

A Project Report On
“Impact of Pandemic on Global Finance”

Submitted in partial fulfilment of the requirement of

University of Mumbai

For the Third Year Degree of **Bachelor of Engineering**

in

COMPUTER ENGINEERING

Submitted by

Battina Babykutty (101805)

Sudiksha Mullick (101842)

Ramesh Angela Infanta Jerome (101852)

Riya Mol Raji (101853)

Vishadh Sawant (101855)

Serena Raju (101856)

Akshat Sharma (101857)

Sherin Shibu(101858)

Rahul Khambe (101867)

Gargi Raje (101870)

Supervised by

Mrs Smita Dange



Department of Computer Engineering
Fr. Conceicao Rodrigues Institute of Technology Sector 9A, Vashi, Navi Mumbai -
400703

UNIVERSITY OF MUMBAI 2020-2021

APPROVAL SHEET

This is to certify that the project entitled

“Impact of Pandemic on Global Finance”

Submitted by

Name	Roll Number
Battina Babykutty	101805
Sudiksha Mullick	101842
Ramesh Angela Infanta Jerome	101852
Riya Mol Raji	101853
Vishadh Sawant	101855
Serena Raju	101856
Akshat Sharma	101857
Sherin Shibu	101858
Rahul Khambe	101867
Gargi Raje	101870

Supervisors : Mrs. Smita Dange

Project Coordinator : Mrs. Smita Dange

Examiners: 1.

2.

Date : 16.05.2021

Head of Department : Dr. Lata Raghe

Place :

DECLARATION

We declare that this written submission for the T.E. The Declaration entitled “Impact of Pandemic on Global Finance” 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 declared that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any ideas/data/fact/source in our submission. We understand that any violation of the above will cause disciplinary action by the institute and also evoke penal action from the sources which have thus not been properly cited or from whom paper permission has not been taken when needed.

INDEX

1.PROBLEM STATEMENT	06
2.DATASET	06
2.1 IFC Investment India and GDP Growth Rate	
2.2 Gold Prices	
2.3 Stock Market	
2.4 Currency Exchange Rate	
2.5 Share Price Investment	
3.PREPROCESSING	10
3.1 Investment and GDP Growth Rate	
3.2 Gold Price	
3.3 Stock Market	
3.4 Currency Exchange Rate	
3.5 Share Price Investment	
4.VISUALIZATION	20
4.1 Investment and GDP Growth Rate	
4.2 Gold Price	
4.3 Stock Market	
4.4 Currency Exchange	
4.5 Share Price Investments	
5.ALGORITHMS USED WITH RATIONALE	27
5.1 Multiple Regression	

5.2 Random Forest Regression	
5.3 LSTM	
5.4 Polynomial Regression	
5.5 Simple Exponential Smoothing	
7.RESULT	34
7.1 Investment and GDP Growth Rate	
7.2 Gold Price Analysis and Prediction	
7.3 Stock Market	
7.4 Currency Exchange Rate Comparison	
7.5 Share Price Investments	
8.CONCLUSION	51

1. PROBLEM STATEMENT

Prior to the COVID-19 crisis, levels and trends in domestic revenues and external flows to developing economies were already considered insufficient to support the Sustainable Development Goals (SDG). With high levels of public debt and additional pressures induced by the pandemic on all major sources of development finance, low- and middle-income countries may struggle to finance their public health, social and economic responses to COVID-19.

This is an opportunity to refocus on sustainability and responsible investment. There is early evidence suggesting that sustainable investment strategies continue to outperform the broader market in this crisis. Investors should incorporate COVID-19 in their stewardship activities, support their portfolio companies in navigating the effects of this crisis and continue to focus on creating long-term value for their beneficiaries.

The pandemic has underscored the complexity and interconnectedness of our world – in terms of trade, commerce, as well as relationships between people and societies – and how quickly these links can collapse if not sustainable. Sustainability risks must be understood as economic risk.

To analyze the financial trends and the impact of the pandemic on these trends, we have analyzed a few parameters which reflect the global financial situation comprehensively.

2. DATASET

2.1.a IFC INVESTMENT INDIA DATASET

Source of data	IFC Investment Services Projects: India
Size of data	84.4KB Number of records: 382
Description of each field	Field 1:Date Disclosed Field 2:Project Name Field 3:Project Type Field 4:Project no

	Field 5:Company Name Field 6:Sector Field 7:Status, Country Field 8:Department Field 9:IFC investment for Risk Management(Million - USD) Field 10:IFC investment for Guarantee(Million - USD) Field 11:IFC investment for Loan(Million - USD) Field 12:IFC investment for Equity(Million - USD) Field 13:Total IFC investment as approved by Board(Million - USD)
--	--

2.1.b GDP GROWTH RATE DATASET

Source of data	<u>Inflation rate in India 1984-2024</u>
Size of data	2.71KB Number of Records:62
Description of each field	Field 1:Date Field 2:Inflation Rate Field 3:Annual Change Field 4:Output Billions of US \$ Field 5:% GDP growth rate

2.2 Gold Prices Dataset

Source of data	<u>https://finance.yahoo.com/quote/GC=F/history/</u>
Size of data	Storage: 248 kB Number of records: 3510
Description of each field	Field 1: Date/ Date of gold prices Filed 2: Open/ The opening value of the gold price for that particular date

	<p>Field 3: High/ The highest value of the gold price for that particular</p> <p>Field 4: Low/ The lowest value of the gold price for that particular date</p> <p>Field 5: Close/ The closing value of the gold price for that particular date</p> <p>Field 6: Adj. Close/ The adjusted closing price amends a gold's closing price to reflect that gold's value after accounting for any</p>
--	---

2.3 Stock Market Dataset

Source of data	<u>NIFTY 50 (^NSEI) Charts, Data & News</u>
Size of data	<p>Storage: 247 kB</p> <p>Number of rows: 3274</p>
Description of each field	<p>Field 1: Date/ Date of gold prices</p> <p>Field 2: Open/ The opening value of the gold price for that particular date</p> <p>Field 3: High/ The highest value of the gold price for that particular</p> <p>Field 4: Low/ The lowest value of the gold price for that particular date</p> <p>Field 5: Close/ The closing value of the gold price for that particular date</p> <p>Field 6: Adj. Close/ The adjusted closing price amends a gold's closing price to reflect that gold's value after accounting for any</p>

2.4 Currency Rate Exchange Dataset

Source of data	https://data.oecd.org/conversion/exchange-rates.htm
Size of data	16.384 Bytes of Data 880 number of rows
Description of each field	Field 1: Date(mm/dd/yy) Field 2: Price(USD)

2.5 SHARE PRICE INVESTMENT DATASET

Source of data	https://data.oecd.org/
Size of data	109.24KB No of Rows: 1962
Description of each field	Field 1: Location Field 2: Time Field 1: Value

3. PREPROCESSING

3.1 A] IFC Investment India Pre Processing

IFC is an international Finance Corporation that offers Investment, Advisory and Asset Managements Services to encourage private-sector development in less developed countries. India is one of the core member of this corporation wherein IFC has been invested in a lot of Indian Projects.

The Dataset which was collected from the World Bank Finance website gave us a clear idea about the Investments done by IFC corporation. The dataset gives an insight on how IFC has invested, in which all projects its been investing, in which all sectors they are giving more investments etc. Also the main thing was to get an insight of how covid pandemic situation affected the investments by IFC for the projects in India.

Since the dataset that was received was in an unstructured and undefined manner, some pre-processing technique had to be done to make it to use.

Data Cleaning:

- Dropping irrelevant columns and keeping relevant columns

```
#dropping irrelevant columns
df1 = df.drop(['Date Disclosed', 'Product Line', 'Sector', 'Environmental Category', 'Department',
              'Status', 'Project Name', 'Document Type', 'Project Number',
              'Company Name', 'Country', 'IFC Country Code', 'Projected Board Date', 'WB Country Code', 'As of Date'], axis=1)
df1
```

- Dropping all duplicate data

```
# Dropping the duplicates
df2 = df1.drop_duplicates()
df2.head(5)
```

- Finding all Missing Values

```
# Finding the null values.
print(df2.isnull().sum())
```

```
IFC investment for Risk Management(Million - USD)      243
IFC investment for Guarantee(Million - USD)            244
IFC investment for Loan(Million - USD)                 81
IFC investment for Equity(Million - USD)               102
Total IFC investment as approved by Board(Million - USD)  1
dtype: int64
```

- Replacing all undefined values with the mean values

```
#Replacing all the NAN values in the columns with its mean valuea
df3 = df2.fillna(df2.mean())
df3
```

	IFC investment for Risk Management(Million - USD)	IFC investment for Guarantee(Million - USD)	IFC investment for Loan(Million - USD)	IFC investment for Equity(Million - USD)
0	21.625	39.583333	41.190000	19.723034
1	21.625	39.583333	10.200000	32.200000
2	21.625	39.583333	42.862229	19.723034
3	21.625	39.583333	46.660000	19.723034
5	21.625	39.583333	74.380000	19.723034
...
373	21.625	39.583333	8.000000	2.000000
374	21.625	39.583333	30.000000	0.000000
376	21.625	39.583333	9.000000	19.723034
377	21.625	50.000000	42.862229	20.000000
380	21.625	39.583333	10.000000	2.410000

B] GDP Growth Rate Pre Processing

The GDP growth dataset consists of data regarding the annual percentage growth rate of GDP based on the measures such as inflation and manufacturing cost. Inflation is a general increase in prices and manufacturing output comprises the bulk of industrial

production. The manufacturing output is calculated in terms of the US Dollar. A general observation says that both inflation rate and manufacturing cost are directly proportional to the GDP growth rate i.e. An increase in inflation rate and manufacturing cost leads to an increase in the GDP growth and a decrease in these factors would eventually lead to a decrease in the GDP rate. Also, a fact that has to be noted is that if one factor's rate increases and another factor's rate decreases, the GDP rate would be decided by the factor that had a major rate of change than the other.

The dataset is small as it comprises values measured on a yearly basis and also as it did not have any such noisy values, there was not much need for preprocessing of the dataset. The only required thing was to replace a missing value with the mean value as shown below:

- Checking for missing values

```
[ ] df.isnull().sum()

date                0
Inflation Rate%     0
Annual Change       1
Output Billions of US $  0
% of GDP Growth Rate  0
dtype: int64
```

- Replacing the missing value with the mean value

```
df1 = df.fillna(df.mean())
df1
```

	date	Inflation Rate%	Annual Change	Output Billions of US \$	% of GDP Growth Rate
0	31-12-1960	1.7799	0.150167	5.461952	14.7501
1	31-12-1961	1.6952	-0.080000	6.023684	15.3538
2	31-12-1962	3.6322	1.940000	6.688202	15.8633
3	31-12-1963	2.9462	-0.690000	7.627609	15.7524
4	31-12-1964	13.3553	10.410000	8.387741	14.8507
...
56	31-12-2016	4.9410	-0.930000	347.942712	15.1622
57	31-12-2017	2.4909	-2.450000	395.099150	14.8939
58	31-12-2018	4.8607	2.370000	395.688247	14.5840
59	31-12-2019	7.6597	2.800000	391.495660	13.6461
60	31-12-2020	4.5900	3.070000	469.159737	17.4000

61 rows x 5 columns

3.2 Gold Price Data Pre Processing

Prices of SPDR® Gold Shares (NYSE Arca : GLD) was downloaded from Yahoo Finance. Data spans from the inception of this share from 11/18/2004 to the date of download, 11/22/2019.

3.2.1 Data Cleaning

Since there are missing data, for eg:- gold prices are missing on non-trading days like weekends and holidays, we resampled the dates using forward fill to fill the missing values in dataframe

```
GLD Data Before Forward Fill: (3510, 7)
```

```
GLD Data After Forward Fill: (5092, 7)
```

After parsing the date column from string to date and making it to to index

```
GLD Prices for All Days, including weekends and holidays: (5092, 6)
```

3.2.2 Data Transformation

We defined a variable such that it is calculating average for 3 days and 9 days for predicting the gold prices and giving a trading signal whether we should buy gold or take no position.

```
df['s_3'] = df['Close'].shift(1).rolling(window=3).mean()
df['s_9'] = df['Close'].shift(1).rolling(window=9).mean()
df = df.dropna()
x = df[['s_3', 's_9']]
x.head()
```

	s_3	s_9
2007-05-10	67.859998	67.665556
2007-05-11	67.109998	67.588889
2007-05-12	66.633331	67.565555
2007-05-13	66.299998	67.449999
2007-05-14	66.449997	67.256665

We chose the Close column to be the column of interest as it is the most relevant value for prediction.

```
#defining dependent variable
y = df['Close']
y.head()
```

Date	
2007-05-10	66.000000
2007-05-11	66.449997
2007-05-12	66.449997
2007-05-13	66.449997
2007-05-14	66.279999

Name: Close, dtype: float64

3.3 Stock Market Pre Processing

Stock Market is one of the parameters that were taken up for analysing and predicting the financial situation during the pandemic because the market affects the economy in three ways which are:

1. Markets Allow Small Investors to Invest in the Economy

2. Markets Help Savers Beat Inflation
3. Markets Help Businesses Fund Growth

The data extracted from the Yahoo Finance Website was raw data that was in need of pre-processing which was carried out in the following manner.

Data Cleaning:

- **Missing values:** Missing values are discarded

```
Shape of training data before removing missing values: (2717, 7)
Shape of training data after removing missing values: (2685, 7)
```

```
Shape of testing data before removing missing values: (558, 7)
Shape of testing data after removing missing values: (555, 7)
```

Data Transformation:

- **Attribute Selection:** We chose the Close column to be the column of interest as it is the most relevant value for prediction.

```
Shape of training data before attribute selection: (2685, 7)
Shape of training data after attribute selection: (2685, 1)
```

- **Normalization:** It is done in order to scale the data values in a specified range, that is 0 to 1 here, using `MinMaxScaler()`.

Training data before normalization

```
[6] ▶ ▶≡ M↓  
training_processed  
  
array([[ 6109.850098],  
       [ 6060.850098],  
       [ 6126.399902],  
       ...,  
       [10817.150391],  
       [10853.200195],  
       [10735.049805]])
```

Training data after normalization:

```
[8] ▶ ▶≡ M↓  
training_scaled  
  
array([[0.40782428],  
       [0.40264335],  
       [0.40957415],  
       ...,  
       [0.90554311],  
       [0.90935478],  
       [0.89686234]])
```

3.4 Currency Exchange Rate Comparison Pre-Processing

An exchange rate is the value of a country's currency vs. that of another country or economic zone. Somewhere the graph peaks whilst somewhere it falls every day per month or year. Lockdown impact can be clearly observed from the graphs but, falling or rising of currency state means that, If prices increase, it means the value of the currency is basically devastated and its purchasing power has fallen. And hence inflation occurs.

Tring to fit data into a model we have applied a Linear Regression Algorithm at the very beginning for preprocessing the data. The aim was to just observe and model the dataset into behavioural graphs for further use and simplification.

<pre>import pandas as pd import numpy as np import matplotlib.pyplot as plt %matplotlib inline from sklearn.preprocessing import MinMaxScaler from keras import optimizers import keras from keras.models import Sequential from keras.layers import Dense, LSTM import keras.backend as K import tqdm</pre>	<pre>data81.plot(kind='scatter', x= 'Month', y="INR") plt.title("Dataset Of year 2018") plt.show() data91.plot(kind='scatter', x= 'DATE', y="INR") plt.title("Dataset Of year 2019") plt.show() data02.plot(kind='scatter', x= 'DATE', y="INR") plt.title("Dataset Of year 2020") plt.show()</pre>
--	--

3.5 Share Price Investments

Share price indices are calculated from the prices of common shares of companies traded on national or foreign stock exchanges. A share price index measures how the value of the stocks in the index is changing, a share return index tells the investor what their “return” is, meaning how much money they would make as a result of investing in that basket of shares. A price index measures changes in the market capitalization of the basket of shares in the index whereas a return index adds on to the price index the value of dividend payments, assuming they are reinvested in the same stocks. Occasionally agencies such as central banks will compile share indices.

1. Removal of Unnecessary Fields and categorizing required countries into separate data frame:

Before:

```
dataset = pd.read_csv('/content/sample_data/demo_prj_original.csv')
dataset
```

	LOCATION	SUBJECT	MEASURE	FREQUENCY	TIME	Value
0	AUT	TOT	AGRWTH	M	2017-11	2.263780
1	AUT	TOT	AGRWTH	M	2017-12	2.154750
2	AUT	TOT	AGRWTH	M	2018-01	1.768173
3	AUT	TOT	AGRWTH	M	2018-02	1.762977
4	AUT	TOT	AGRWTH	M	2018-03	1.851852
...
1956	EU27_2020	TOT	AGRWTH	M	2020-08	0.400000
1957	EU27_2020	TOT	AGRWTH	M	2020-09	0.200000
1958	EU27_2020	TOT	AGRWTH	M	2020-10	0.200000
1959	EU27_2020	TOT	AGRWTH	M	2020-11	0.200000
1960	EU27_2020	TOT	AGRWTH	M	2020-12	0.200000

1961 rows x 6 columns

After:

```
# Remove columns name is SUBJECT MEASURE FREQUENCY
df = dataset.drop(['SUBJECT', 'MEASURE', 'FREQUENCY'], axis = 1)
df_new = df[df['LOCATION'] == 'IND']
df_new.head()
```

	LOCATION	TIME	Value
1241	IND	2017-11	3.971119
1242	IND	2017-12	4.000000
1243	IND	2018-01	5.109489
1244	IND	2018-02	4.744525
1245	IND	2018-03	4.363636

2. Changing the Date-Time format using Ordinal: This is done to ensure that further processing doesn't face difficulties due to the presence of hyphen/colon in between the date-month-year.

Before:-	After:-
----------	---------

	LOCATION	TIME	Value
1923	EU27_2020	2017-11	1.6
1924	EU27_2020	2017-12	1.4
1925	EU27_2020	2018-01	1.4
1926	EU27_2020	2018-02	1.2
1927	EU27_2020	2018-03	1.4
1928	EU27_2020	2018-04	1.3
1929	EU27_2020	2018-05	2.0
1930	EU27_2020	2018-06	2.0
1931	EU27_2020	2018-07	2.2
1932	EU27_2020	2018-08	2.1
1933	EU27_2020	2018-09	2.1
1934	EU27_2020	2018-10	2.3
1935	EU27_2020	2018-11	1.9

	LOCATION	TIME	Value	Date
1923	EU27_2020	2017-11	1.6	736634
1924	EU27_2020	2017-12	1.4	736664
1925	EU27_2020	2018-01	1.4	736695
1926	EU27_2020	2018-02	1.2	736726
1927	EU27_2020	2018-03	1.4	736754
1928	EU27_2020	2018-04	1.3	736785
1929	EU27_2020	2018-05	2.0	736815
1930	EU27_2020	2018-06	2.0	736846
1931	EU27_2020	2018-07	2.2	736876
1932	EU27_2020	2018-08	2.1	736907
1933	EU27_2020	2018-09	2.1	736938
1934	EU27_2020	2018-10	2.3	736968
1935	EU27_2020	2018-11	1.9	736999

4. VISUALIZATIONS

4.1 A] IFC Investment India Visualizations



Fig.4.1.1 Plotting Heatmap to find the correlation between the attributes

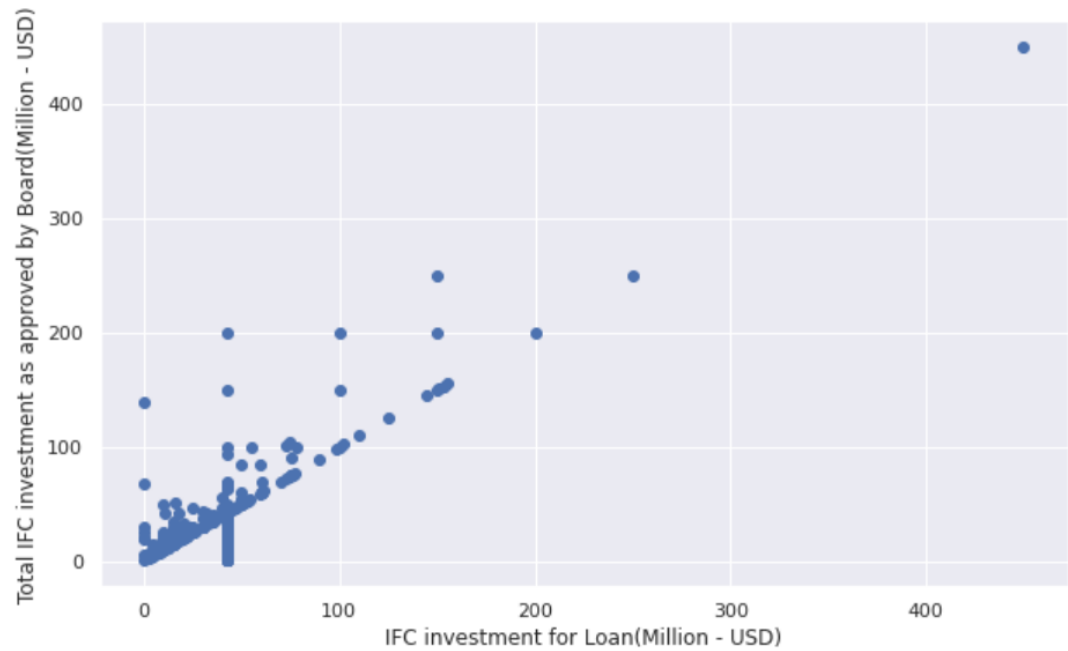


Fig.4.1.2 Scatter Plot for visualizing the linear relation between Loan and Investment approved by Board

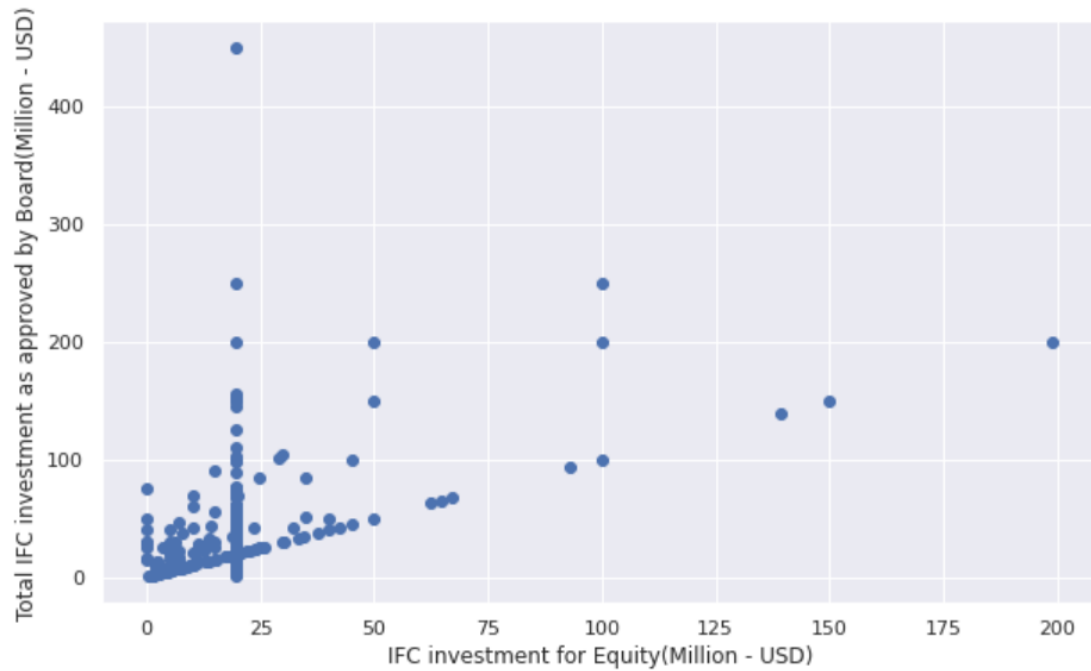
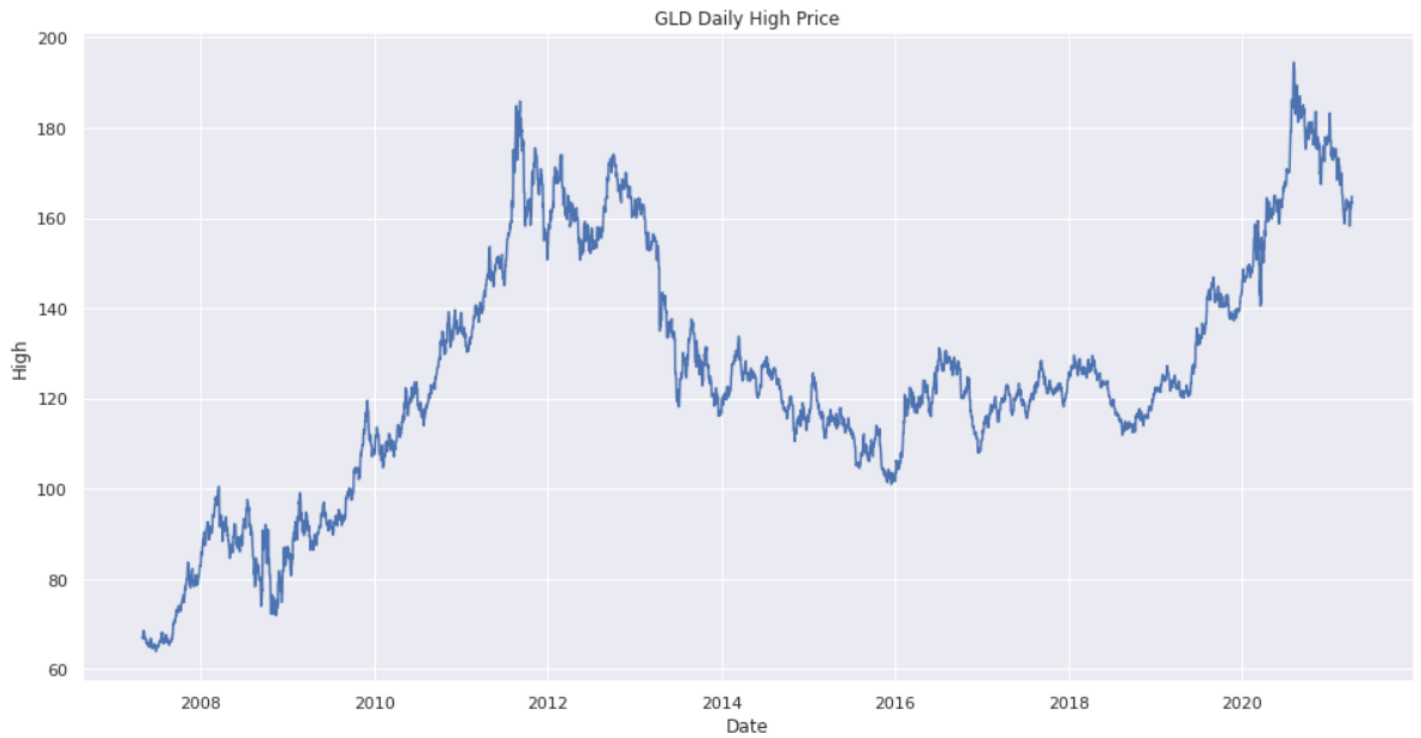


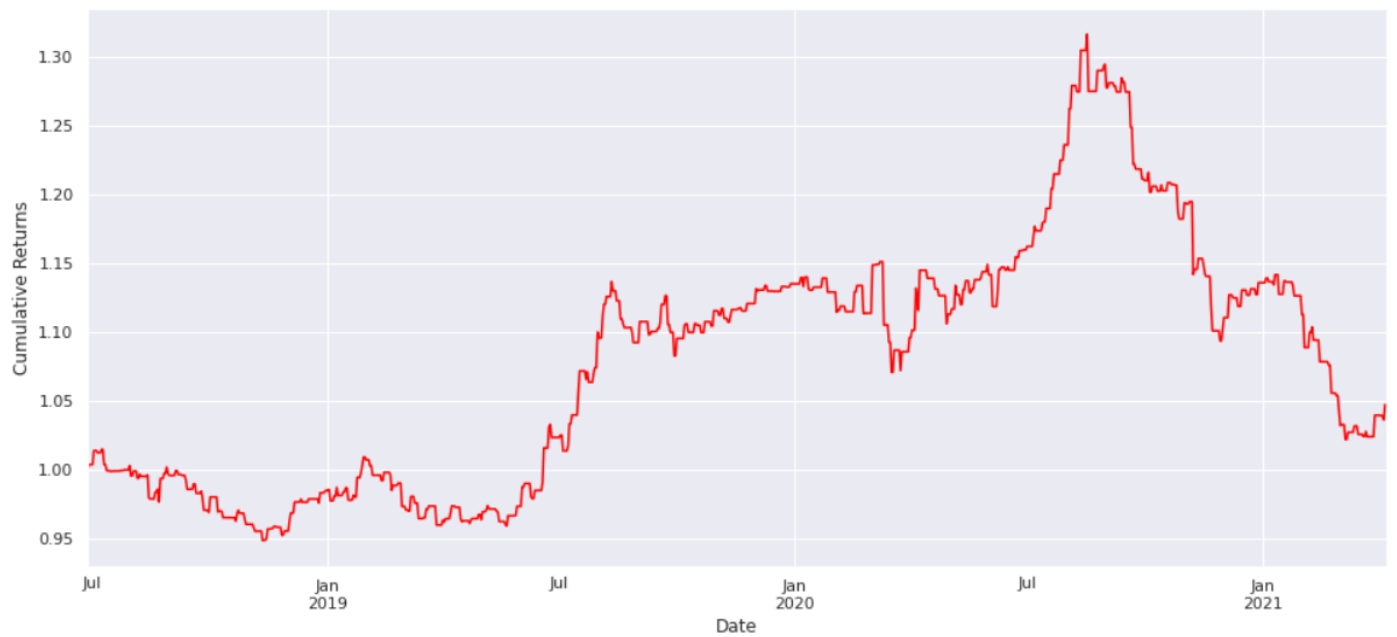
Fig.4.1.3 Scatter Plot for visualizing the linear relation between Equity and Investment approved by Board

B) GDP Growth Rate Visualization

4.2 Gold Price Visualizations



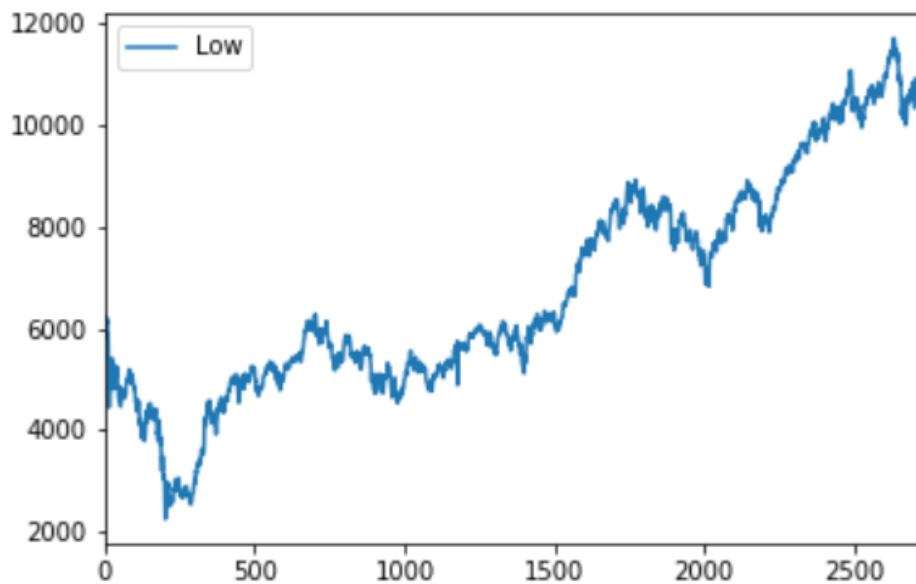
4.2.1 Dataset Plot



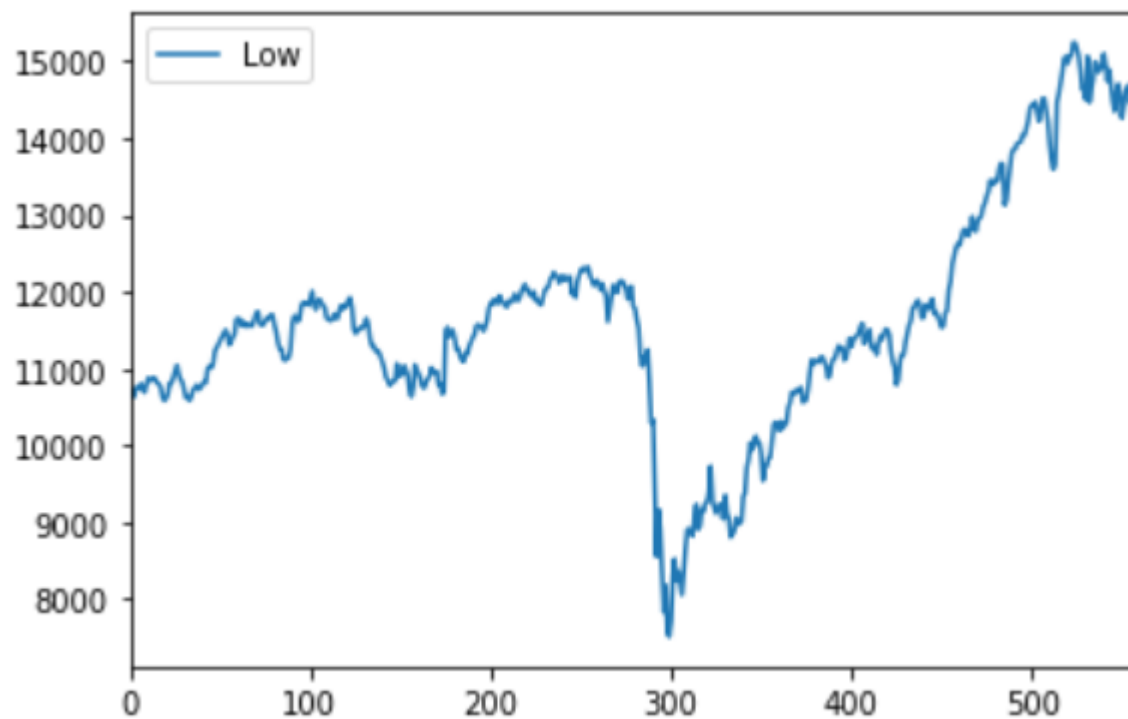
4.2.2 Cumulative Returns Plot

4.3 Stock Market Visualizations

Training Data:



Testing Data:



4.4 Currency Exchange Visualization

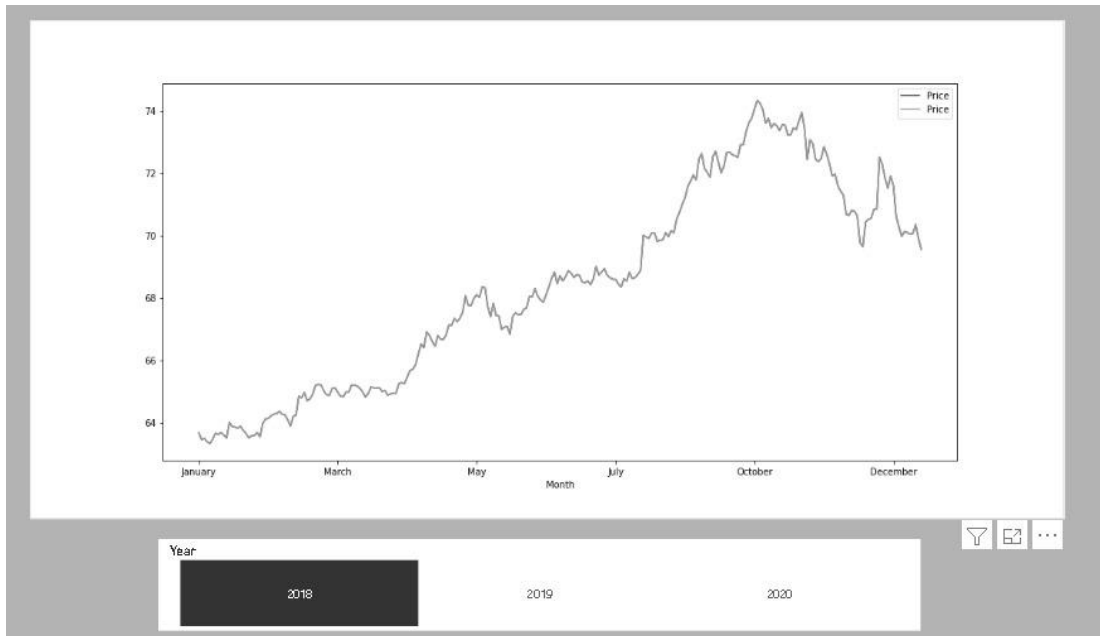


Fig 4.4.1 2018 Dataset Plot

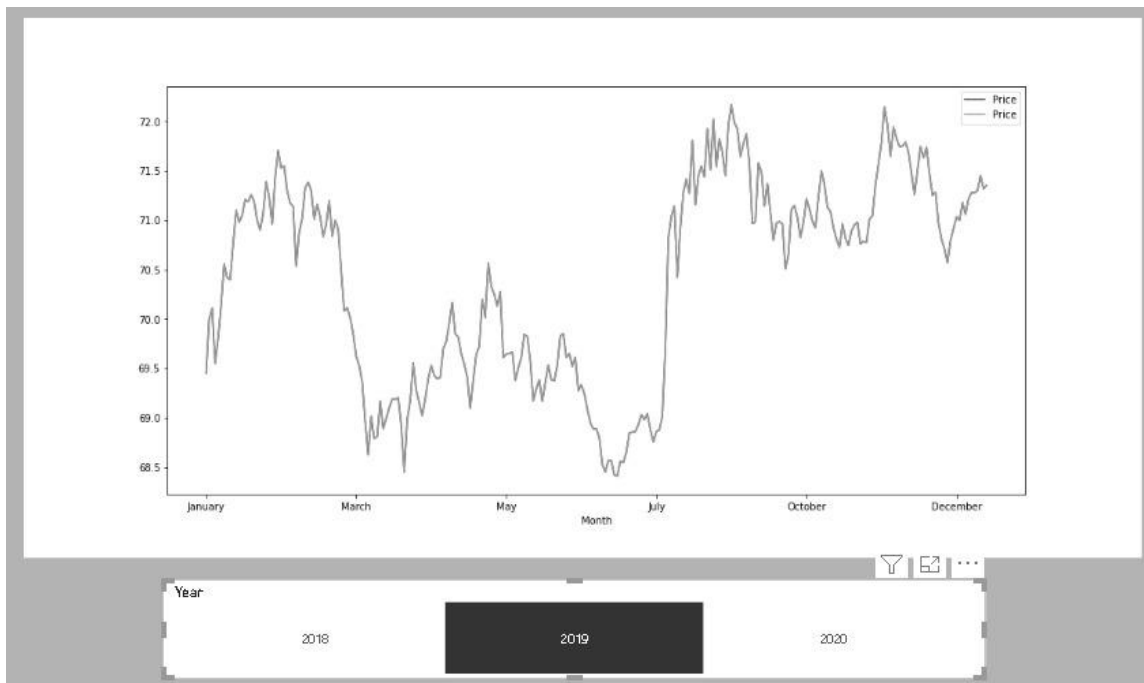


Fig 4.4.2 2019 Dataset Plot

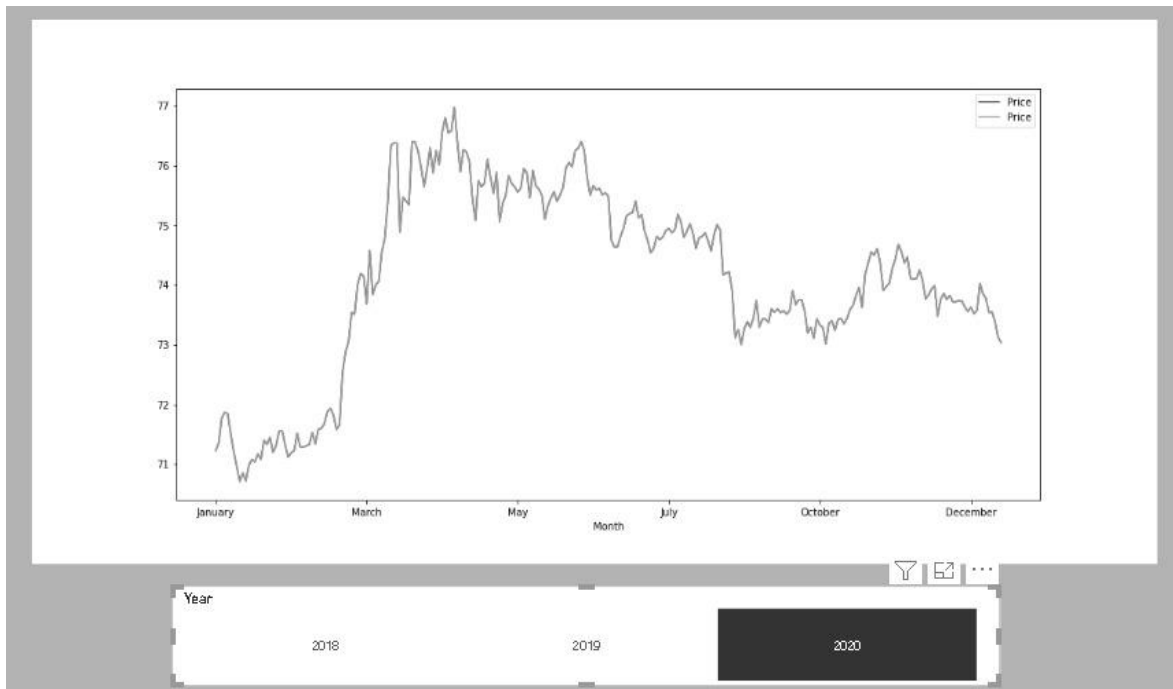


Fig 4.4.3 2020 Dataset Plot

4.5 Share Price Investment

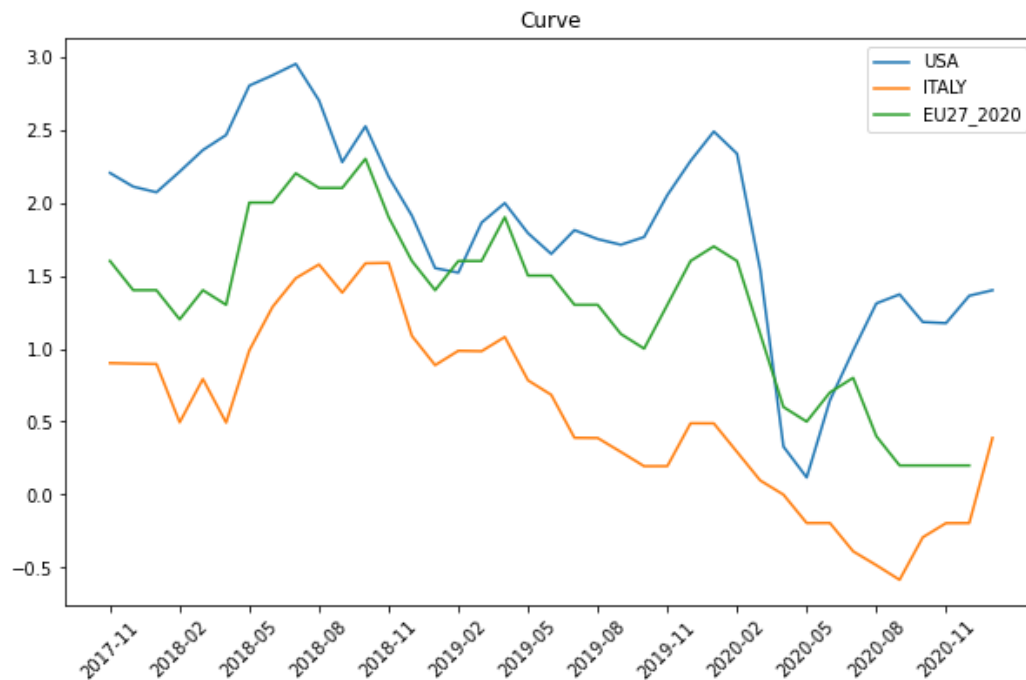


Fig. 4.5.1 Visual showing Top 3 most affected countries

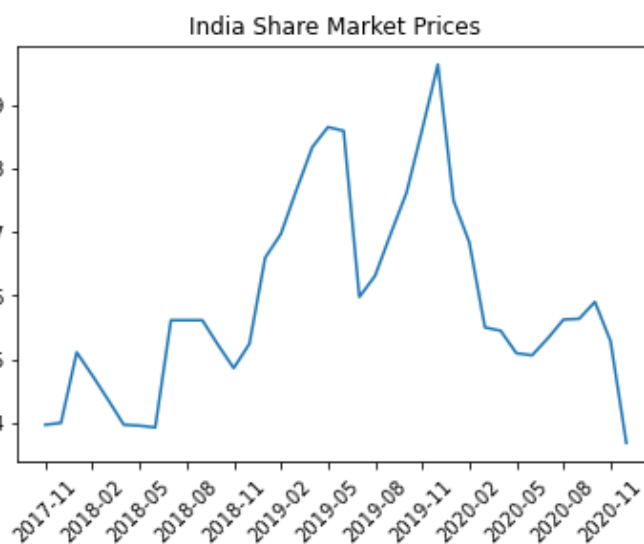


Fig. 4.5.2 Indian Share Market Prices

5. ALGORITHMS EXPLORED

5.1 Multiple Linear Regression

Multiple linear regression (MLR), also known simply as multiple regression, is a statistical technique that uses several explanatory variables to predict the outcome of a response variable. Multiple regression is an extension of linear (OLS) regression that uses just one explanatory variable. MLR is used extensively in econometrics and financial inference. The goal of multiple linear regression (MLR) is to model the Linear Relationship between the explanatory (independent) variables and response (dependent) variables.

Multiple linear regression refers to a statistical technique that is used to predict the outcome of a variable based on the value of two or more variables. It is sometimes known simply as multiple regression, and it is an extension of linear regression. The variable that we want to predict is known as the dependent variable, while the variables we use to predict the value of the dependent variable are known as independent or explanatory variables.

Formula can be represented as $Y = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \epsilon$, Or

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \epsilon$$

where, for $i = n$ observations:

y_i = dependent variable

x_i = explanatory variables

β_0 = y-intercept (constant term)

β_p = slope coefficients for each explanatory variable

ϵ = the model's error term (also known as the residuals)

5.2 Random Forest Regression

Random Forest operates among multiple decision trees to get the optimum result by choosing the majority among them as the best value. It basically splits the dataset in samples and feeds it to the decision tree for training the model. Another great quality of the random forest algorithm is that it is very easy to measure the relative importance of each feature on the prediction. Sklearn provides a great tool for this that measures a feature's importance by looking at how much the tree nodes that use that feature reduce impurity across all trees in the forest. It computes this score automatically for each feature after training and scales the results so the sum of all importance is equal to one.

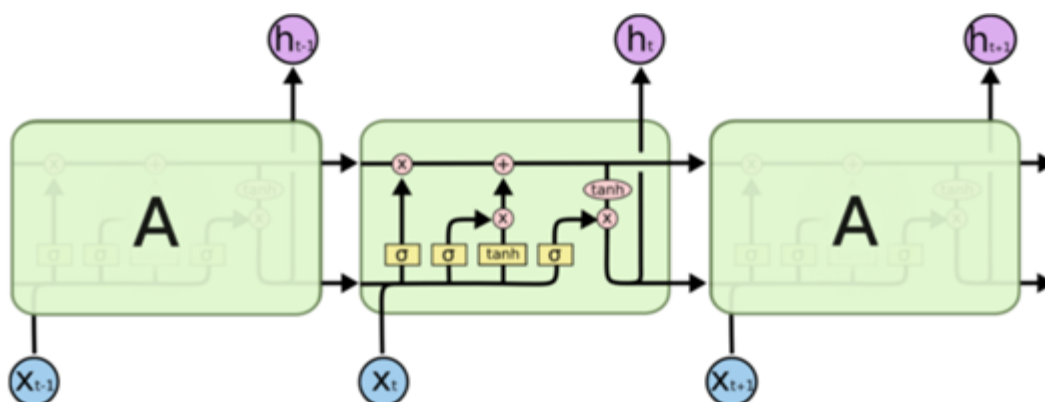
Gold price fluctuation trend prediction is an important issue in the financial world. Even small improvements in predictive performance can make lots of profits. We used random forests to predict the trend of fluctuations of the gold price.

The hyperparameters in random forest are either used to increase the predictive power of the model or to make the model faster. We used the following hyperparameters of sklearn's built-in random forest function.

1. For increasing the predictive power - `n_estimators`
2. For increasing the model speed - `random_state`

5.3 LSTM

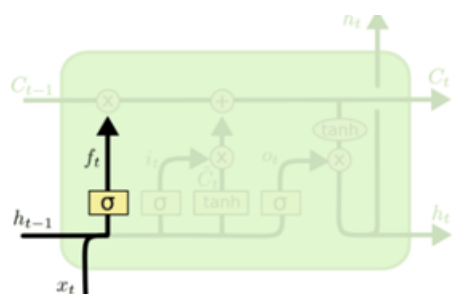
An LSTM has a similar control flow as a recurrent neural network. It processes data passing on information as it propagates forward. The differences are the operations within the LSTM's cells.



The repeating module in an LSTM contains four interacting layers.

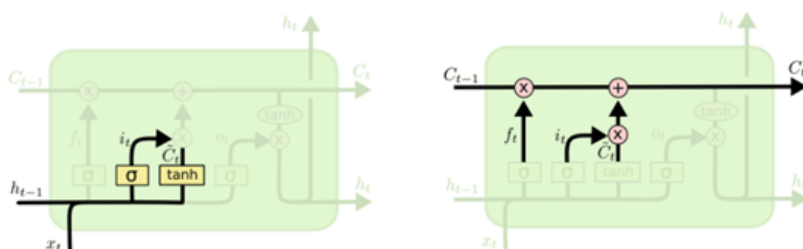
The core concept of LSTM is the cell state and its various gates. The cell state acts as a transport highway that transfers relative information all the way down the sequence chain. As the cell state goes on its journey, information gets added or removed to the cell state via gates. The gates are different neural networks that decide which information is allowed on the cell state. The gates can learn what information is relevant to keep or forget during training.

Forget gate: This gate decides what information should be thrown away or kept.

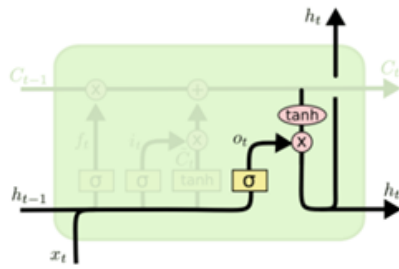


$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

Input Gate: To update the cell state, we have the input gate.



Output Gate: The output gate decides what the next hidden state should be.

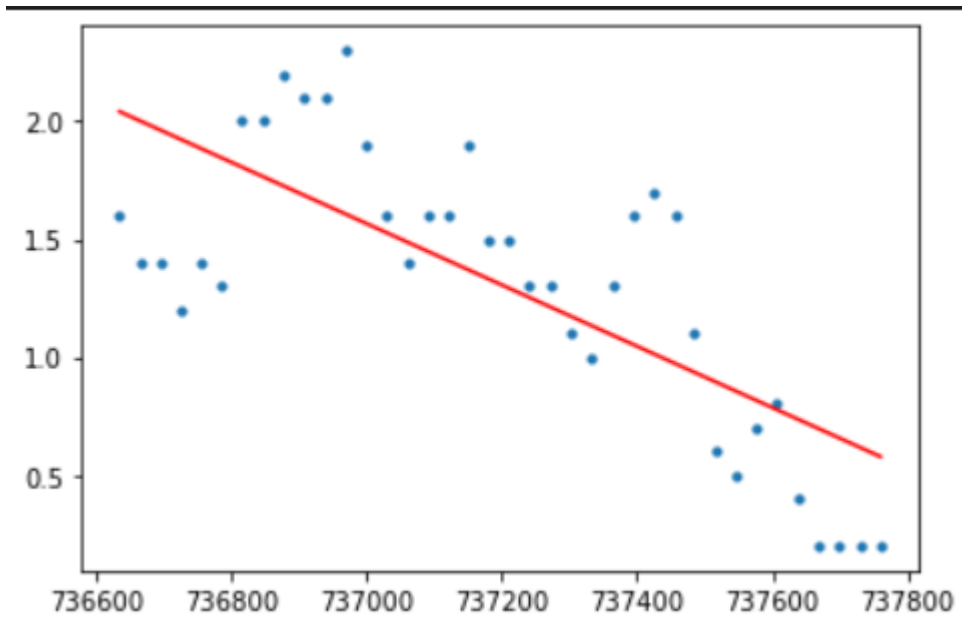


$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

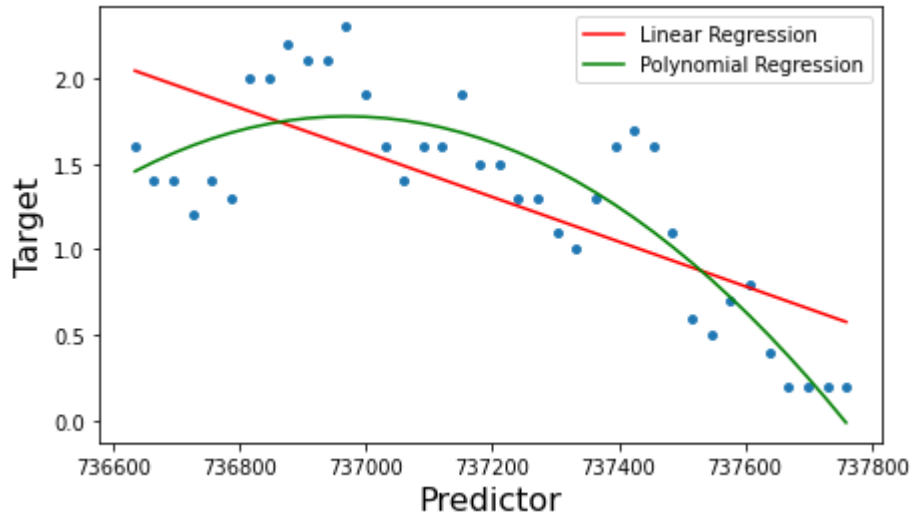
$$h_t = o_t * \tanh(C_t)$$

5.4 Polynomial Regression

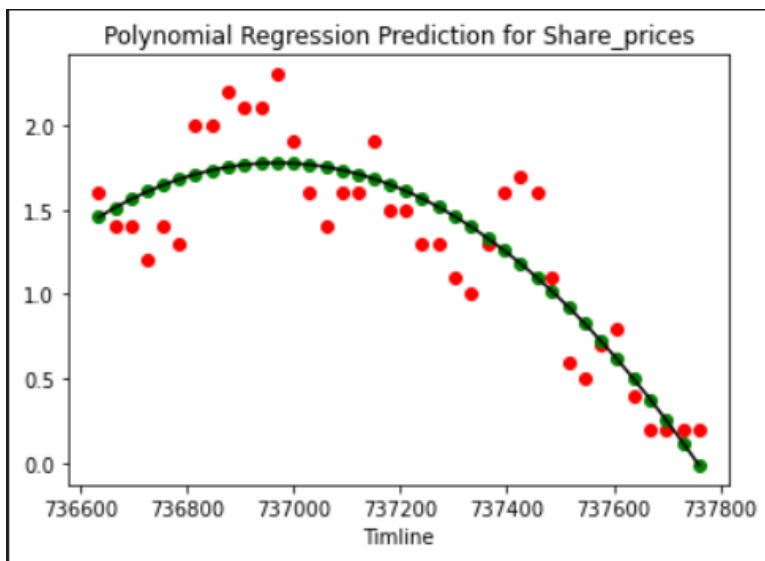
Our data which is based on Investment Analysis i.e Share Markets/Real Estate Investments,etc is majorly based on time, sales and prediction.In this we have used Linear and Polynomial Regression to predict the results.Polynomial regression is a form of regression analysis in which the relationship between the independent variable x and the dependent variable y is modelled as an n th degree polynomial in x .In our dataset we initially used Linear Regression as a starting point to predict the results and made a graph.



But in the above graph we can see that using Linear Regression the graph is an underfit as the predicted and actual values are very far off from each other. So to increase our accuracy we increased our degree i.e. we made use of Polynomial Regression



Here in the above graph the green line is for Polynomial Regression and the red line is for Linear Regression. As compared to the graph of the Linear Regression the difference between the actual and predicted values in the Polynomial Regression of degree 4 is less that means Polynomial Regression is more accurate than Linear Regression.



The above graph is made to make Polynomial Regression more understandable. In this graph the green line is the predicted values and the red dots are the actual values.

5.5 Simple Exponential Smoothing

Our data which is based on Investment Analysis i.e Share Markets/Real Estate Investments, etc is majorly based on time, sales and prediction, for which Polynomial Regression didn't provide accurate results. Therefore, one of the best algorithms to choose would be either LSTMs or ARIMA i.e. (Autoregressive Integrated Moving Average) or (Vector Autoregressive Moving-Average) and many more. So, here is this method called exponential smoothing. To be precise, called Simple/Single exponential smoothing which is an alternative to ARIMA based time forecasting methods. Single Exponential Smoothing, SES for short, also called Simple Exponential Smoothing, is a time series forecasting method for univariate data without a trend or seasonality. It requires a single parameter, called *alpha* (α), also called the smoothing factor or smoothing coefficient. This parameter controls the rate at which the influence of the observations at prior time steps decay exponentially. Alpha is often set to a value between 0 and 1. Large values mean that the model pays attention mainly to the most recent past observations, whereas smaller values mean more of the history is taken into account when making a prediction. So to be precise, it is called Simple/Single exponential smoothing which is an alternative to ARIMA based time forecasting methods.

Hyperparameters:

- **Alpha:** Smoothing factor for the level.

Single Exponential Smoothing or simple smoothing can be implemented in Python via the SimpleExpSmoothing Statsmodels class. First, an instance of the

SimpleExpSmoothing class must be instantiated and passed the training data. The fit() function is then called providing the fit configuration, specifically the alpha value called smoothing_level. If this is not provided or set to None, the model will automatically optimize the value. This fit() function returns an instance of this class that contains the learned coefficients. The forecast() or the predict() function on the result object can be called to make a forecast. Let's see the fit of the model here down.

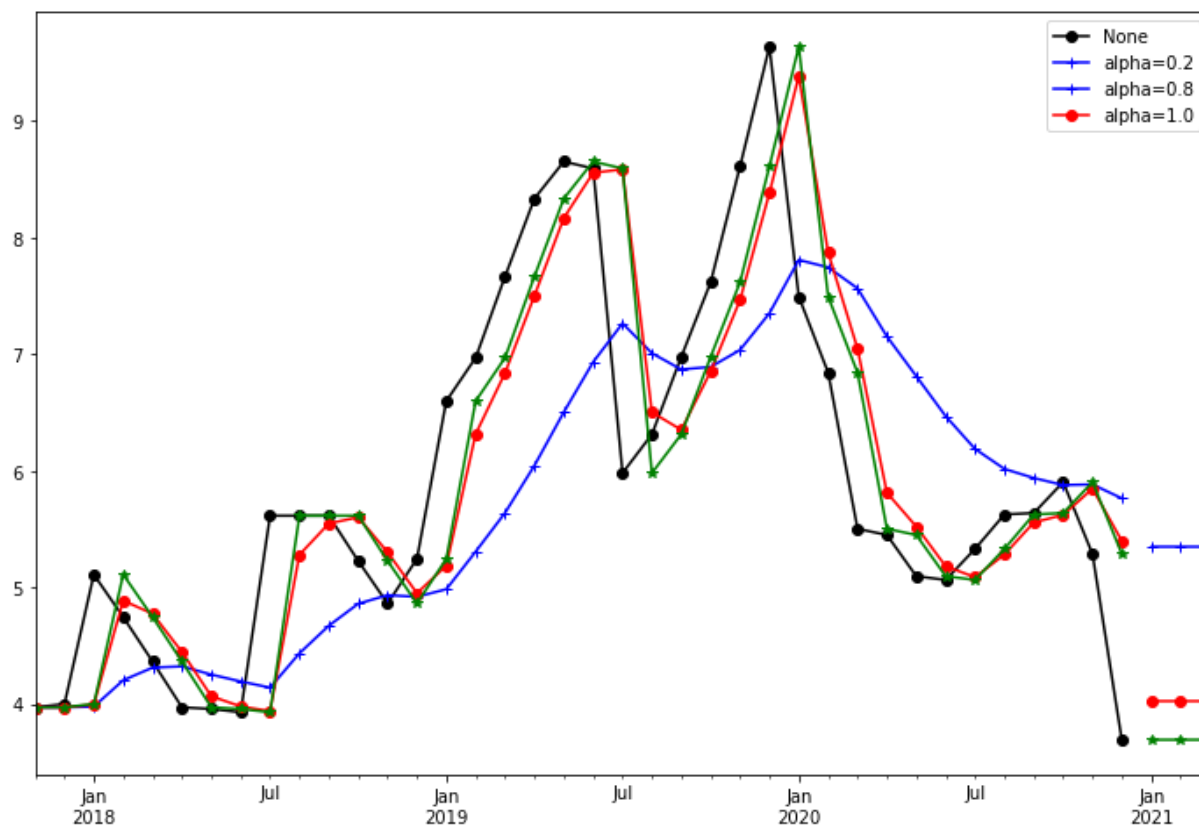


Fig. 5.5.1 Simple Exponential Smoothing

In the above-shown Figure, the Black coloured graph represents the actual data. The Blue and Red coloured graph represents Prediction when $\alpha = 0.2$ and 0.8 respectively. When the value of alpha is optimized by stats model, the graph represents the Green coloured path which looks ideal.

7. RESULT

7.1 A IFC Investment India Analysis For Pre and Post Covid Phase

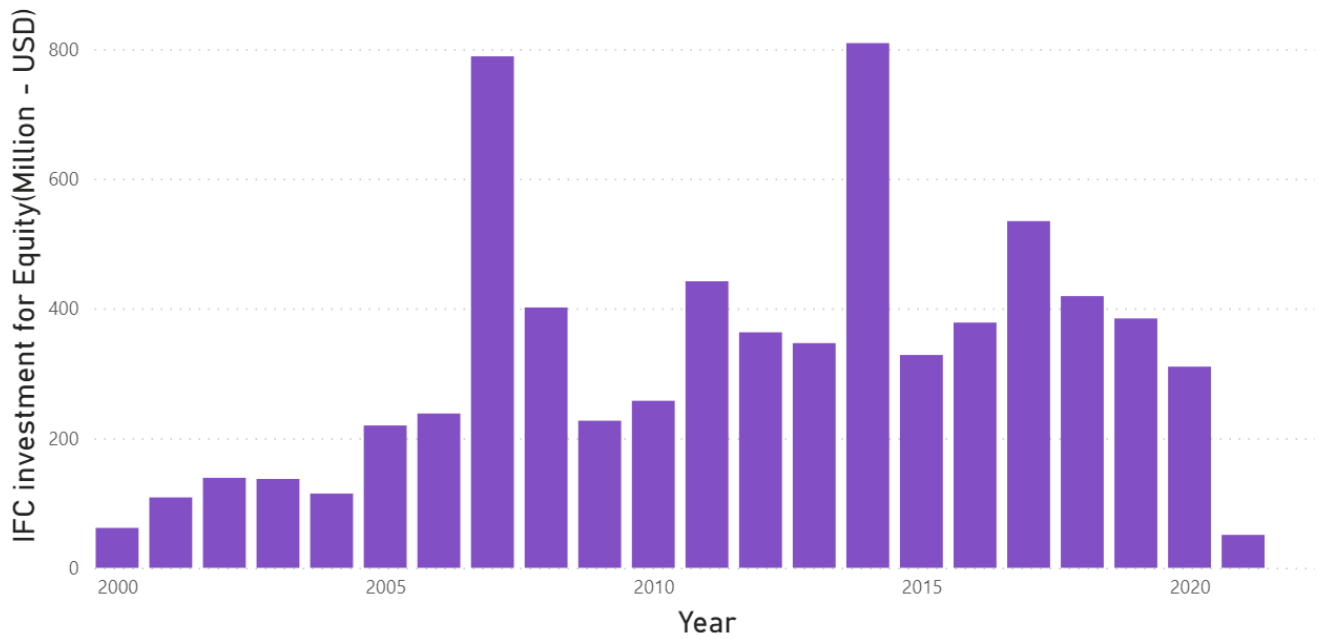


Fig.7.1.1 IFC Investment Equity by Year

IFC investment for Loan

IFC investment for Loan(Million - USD) by Year

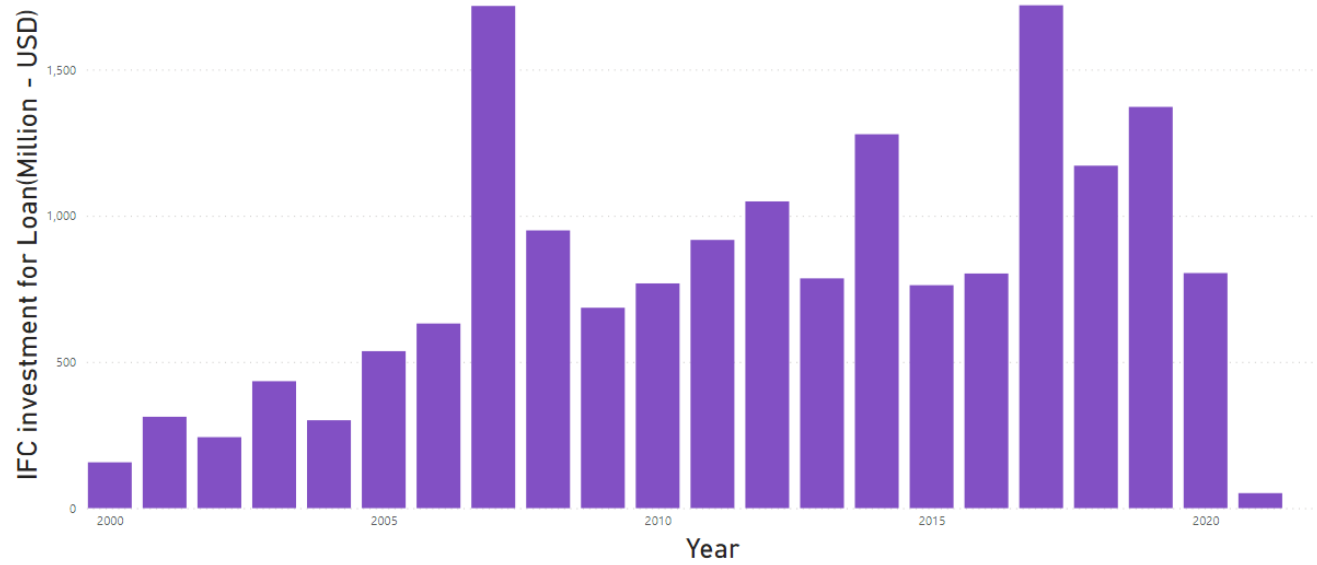


Fig.7.1.2 Investment for loan by Year

Total investment value Vs Predicted value

Total IFC investment as approved by Board(Million - USD) and prediction by Year

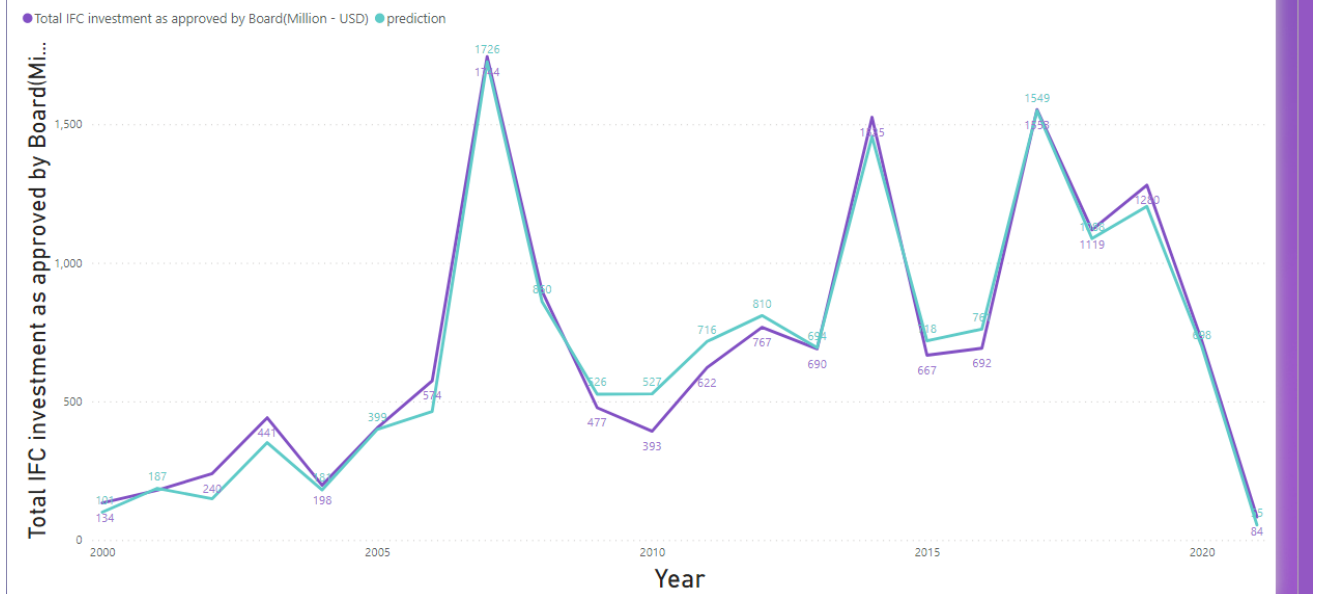


Fig.7.1.3 Predicted and Actual Investment Values

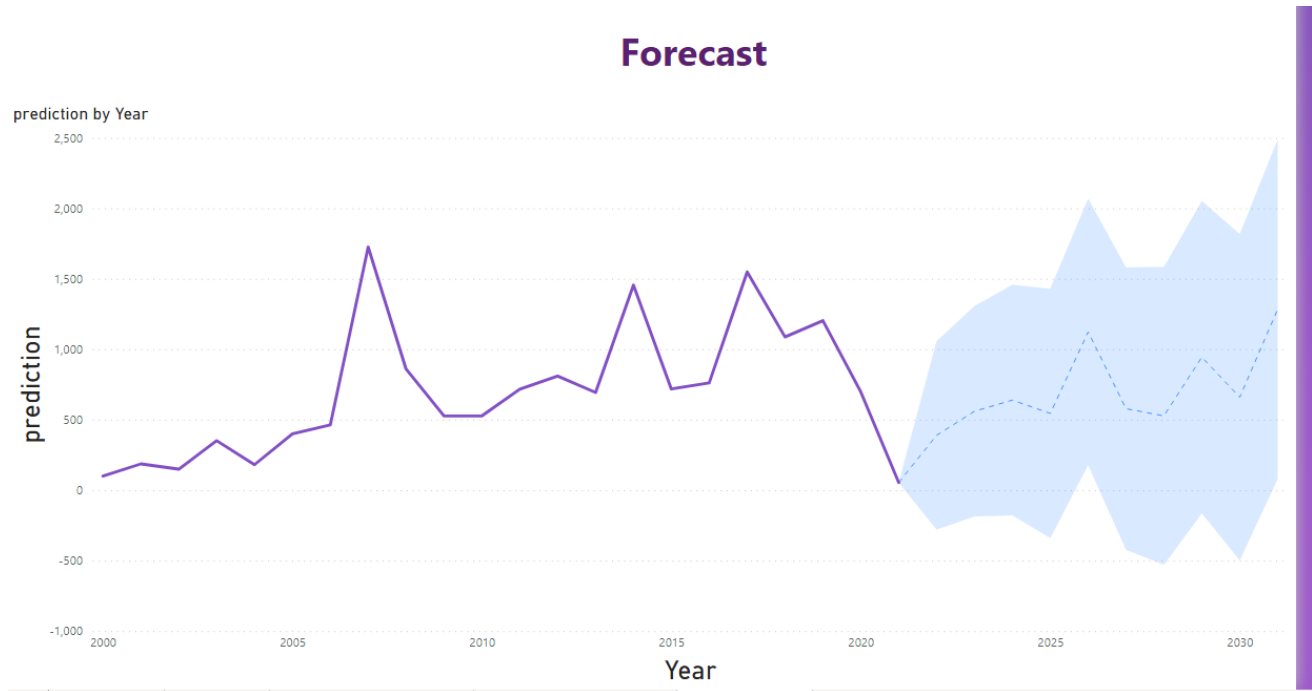


Fig.7.1.3 Forecasting the Future Investment Value For Next 5 to10 Yrs

7.1 B GDP Growth Rate Analysis

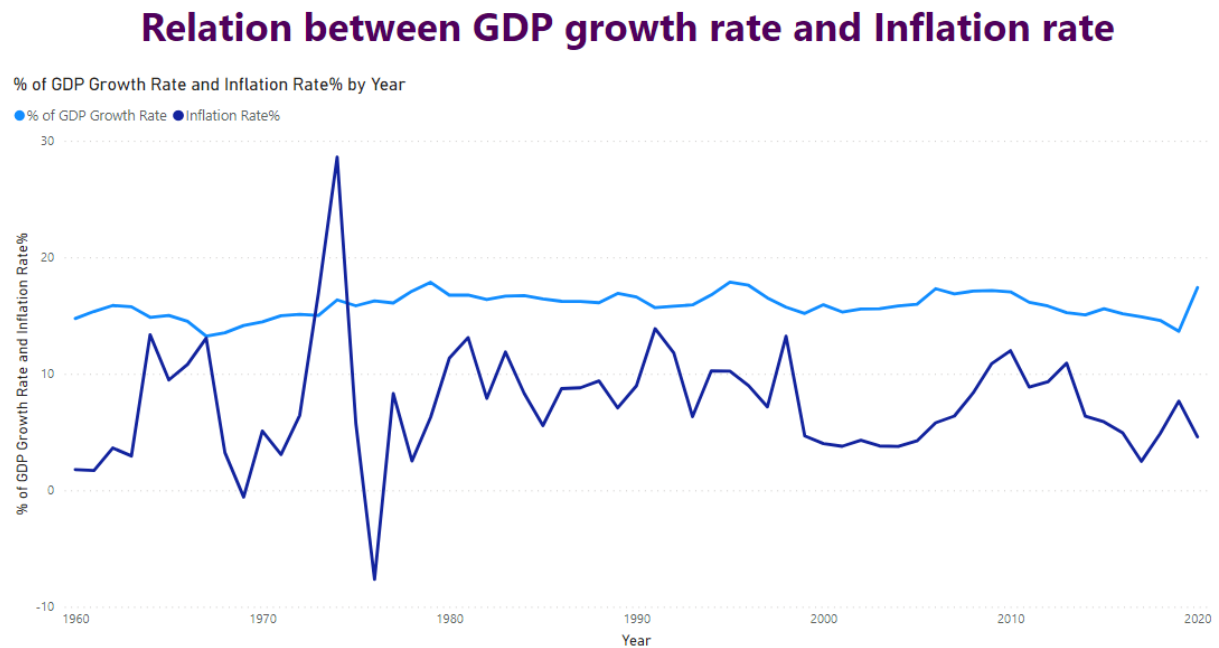


Fig.7.1.4 Relation between GDP growth rate and Inflation rate

Actual gdp value Vs Predicted value

% of GDP Growth Rate and Predicted %gdp growth by Year

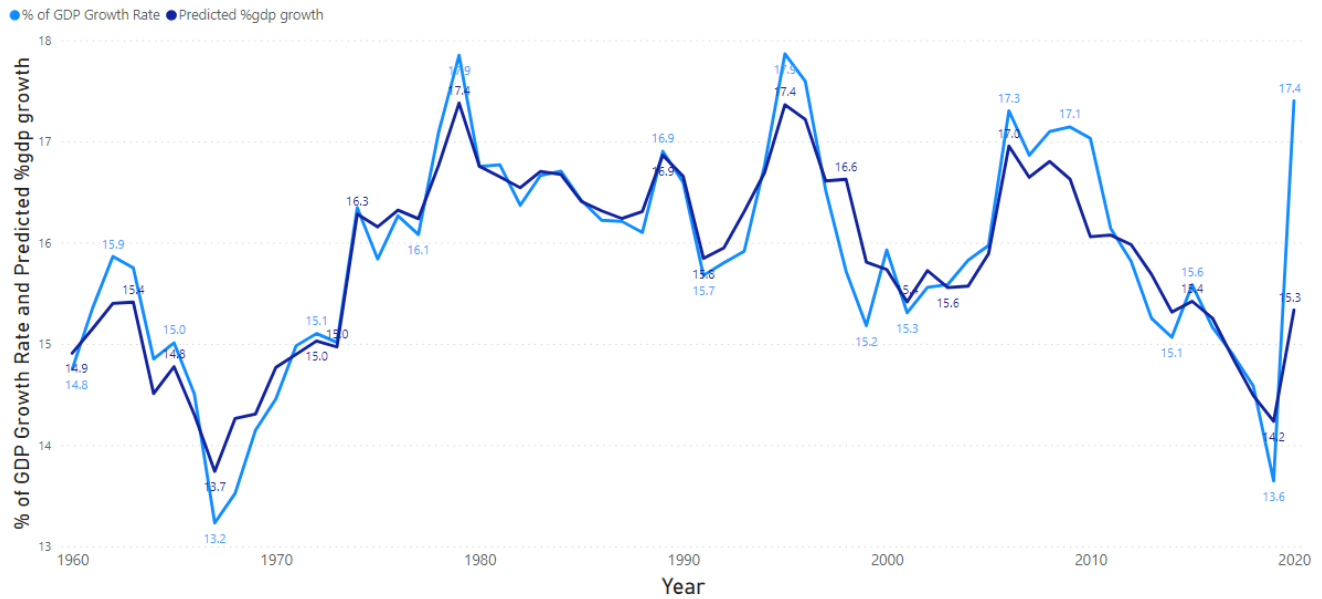


Fig.7.1.5 Actual vs Predicted GDP values

Forecast

Predicted %gdp growth by Year

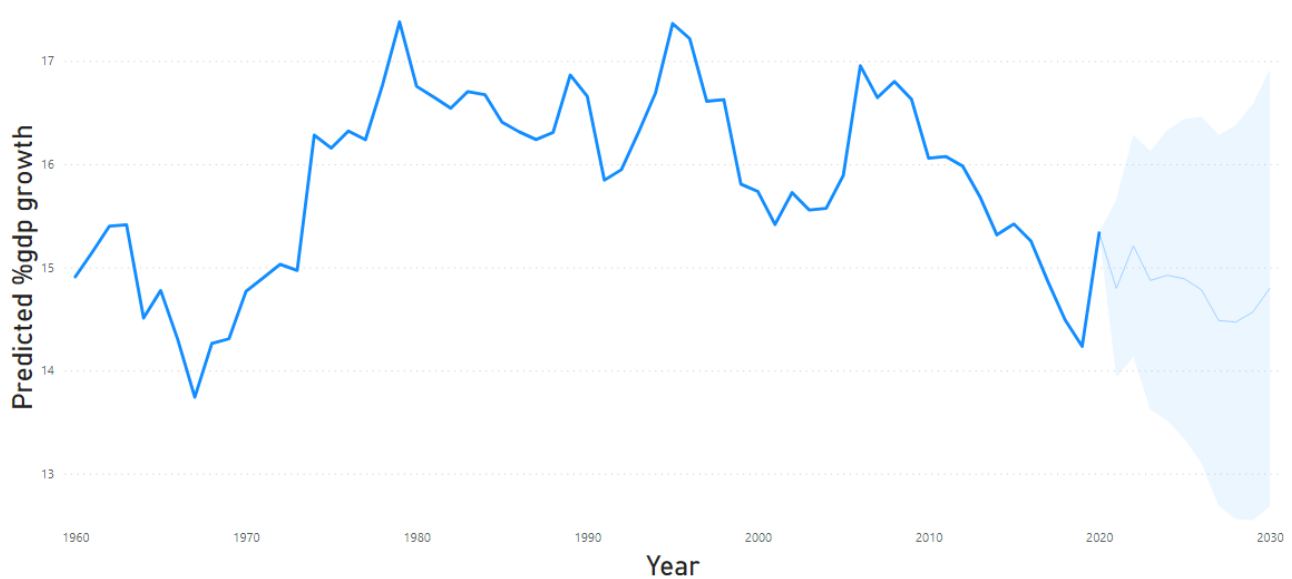
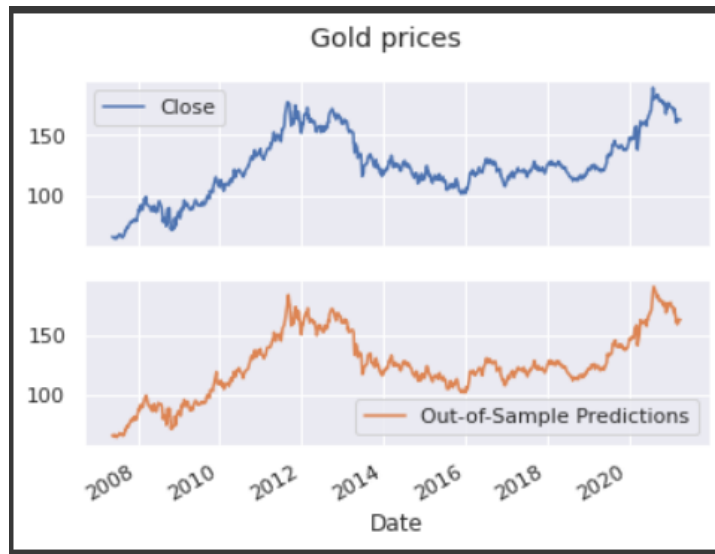


Fig.7.1.6 Forecasting Future GDP growth Rate in next 5 to 10 yrs

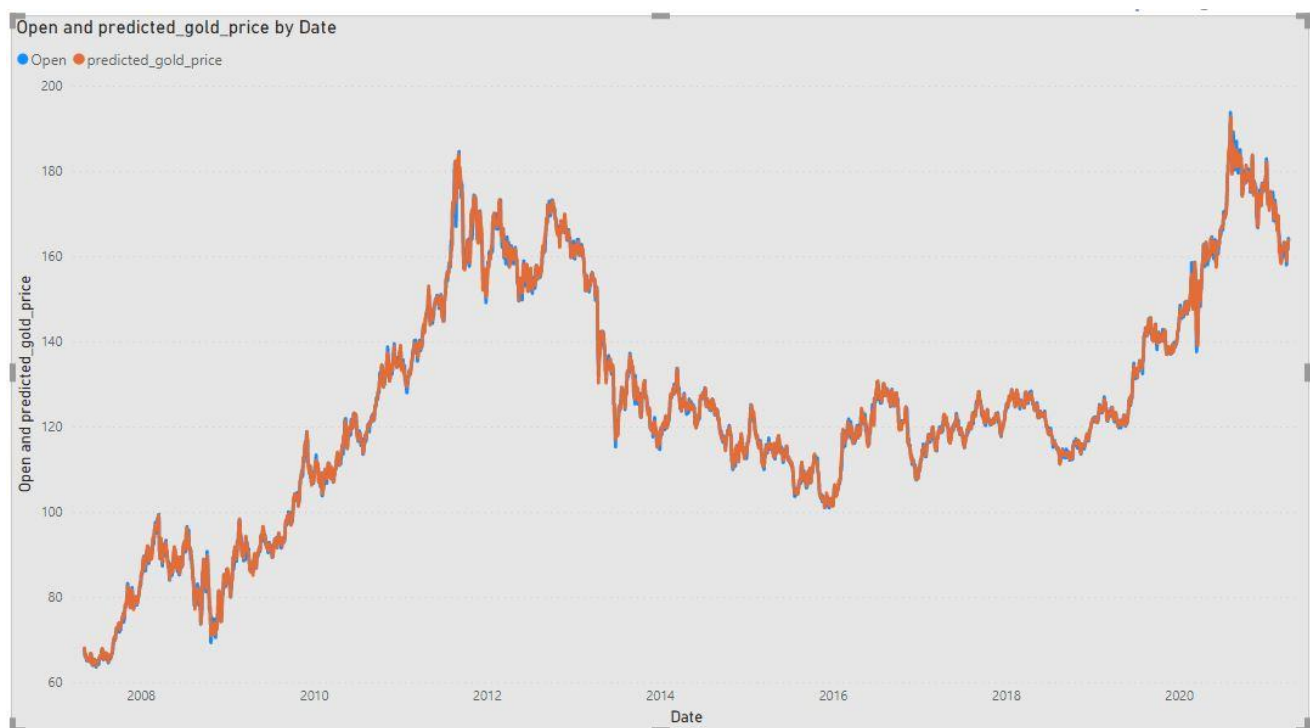
7.2 Gold Price Analysis and Prediction Results



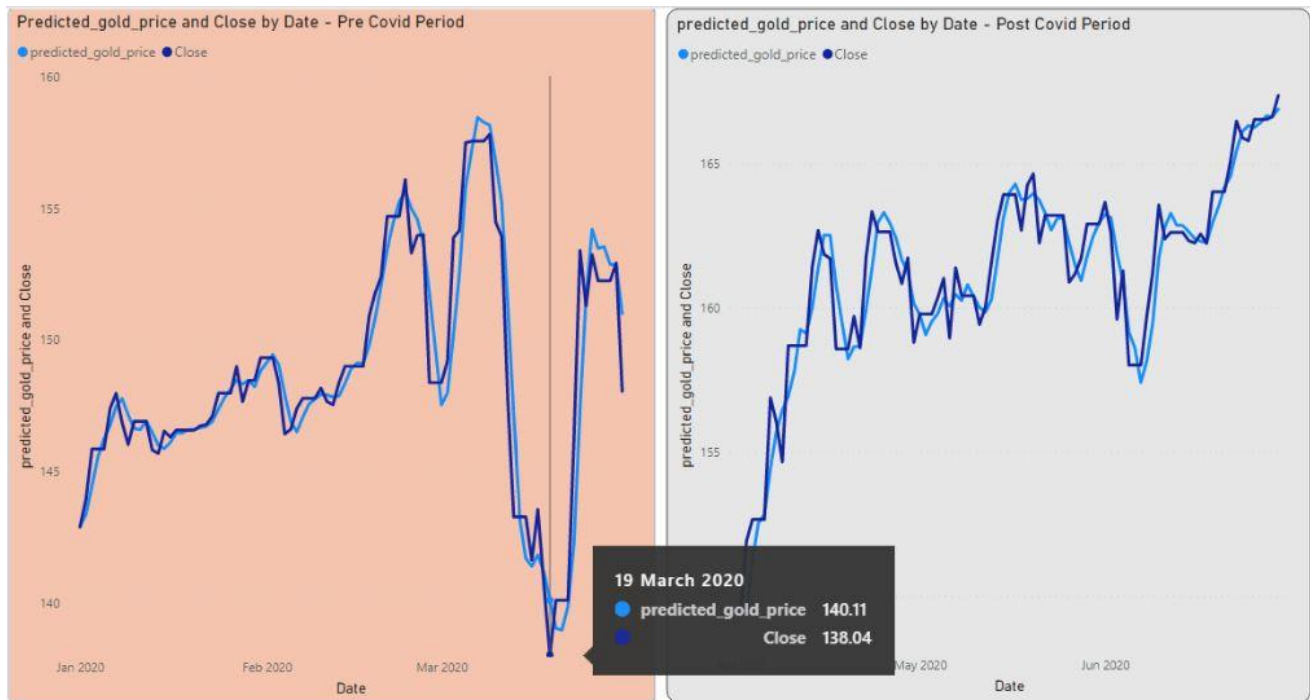
7.2.1 Analysis of fluctuations of Gold Prices from 2008-2020



7.2.2 Out of Sample Predictions



7.2.3 Actual v/s Predicted Gold Prices



7.2.4 Pre-covid v/s Post-covid Analysis

Cumulative Returns				
Year	Quarter	Month	Day	signal
2020	Qtr 2	June	1	Buy
2020	Qtr 2	June	15	No Position
2020	Qtr 2	June	30	Buy
2020	Qtr 3	July	1	No Position
2020	Qtr 3	July	15	Buy
2020	Qtr 3	July	30	Buy
2020	Qtr 3	August	1	No Position
2020	Qtr 3	August	15	Buy
2020	Qtr 3	August	30	Buy
2020	Qtr 3	September	1	Buy
2020	Qtr 3	September	15	Buy
2020	Qtr 3	September	30	Buy
2020	Qtr 4	October	1	Buy
2020	Qtr 4	October	15	No Position
2020	Qtr 4	October	30	No Position
2020	Qtr 4	November	1	Buy
2020	Qtr 4	November	15	Buy
2020	Qtr 4	November	30	No Position
2020	Qtr 4	December	1	Buy
2020	Qtr 4	December	15	Buy
2020	Qtr 4	December	30	Buy
2021	Qtr 1	January	1	Buy
2021	Qtr 1	January	15	No Position
2021	Qtr 1	January	30	Buy
2021	Qtr 1	February	1	Buy
2021	Qtr 1	February	15	No Position
2021	Qtr 1	March	1	Buy
2021	Qtr 1	March	15	Buy
2021	Qtr 1	March	30	No Position
2021	Qtr 2	April	1	Buy

7.2.5 Cumulative Returns of Recent Predicted Data

7.3 Stock Market Results:

Effect of COVID-19 on the stock market

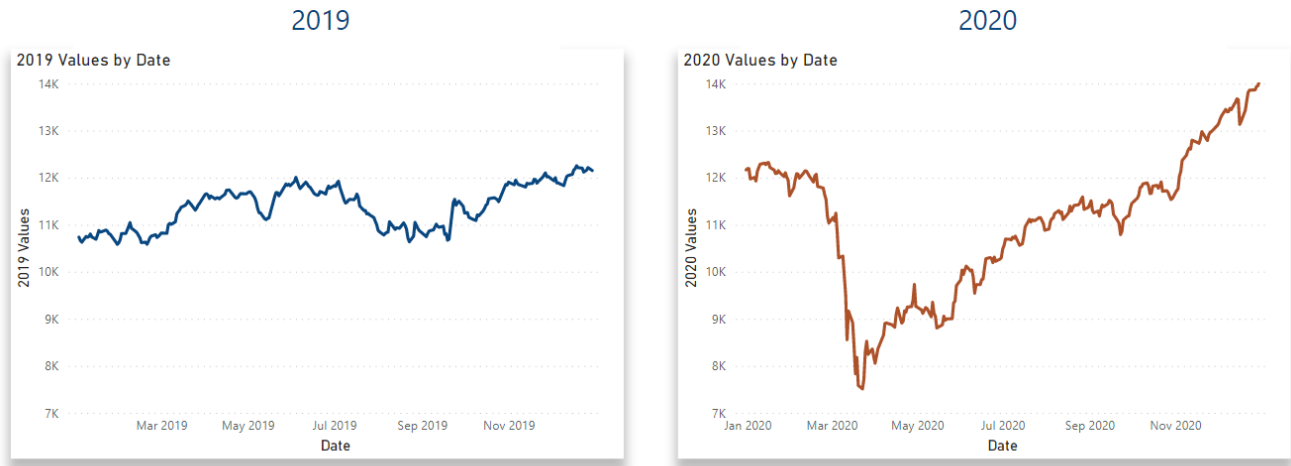


Fig. 7.3.1 2019 vs 2020 Market Analysis

This depicts the impact of COVID-19 on the 2020 market

The performance of the LSTM model is documented as follows:

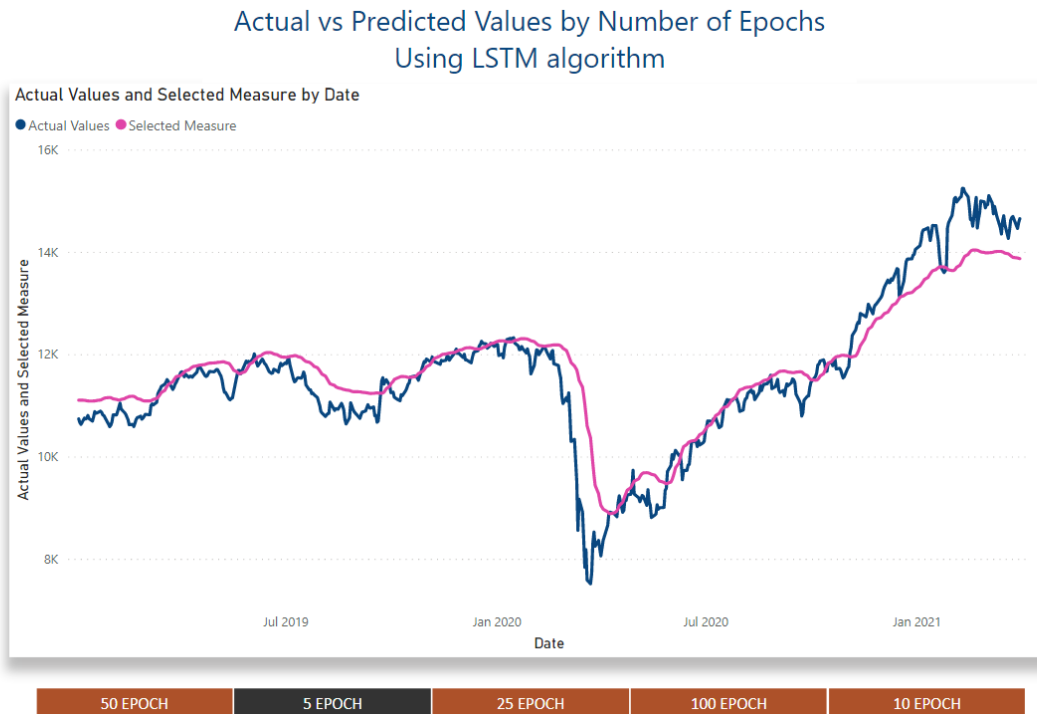


Fig. 7.3.2 Actual values vs Prediction after 5 epochs of training

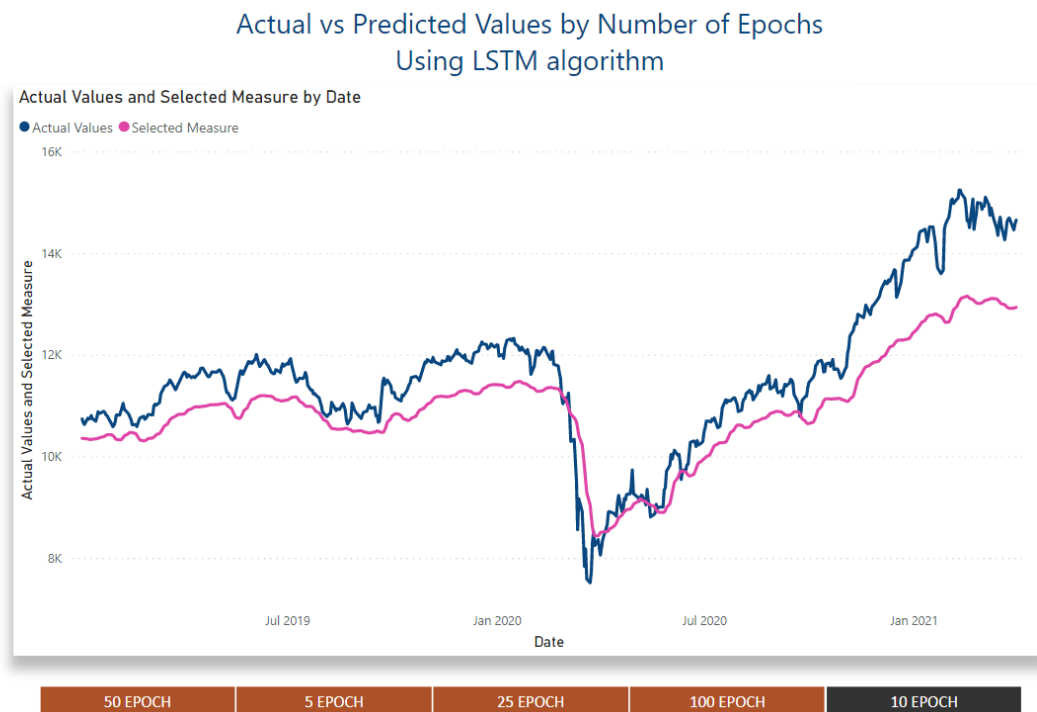


Fig. 7.3.3 Actual values vs Prediction after 10 epochs of training

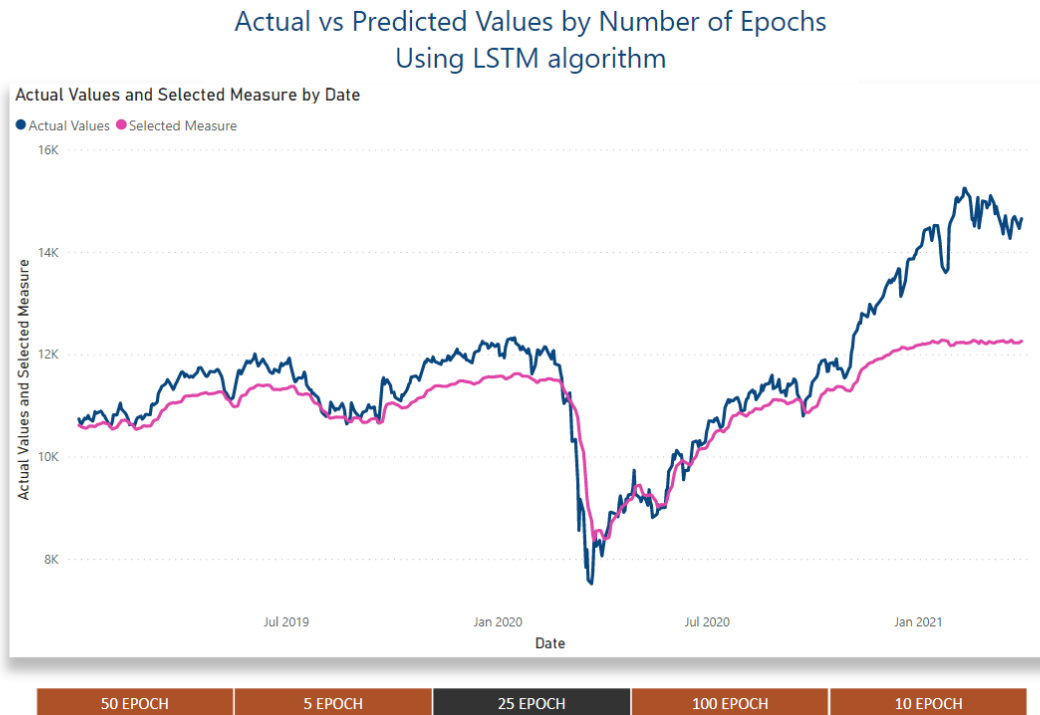


Fig. 7.3.4 Actual values vs Prediction after 25 epochs of training

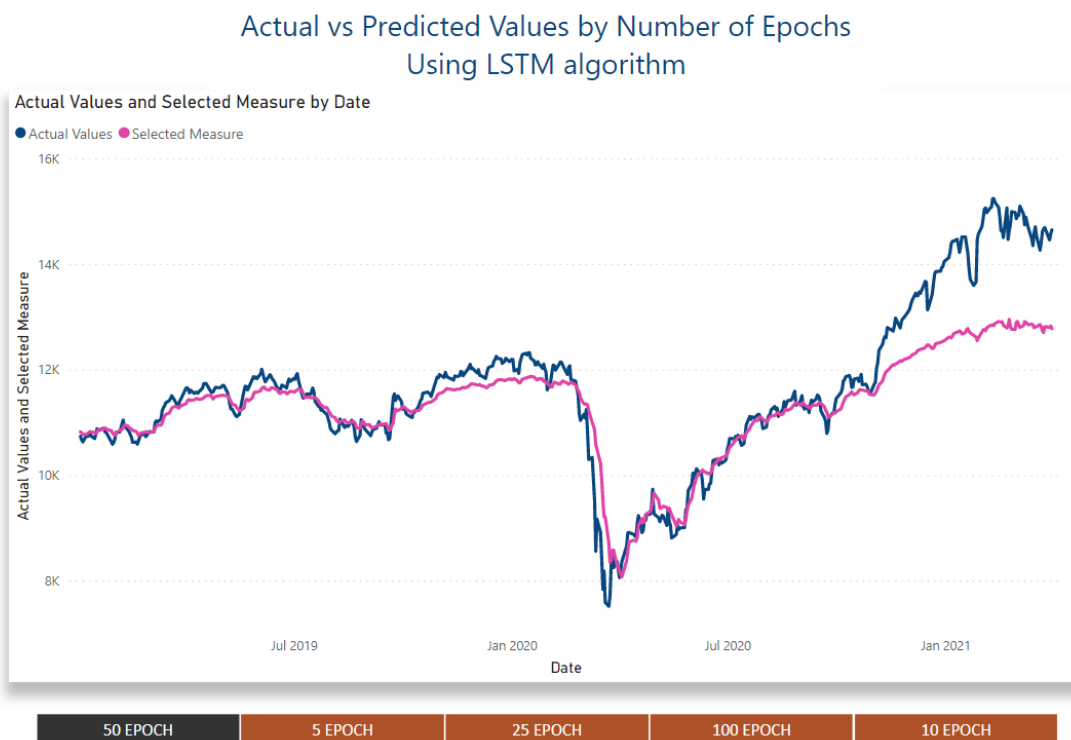


Fig. 7.3.5 Actual values vs Prediction after 50 epochs of training

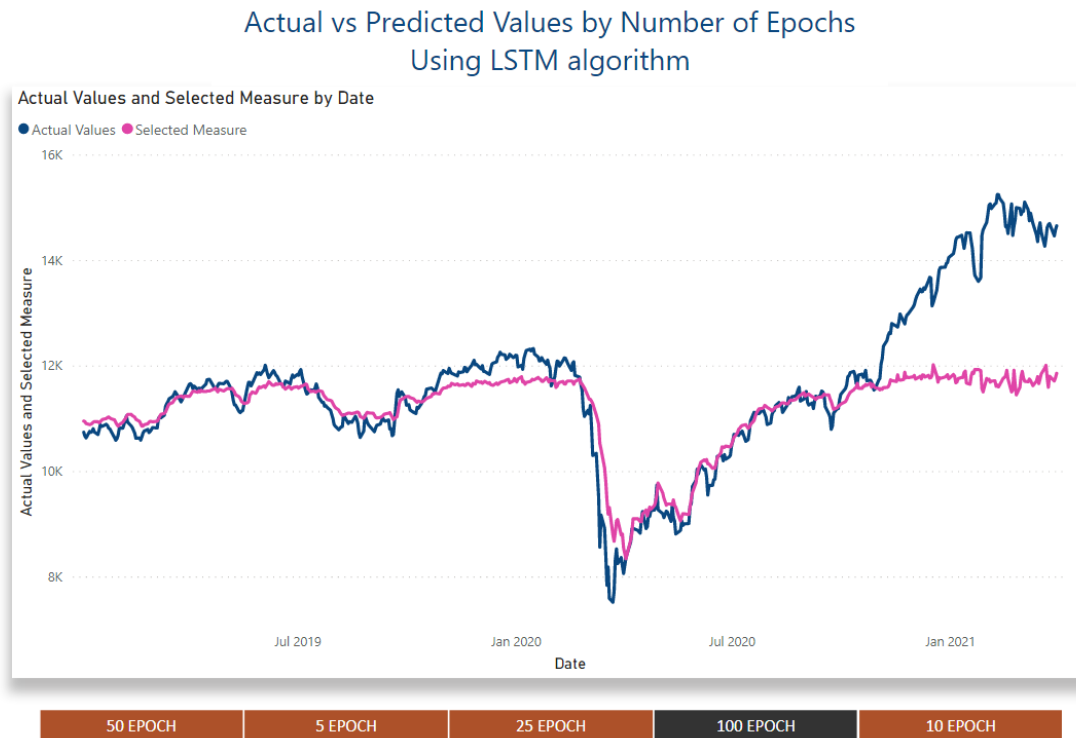


Fig. 7.3.6 Actual values vs Prediction after 100 epochs of training

7.4 Currency Rate Analysis

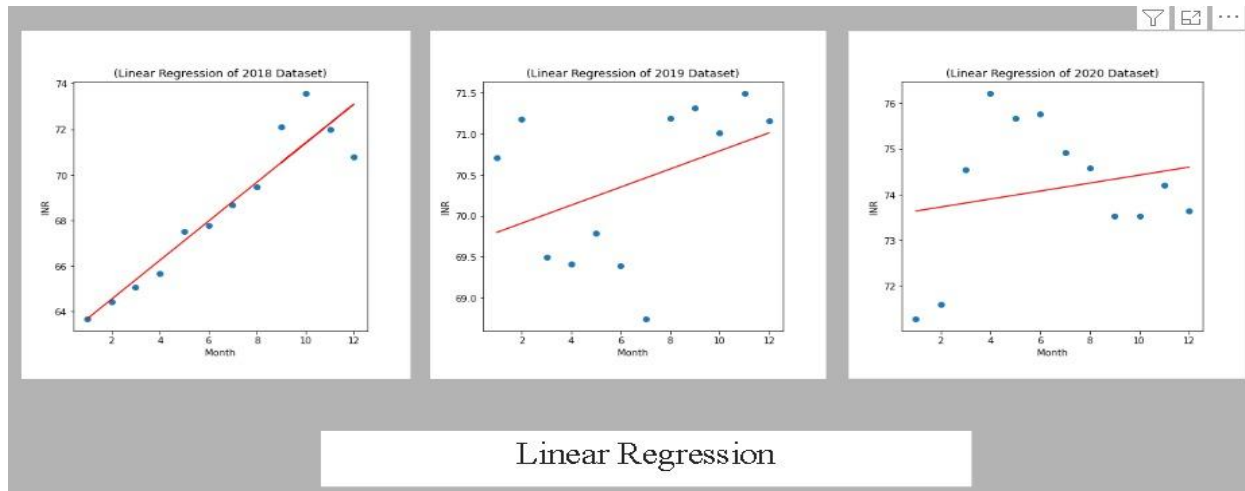


Fig 7.4.1 Linear Regression Analysis

Comparison between 2018-2019-2020 Currency Rates

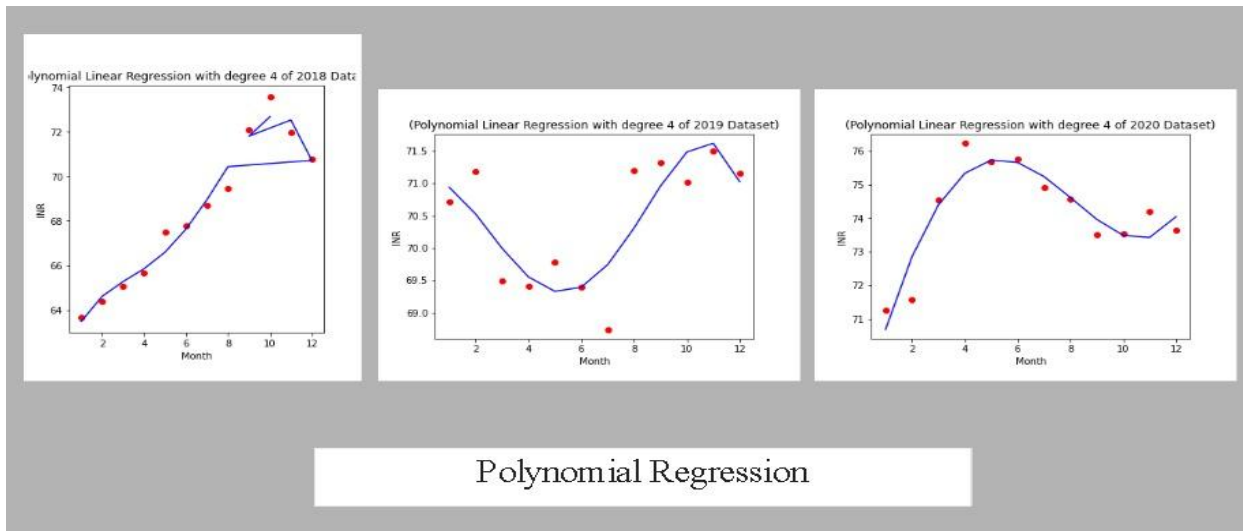


Fig 7.4.2 Polynomial Regression Analysis
Comparison between 2018-2019-2020 Currency Rates

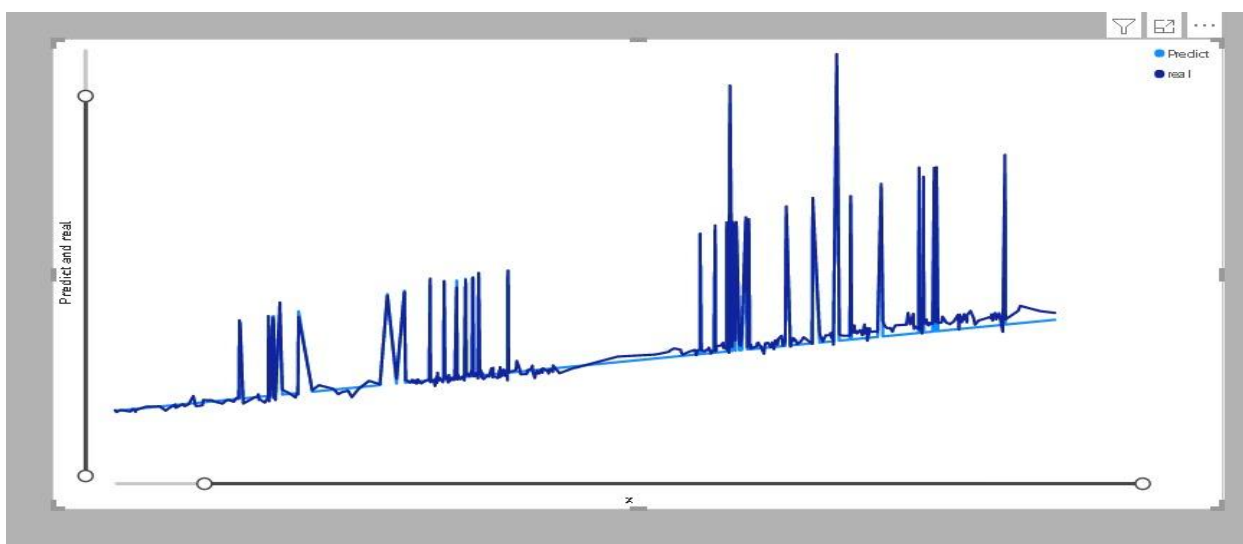


Fig 4.3.6 LSTM Visualization for dataset

7.4 Currency Exchange Results

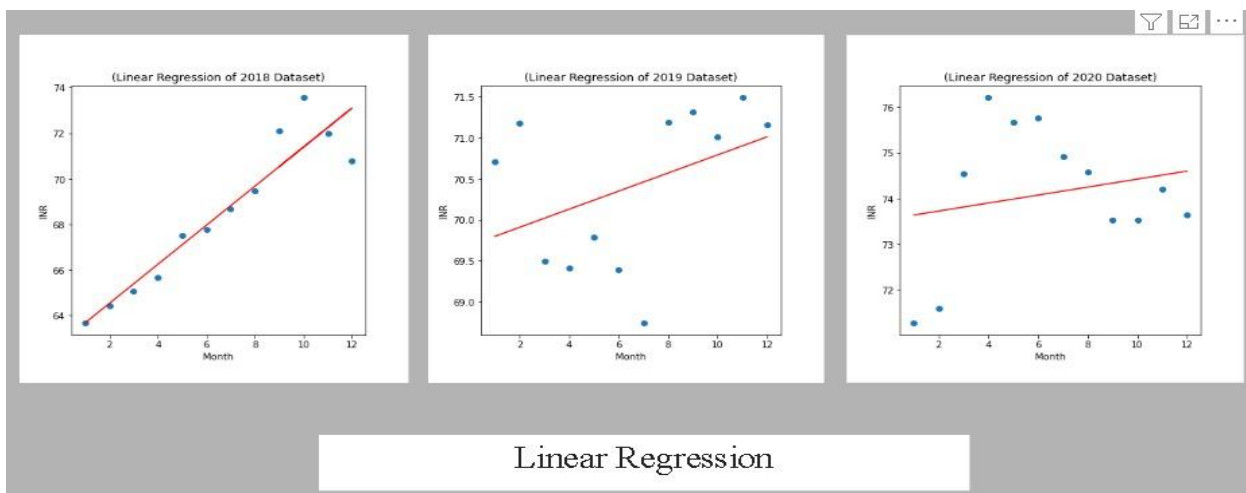


Fig 7.4.1 Linear Regression Analysis Results
Comparison between 2018-2019-2020 Currency Rates

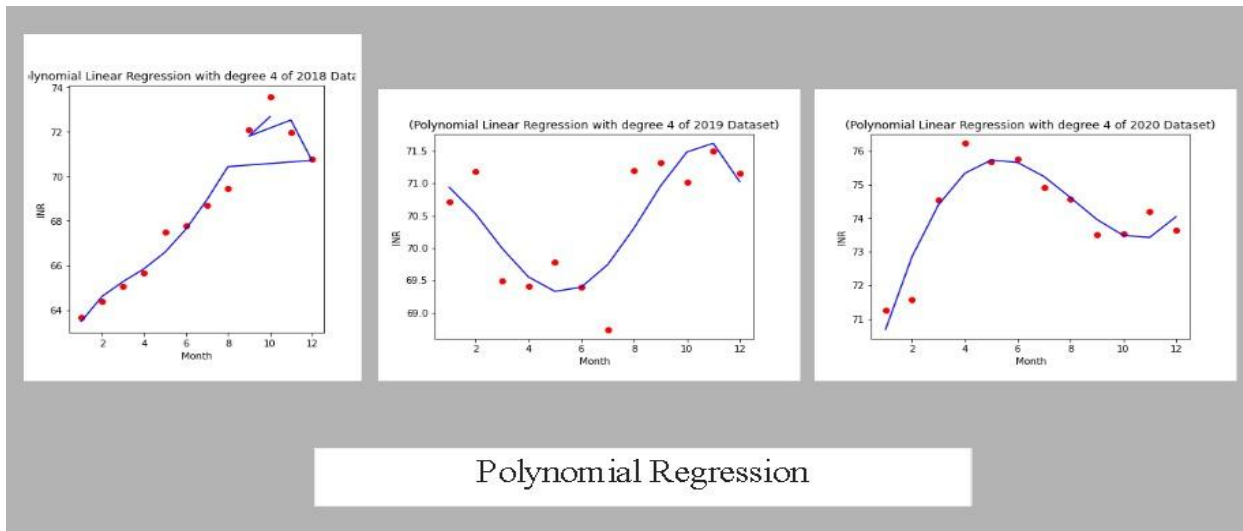


Fig 7.4.2 Polynomial Regression Analysis Results
Comparison between 2018-2019-2020 Currency Rates

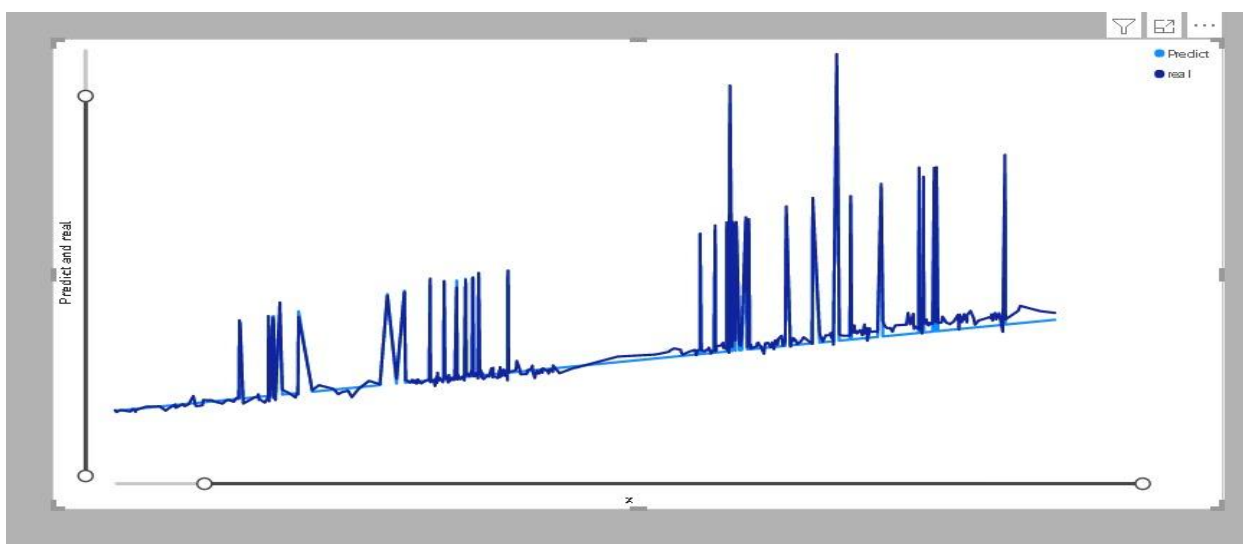


Fig 4.3.6 LSTM Visualization for dataset

7.5 Share Price Investment Analysis

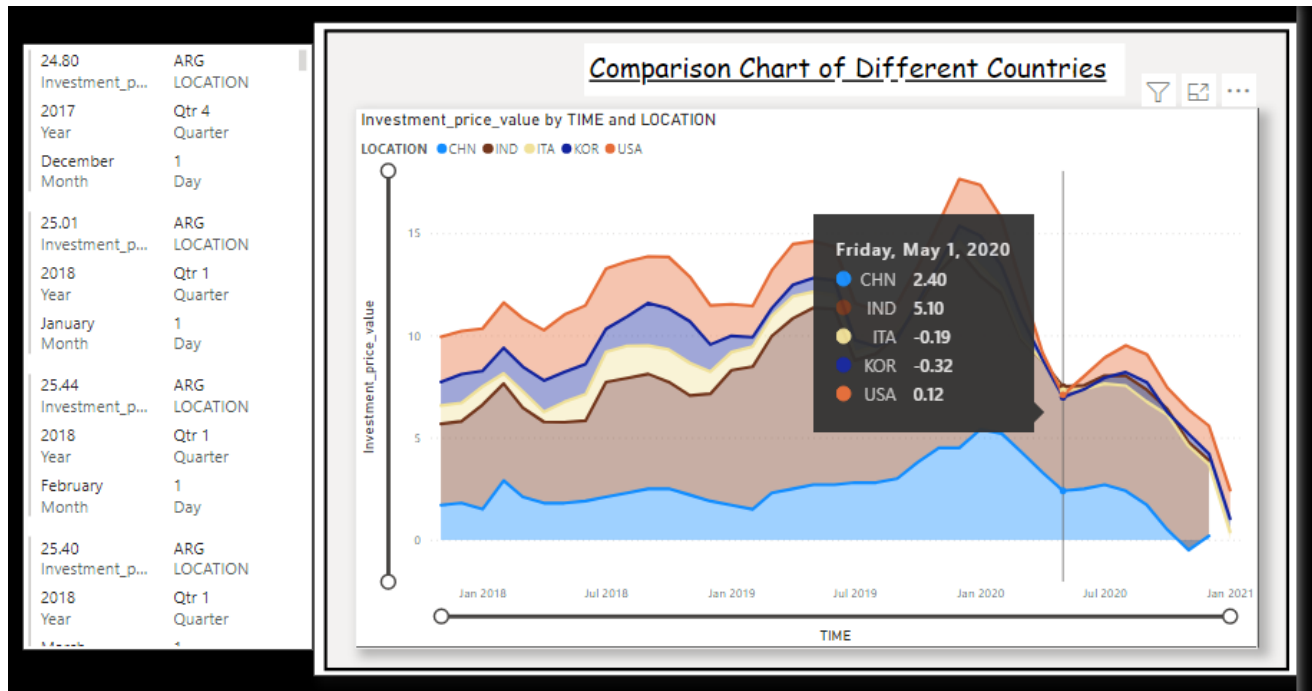


Fig. 7.5.1 Comparison Chart of Different Countries

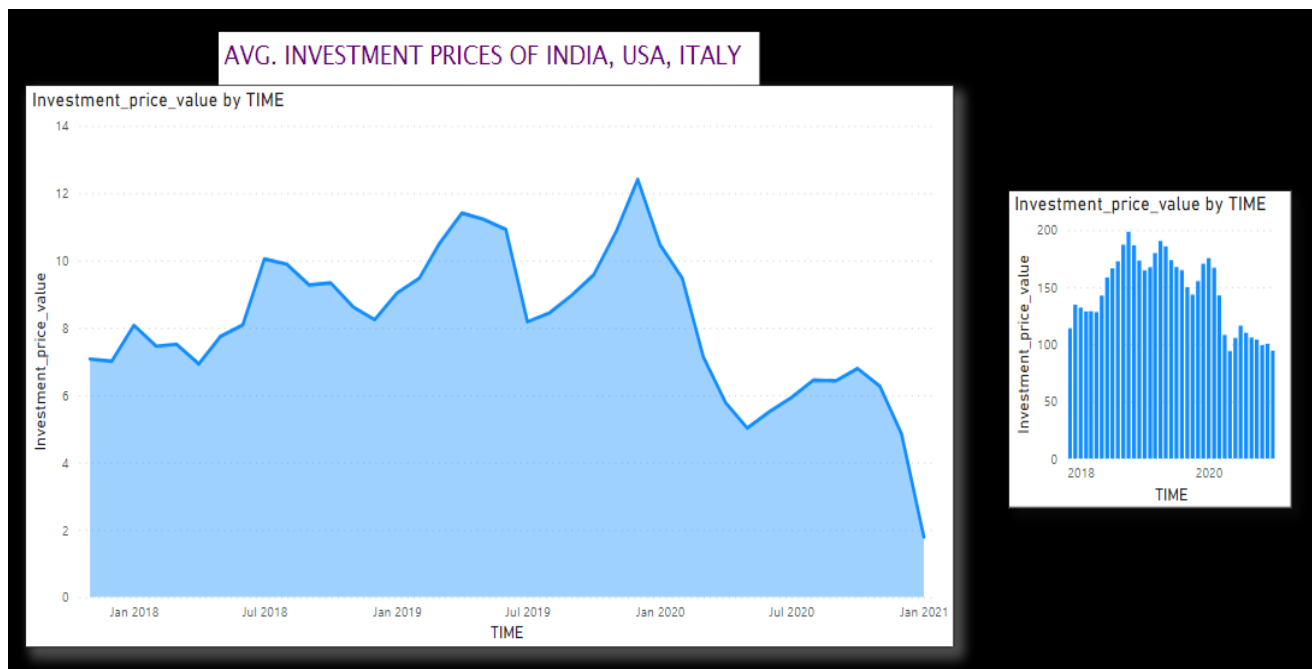


Fig. 7.5.2 Average Investment Prices of India, USA and Italy

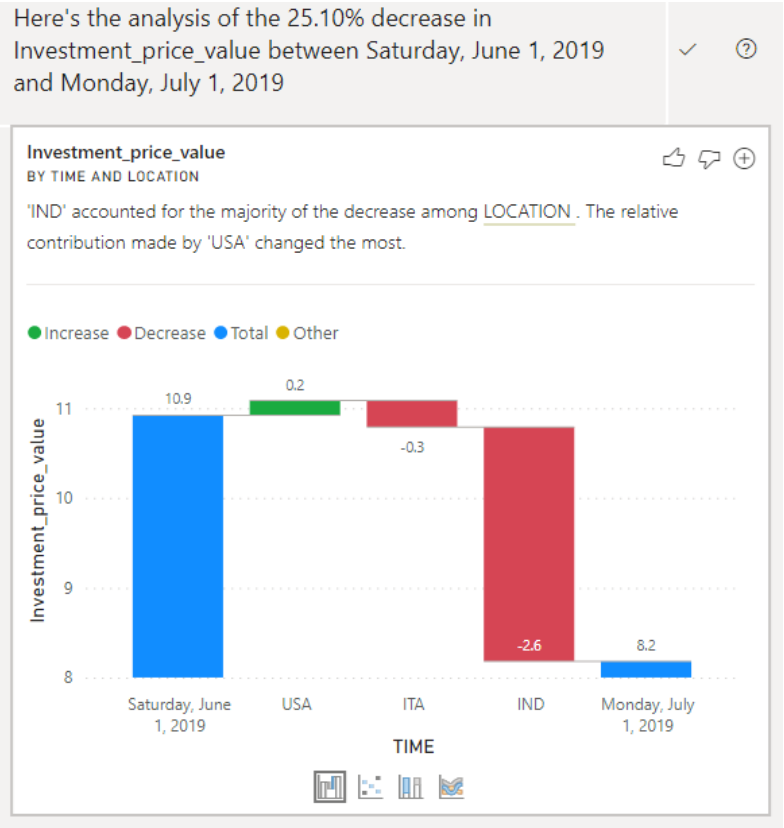


Fig. 7.5.3 Analysis of Sharp Decrease dated June 1, 2019

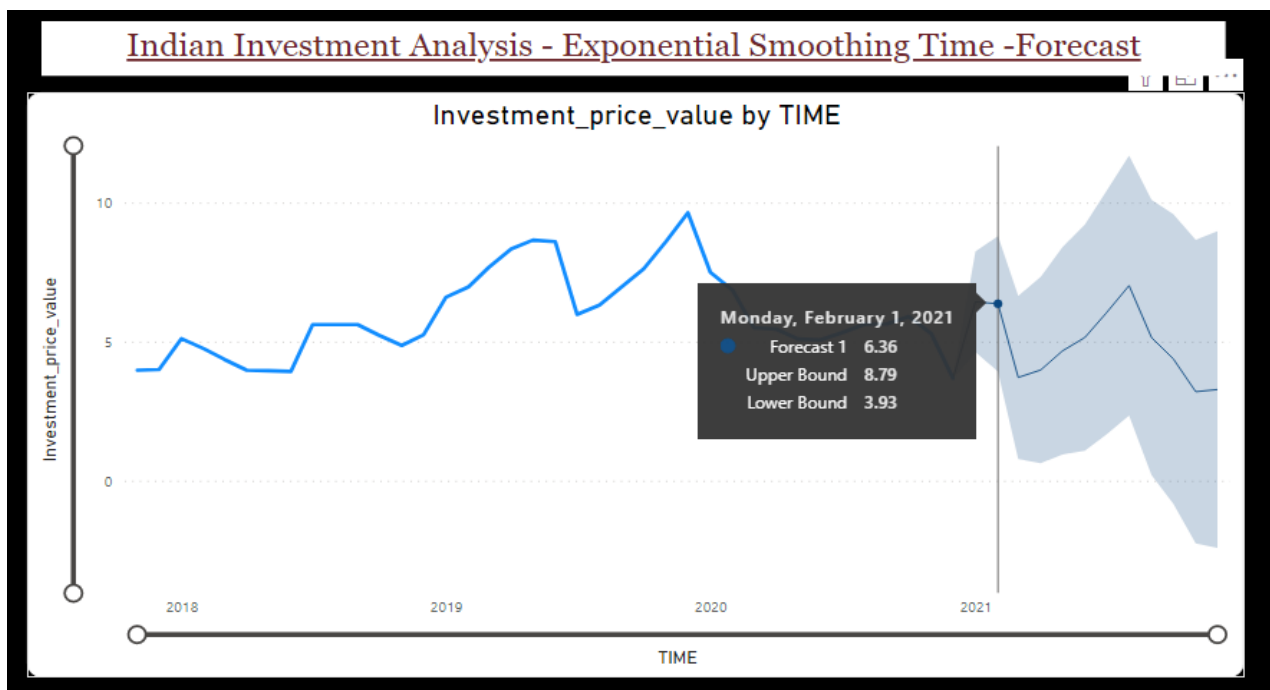


Fig. 7.5.4 Indian Investment Analysis - Exponential Smoothing Time -Forecast

8. CONCLUSION

The following aspects of global finance were thoroughly analysed to extract striking as well as latent trends:

- 1 Investment and GDP Growth Rate
- 2 Gold Price Analysis and Prediction
- 3 Stock Market
- 4 Currency Exchange Rate Comparison
- 5 Share Price Investments

The analysis was followed by a prediction of these aspects in the near future using relevant machine learning algorithms.