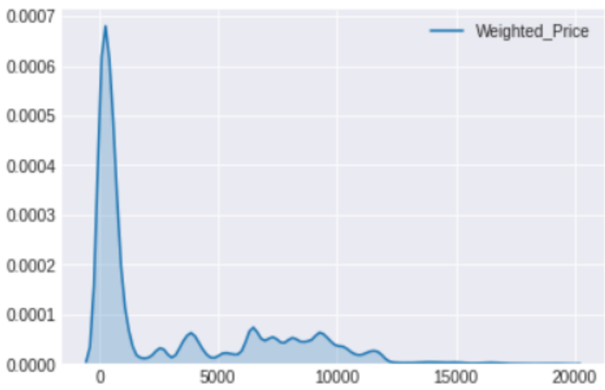


FIG.3

Visualising using KDEs

So there is a downward trend in Crypto Currency prices from Dec-17 onwards till March 2019. We will investigate it further by investigation and with some findings during that period.

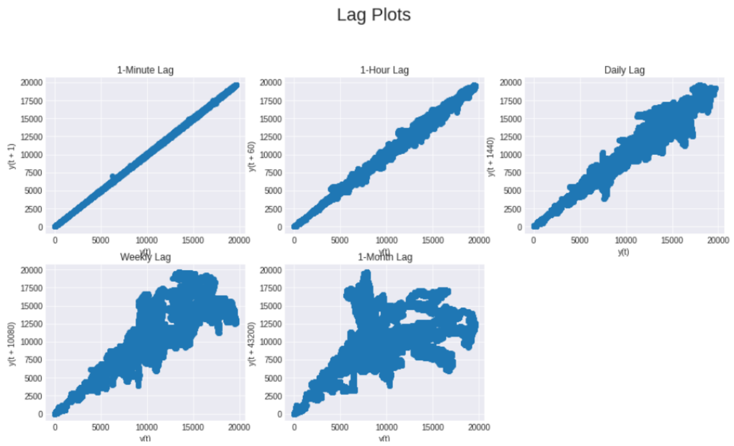


FIG.4 LAGG PLOTS

Visualizing using Lag Plots

We can see that there is a positive correlation for minute, hour and daily lag plots. We observe absolutely no correlation for month lag plots.

It makes sense to re-sample our data at most at the Daily level, thereby preserving the autocorrelation as well.

Time resampling

- data.resample() is used to resample the Crypto Currency data.
- The '1H' stands for hourly frequency, and denotes the offset values by which we want to resample the data.
- mean() indicates that we want the average Crypto Currency price during this period.

KPSS and ADF Test Conclusion

KPSS says series is not stationary and ADF says series is stationary. It means series is difference stationary, we will use differencing to make series stationary.

Feature Extraction

Rolling windows

Time series data can be noisy due to high fluctuations in the market. As a result, it becomes difficult to gauge a trend or pattern in the data.

As we're looking at daily data, there's quite a bit of noise present. It would be nice if we could average this out by a week, which is where a rolling mean comes in.

A rolling mean, or moving average, is a transformation method which helps average out noise from data. It works by simply splitting and aggregating the data into windows according to function, such as mean(), median(), count(), etc.

Benefits : The key benefits of calculating a moving average or using this rolling method is that Our data becomes a lot less noisy and more reflective of the trend than the data itself.

Model Building

To measure the performance of our forecasting model, We typically split the time series into a training period and a validation period. This is called fixed partitioning.

we will opt for a ***hold-out based validation***. Hold-out is used very frequently with time-series data. In this case, we will select all the data for 2020 as a hold-out and train our model on all the data from 2012 to 2019.

We are further building our LSTM model as follows:

```
# Initialising the LSTM
regressor = Sequential()

# Adding the first LSTM layer and some Dropout regularisation
```

```
regressor.add(LSTM(units = 50, return_sequences = True, input_shape = (X_train.shape[1], 1)))
regressor.add(Dropout(0.2))

# Adding a second LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))

# Adding a third LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))

# Adding a fourth LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50))
regressor.add(Dropout(0.2))

# Adding the output layer
regressor.add(Dense(units = 1))

# Compiling the RNN
regressor.compile(optimizer = 'adam', loss = 'mean_squared_error')
```

1.3.3 Applicability

Different organization may consider it as investment portal anyone who wants to buy Crypto Currency i.e Bitcoin can take look at this system. This will help them to properly invest money in with digital Currency lesser chances of losing it. It will majorly be beneficial for the digital Currency brokerage institution as they will get an idea whether the price will rise or fall and as a result will provide a better understanding of the price pattern.

1.4 Achievements

We have successfully build a deep learning Bitcoin prediction model which predicts the bitcoin prices for upcoming 30 days using LSTM. We have roughly build the logic of the final system i.e working of our Final Product.

Chapter 2

LITERATURE SURVEY

2.1 Literature Survey

1. A review of missing values handling methods on Time-Series data:

(Authors: Irfan Pratama, Rini Indrayani, Adhistya Erna Permanasari, October 2016)

In this paper, the description of several previous studies about missing values handling methods or approach on time series data is explained. This paper also discuss some plausible option of methods to estimate missing values to be used by other researchers in this field of study. The discussion's aim is to help figure out what method is commonly used now along with its advantages and drawbacks.

Missing values becomes one of the problems that frequently occur in the data observation or data recording process. The needs of data completeness of the observation data for the uses of advanced analysis becomes important to be solved. Conventional method such as mean and mode imputation, deletion, and other methods are not good enough to handle missing values as those method can caused bias to the data. Estimation or imputation to the missing data with the values produced by some procedures or algorithms can be the best possible solution to minimized the bias effect of the conventional method of the data. So that at last, the data will be completed and ready to use for another step of analysis.

This paper figures missing values handling method from the conventional one to the modern one. Methods such as deletion, mean imputation, and hot decking are considered as conventional method which can be used for more general dataset, while estimation techniques is modern method that specifically picked to handle missing values in time series data.

2. Resampling strategies for imbalanced time series:
(Authors: Nuno Moniz, Luis Torgo, Paula Branco, October 2016)

The objective of this paper is to provide solutions capable of significantly improving the predictive accuracy of rare cases in forecasting tasks using imbalanced time series data. The Paper Extent application of resampling strategies to the time series context and introduce the concept of temporal and relevance bias in the case selection process of such strategies, presenting new proposals. This paper evaluate the results of standard regression tools and the use of resampling strategies, with and without bias over 24 time series data sets from 6 different sources. Results show a significant increase in predictive accuracy of rare cases associated with the use of resampling strategies, and the use of biased strategies further increases accuracy over the nonbiased strategies.

Time series forecasting is a challenging task, where the non-stationary characteristics of the data portrays a hard setting for predictive tasks. A common issue is the imbalanced distribution of the target variable, where some intervals are very important to the user but severely underrepresented. Standard regression tools focus on the average behaviour of the data. However, the objective is the opposite in many forecasting tasks involving time series: predicting rare values. A common solution to forecasting tasks with imbalanced data is the use of resampling strategies, which operate on the learning data by changing its distribution in favour of a given bias.

3. Crypto Currency Price Prediction Using Long-Short Term Memory Model: (Authors: Prashanth J R, Vineetha S Das, July 2018)

This paper tries to predict the price of Cryptocurrencies. Machine learning techniques were implemented and the use of Adam optimizer and Long Short Term Memory (LSTM) network proved very efficient in predicting the prices of digital currencies.

There are lot of cryptocurrencies in the market and in this paper the following cryptocurrencies are selected for study and price prediction, Bitcoin, Ethereum, Ripple, Monero, Litecoin and Dash. The historical data required for price prediction of cryptocurrencies are collected from https://coinmarketcap.com. The methodology of the work consists of several steps data collection, data processing, feature extraction, training Long Short – Term Memory network and predictions using the trained network. The pre-processing involves data reduction, data normalization and data cleaning to get the required dataset. Then it is divided into test dataset and train dataset. Feature extraction selects the features that are to be fed to the LSTM network. In the current case it includes opening, high, low and closing price. Training of LSTM network involves feeding the neural network with data and training the same. The prediction involves assigning random biases and weights. The proposed LSTM model is composed of a sequential input layer an LSTM layer and a dense output layer with linear activation function. The prediction from the model is taken and the mean absolute error is used to ascertain its effectiveness.

4. Prediction of Bitcoin using Recurrent Neural Network:
(Authors: Pratik Mehta, E. Sasikala, march 2020)

The main objective of the work is to predict the Bitcoin prices, one of the most popular and widely used crypto Currency which is a source of attraction for many investors as a source of profit or investment. But the market for the cryptocurrencies been volatile since the day it was first introduced. So, the approach towards the survey is to use LSTM RNN and use the available dataset and train the model to give the highest possible accuracy and to provide a real-time price of the Bitcoin for the following days.

Using Neural Networking Systems the connection between the performance of Bitcoin and the next day's price change of Bitcoin using an Artificial Neural Network Ensemble solution called the Selective Neural Network Ensemble Dependent Genetic Algorithm was discussed, then the neural network using Multi-Layered Perceptron was constructed. The organization was used to predict the price of Bitcoin's next day course through a sequence of nearly 200 blockchain apps over a 2-year cycle to better understand Bitcoin's practicality and utility of real-world applications. With a series of almost 200 blockchain apps over a period of 2 years, the firm was used to predict the next day path of Bitcoin's price to better understand the practicality and utility of it in real world applications. The program was used to predict the next day's market path for Bitcoin with a selection of about 200 blockchain apps over a 2-year span to better understand the practicality and efficacy of real-world applications. An ensemble-based trading methodology was compared over a span of 50 days with a previous day trend following a back-test trading strategy. The former trading strategy produced about 85 percent returns, outperforming the previous day trend following a special trading strategy that yielded about 38 percent returns and a trading strategy that follows the one-time, best MLP (Multilayer Perceptron) model in the ensemble that yielded around about 53 percent. Provides multi-layered perceptron for estimating bitcoin level. Jang and Lee's work which predicts the bitcoin price using Bayesian Neural Network and blockchain information. There are multiple online platforms nowadays, such as CoinTracking, BitcoinCharts, Bitcoinity, and BitcoinWisdom, that enable traders to use many technological analytics tools to identify trends and market feelings that are useful for entering a trade. Several Regression models which was based on Linear Regressions, Random Forests , Gradient Boosting Technology, and Basic Neural Networks. Kim et al. and Li et al found the Bitcoin price volatility to be expected by social evidence.

5. Bitcoin Price Prediction using ARIMA Model:
(Authors: Dr. Jinan Fiaidhi, Ahmer Sabah, Mahpara Anwer Ansari, Zeba Ayaz, preprint 2020)

In this research work, we have investigated bitcoin closing price prediction by using an ARIMA model. Towards this end, at first, we have preprocessed time series data to make it stationary, and then, have searched over feasible (p, q, d) parameters for finding the ARIMA model which minimizes the MSE (Mean Squared Error) of prediction. The results we get indicates that the bitcoin price prediction using the value "closing price" history could result in large MSE values since bitcoin's price is vulnerable to high jumps and fall-downs. On the other hand, the results also confirm that the ARIMA model could be still used for price prediction in sub-periods of the timespan, which is by dividing the timespan to several timespans over which, dataset has a unique trend. Furthermore, we have investigated the effect of the different parameter p, q and d value on the achieved MSE in price prediction. We have elaborated this work by creating web service and high chart for better resolution of graph obtained.

To predict the BTC prices, we have modeled time series using ARIMA algorithm. Models with lower MSE are considered to be the ideal ones. First, we fit an ARIMA (2,1,0) model. This sets the lag value to 2 for autoregression, uses a difference order of 1 to make the time series stationary, and uses a moving average model of 0. Second, we try to fit an ARIMA (0,1,18) model. This sets the lag value to 0 for autoregression, uses a difference order of 1 to make the time series stationary, and uses a moving average model of 18. We tried many combinations of ARIMA for obtaining the lesser MSE value so that we can find the best fit for our model. After fitting the model by passing its parameters we have loaded the testing dataset from the drive again in the same way how we read training dataset. In training we have stored the BTC data collected for January 1st until January 7th, 2020. Finally, we are going to predict the bitcoin closing price and display the Mean Squared error which is the evaluation metric for our predicted Model. We assign the timestamp of the dates to the data frame dates and predict the bitcoin price for seven days using forecast function.

Chapter 3

SURVEY OF METHODOLOGY

3.1 Deep Learning:

Deep learning (also known as deep structured learning) is part of a broader family of machine learning methods based on artificial neural networks with representation learning. Learning can be supervised, semi-supervised or unsupervised.

Deep-learning architectures such as deep neural networks, deep belief networks, recurrent neural networks and convolutional neural networks have been applied to fields including computer vision, machine vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bioinformatics, drug design, medical image analysis, material inspection and board game programs, where they have produced results comparable to and in some cases surpassing human expert performance.

3.2 Tensorflow:

TensorFlow is an end-to-end, open-source machine learning platform. You can think of it as an infrastructure layer for differentiable programming. It combines four key abilities:

- Efficiently executing low-level tensor operations on CPU, GPU, or TPU.
- Computing the gradient of arbitrary differentiable expressions.
- Scaling computation to many devices (e.g. the Summit supercomputer at Oak Ridge National Lab, which spans 27,000 GPUs).
- Exporting programs ("graphs") to external runtimes such as servers, browsers, mobile and embedded devices.

3.3 Keras:

Keras is the high-level API of TensorFlow 2.0. It is an approchable, highly-productive interface for solving machine learning problems, with a focus on modern deep learning. It provides essential abstractions and building blocks for developing and shipping machine learning solutions with high iteration velocity.Keras empowers engineers and researchers to take full advantage of the scalability and cross-platform capabilities of TensorFlow. You can run Keras on TPU or on large clusters of GPUs, and you can export your Keras models to run in the browser or on a mobile device.

3.4 Time Series:

A time series is a series of data points indexed (or listed or graphed) in time order Time series analysis comprises methods for analyzing time series data in order to extract meaningful statistics and other characteristics of the data. Time series forecasting is the use of a model to predict future values based on previously observed values. While regression analysis is often employed in such a way as to test theories that the current values of one or more independent time series affect the current value of another time series, this type of analysis of time series is not called "time series analysis", which focuses on comparing values of a single time series or multiple dependent time series at different points in time. Interrupted time series analysis is the analysis of interventions on a single time series.

3.5 Long-Short Term Memory:

Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning. LSTM networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series. LSTMs have an edge over conventional feed-forward neural networks and RNN in many ways. This is because of their property of selectively remembering patterns for long durations of time. The purpose of this article is to explain LSTM and enable you to use it in real life problems .

3.6 Recurrent Neural Network:

A recurrent neural network (RNN) is a class of artificial neural networks where connections between nodes form a directed graph along a temporal sequence. This allows it to exhibit temporal dynamic behavior. Derived from feedforward neural networks, RNNs can use their internal state (memory) to process variable length sequences of inputs. This makes them applicable to tasks such as unsegmented, connected handwriting recognition or speech recognition.

The term “recurrent neural network” is used indiscriminately to refer to two broad classes of networks with a similar general structure, where one is finite impulse and the other is infinite impulse. Both classes of networks exhibit temporal dynamic behavior. A finite impulse recurrent network is a directed acyclic graph that can be unrolled and replaced with a strictly feedforward neural network, while an infinite impulse recurrent network is a directed cyclic graph that can not be unrolled.

3.7 Pandas:

pandas is a fast, powerful, flexible and easy to use open source data analysis and manipulation tool, built on top of the Python programming language. Its library highlights are as follows:

- A fast and efficient DataFrame object for data manipulation with integrated indexing;
- Tools for reading and writing data between in-memory data structures and different formats: CSV and text files, Microsoft Excel, SQL databases, and the fast HDF5 format;
- Intelligent data alignment and integrated handling of missing data: gain automatic label-based alignment in computations and easily manipulate messy data into an orderly form;
- Flexible reshaping and pivoting of data sets;
- Intelligent label-based slicing, fancy indexing, and subsetting of large data sets;
- Columns can be inserted and deleted from data structures for size mutability.
- High performance merging and joining of data sets;
- Highly optimized for performance, with critical code paths written in Python or C.
- Python with *pandas* is in use in a wide variety of academic and commercial domains, including Finance, Neuroscience, Economics, Statistics, Advertising, Web Analytics, and more.

Chapter 4

REQUIREMENTS AND ANALYSIS

4.1 Problem Definition

The Cryptocurrencies like Bitcoin are influenced by many uncertainties factor such as political issue, the economic issue at impacted to local or global levels One reason why **bitcoin** may **fluctuate** against fiat currencies is the perceived store of **value** versus the fiat Currency. Cryptocurrencies like **Bitcoin** has properties that make it similar to gold. It is governed by a design decision by the developers of the core technology to limit its production to a fixed quantity of 21 million **BTC**. To solve the problem regarding the fluctuations there's a need automation tool for prediction to help investors decide for bitcoin or other crypto Currency market investment.

4.2 Requirements Specification

For implementation in software we will require the following software and hardware specifications:

4.2.1 Software Specification

For implementation we will require applications such as Jupiter Notebook ,Python3.6 or better, Spyder IDE,MS-Excel etc. That can be used to build an environment based on neural network and to train machine based on it.

4.2.2 Hardware Specification

To implement the project we will require a computer with specification such as multicore CPU, graphics card, hard disk upto 500GB, upto 8GB RAM.
Input devices such as keyboard, optical mouse.
Output device: LCD monitor.

4.3 Preliminary Product Description

For making it a hard-core product we will be making a website, which will be using API's of with tech stack of frameworks as,

Frontend – Reactjs, context API/redux, html5, css3, bootstrap5, materialcss.
Backend – django/flask
Database – Mongodb
Tools – GIT, visualstudio code, etc

Our website will have functionalities like crypto Currency price prediction for specific period of time & visualizing/analysing pattern of bitcoin data using different plotting techniques.

Result:

We observed remarkable results using LSTMs. They really work a lot better for most sequence tasks.

LSTM model Prediction Result plot

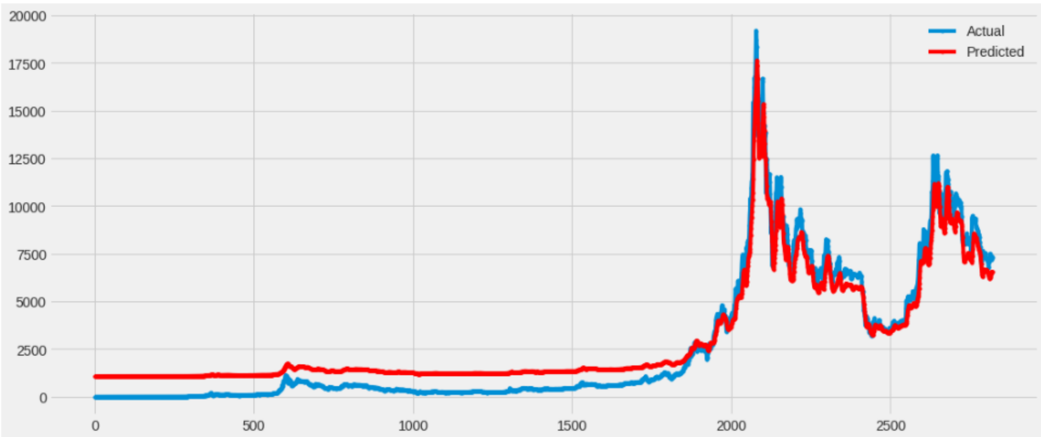


FIG.5.1 LSTM MODEL RESULT PLOT

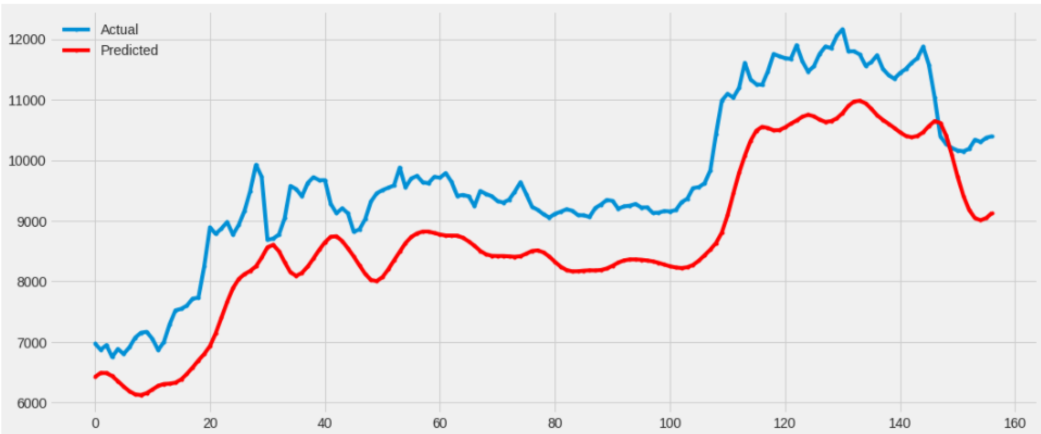


FIG.5.2 LSTM MODEL RESULT PLOT

- from sklearn.metrics import mean_absolute_error, mean_squared_error

```
Train RMSE: 0.04792889021418374
Train MAE: 0.20979423661732005
Test RMSE: 0.0544482676350978
Test MAE: 0.22614883920646772
```

Chapter 5

CONCLUSIONS

5.1 Conclusion

In building our model, the steps involved are as follows:

During visualization of our historical dataset we encountered a quite no of missing values.

	Total Missing Values	Missing %
Timestamp	0	0.000000
Open	1241716	27.157616
High	1241716	27.157616
Low	1241716	27.157616
Close	1241716	27.157616
Volume_(BTC)	1241716	27.157616
Volume_(Currency)	1241716	27.157616
Weighted_Price	1241716	27.157616

These Missing values are imputed using Linear Interpolation Imputation Technique. As we can see the results after imputation in below fig.

```
   Volume_(Currency)  Weighted_Price
0           2.000000            4.39
1           2.436653            4.39
2           2.873305            4.39
3           3.309958            4.39
4           3.746611            4.39
Timestamp            0
Open                 0
High                 0
Low                  0
Close                0
Volume_(BTC)         0
Volume_(Currency)    0
Weighted_Price       0
dtype: int64
```

Then we did the Exploratory data analysis in which we have visualized the dataset using KDE's density plot which concluded that there is a downward trend in Crypto Currency prices from Dec-17 onwards till March 2019.

Further we did Time resampling as Examining Crypto Currency price data for every single day isn't of much use to financial institutions, who are more interested in spotting market trends. To make it easier, we use a process called time resampling to aggregate data into a defined time period, such as by month or by quarter. Institutions can then see an overview of Crypto Currency prices and make decisions according to these trends. Further we did Time Series Decomposition. Post time series decomposition we don't observe any seasonality. Also, there is no constant mean, variance and covariance, hence the series is **Non Stationary.** We performed statistical tests like KPSS and ADF to confirm our understanding.

The output of the KPSS test contains 4 things:

- The KPSS statistic

- p-value
- Number of lags used by the test
- Critical values

The **p-value** reported by the test is the probability score based on which you can decide whether to reject the null hypothesis or not. If the p-value is less than a predefined alpha level (typically 0.05), we reject the null hypothesis.

The **KPSS statistic** is the actual test statistic that is computed while performing the test.

The number of **lags** reported is the number of lags of the series that was actually used by the model equation of the kpss test.

In order to reject the null hypothesis, the test statistic should be greater than the provided critical values. If it is in fact higher than the target critical value, then that should automatically reflect in a low p-value. That is, if the p-value is less than 0.05, the kpss statistic will be greater than the 5% critical value.

In **ADF** test, The only difference here is the Null hypothesis which is just opposite of KPSS. The null hypothesis of the test is the presence of **unit root**, that is, the series is **non-stationary**.

The KPSS and ADF test concluded that KPSS says series is not stationary and ADF says series is stationary. which means series is **difference stationary**, we used **differencing** to make series stationary.

After that we used Rolling Windows Method during our Feature Extraction as Time series data can be noisy due to high fluctuations in the market. As a result, it becomes difficult to gauge a trend or pattern in the data. A rolling mean, or moving average, is a transformation method which helps average out noise from data. It works by simply splitting and aggregating the data into windows according to function, such as mean(), median(), count(), etc. In this, we used a rolling mean for 3, 7 and 30 days which resulted into that Our data becomes a lot less noisy and more reflective of the trend than the data itself.

Further we did our Model Building Using LSTM, In which we did cross validation i.e we measure the performance of our forecasting model, We typically split the time series into a training period and a validation period which is called fixed partitioning. we opted for a ***hold-out based validation***.

Hold-out is used very frequently with time-series data. In this case, we select all the data for 2020 as a hold-out and train our model on all the data from 2012 to 2019.

We used the LSTM model where Initialized the LSTM and added Four LSTM layer and some Dropout regularisation and then we compiled the RNN. Further we Fitted the RNN to Training set and Finally we did the prediction and performance checking and We observed remarkable results using LSTMs.

Summary:

- We are visualising historical bitcoin data.
- The Missing values in the dataset is handled by using Imputation Technique i.e Interpolation which imputes the missing values in time-series.
- Exploratory data analysis is done by visualising using KDEs, using lag plots & further time resampling i.e aggregate data into a defined time period, such as by month or by quarter.
- Feature extraction is done using rolling windows technique.
- Model Selection and Model Building.
- Prediction using LSTMs

Hence we overall Concluded that,

Our Proposed model has been succeeded to provide the result prediction bitcoin from Historical bitcoin dataset. Our model with time series techniques can build produce the results and the results can predict the price for the next 30 days with split the data to train and test that we mention above. Afterward, as we mentioned before in the article, the Crypto Currency market is influenced by many uncertainty factors. The Cryptocurrencies are influenced by many uncertainties factor such as political issue, the economic issue at impacted to local or global levels. So prediction price bitcoin using LSTM can't good enough to make the decision to invest in bitcoin, it is another side for taking the decisions.

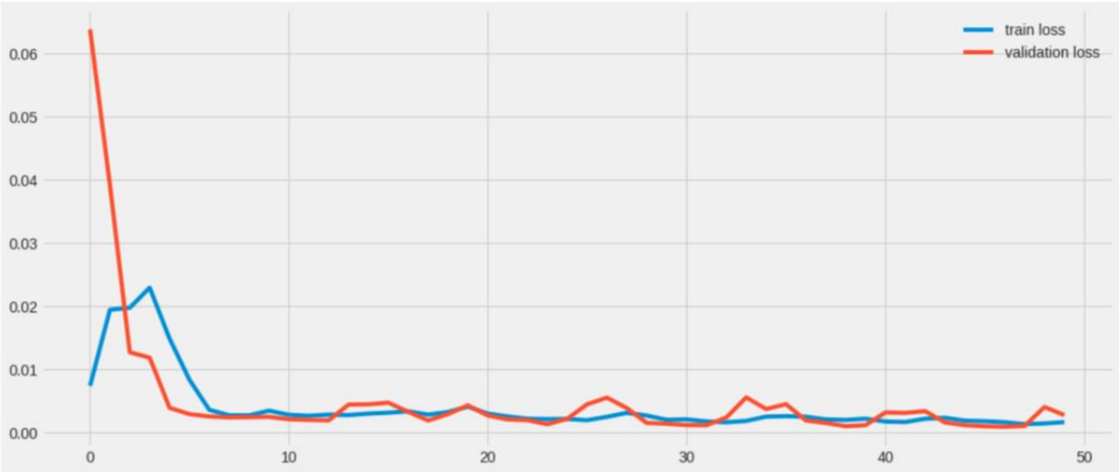
5.2 Limitations of the System

For evaluating the performance of the project, we use validation split of i.e after training we validate before testing about the bias as

```
history = regressor.fit(X_train, y_train, validation_split=0.1, epochs = 50, batch_size = 32, verbose=1, shuf
fle=False)
```

```
plt.plot(history.history["loss"], label= "train loss")
plt.plot(history.history["val_loss"], label= "validation loss")
```

```
plt.legend()
```



The lower the **loss,** the better a model (unless the model has over-fitted to the training data). The loss is calculated on **training** and **validation** and its interperation is how well the model is doing for these two sets

So after increasing the number of epochs to 50 and beyond we notice that loss gradually decreases hence we optimized it a bit & we will try to optimize it further by maybe improving number of lag features can be increased beyond 100 to help learning the model.

5.3 Future Scope of the Project

we will be making a website, which will be using API's of with tech stack of frameworks as,

Frontend – Reactjs, context API/redux, html5, css3, bootstrap5, materialcss.
Backend – django/flask
Database – Mongodb
Tools – GIT, visualstudio code, etc

Our website will have functionalities like crypto Currency price prediction for specific period of time & visualizing/analysing pattern of bitcoin data using different plotting techniques.

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