Stock Market Price Prediction Using Time Series Models

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Disclaimer

I hereby certify that this material, which I now submit for assessment on the programme of study leading to the Degree of Master of Science in Big Data Management and Analytics at Griffith College Dublin, is entirely my own work and has not been submitted for assessment for an academic purpose at this or any other academic institution other than in partial fulfilment of the requirements of that stated above.

Signed: AKASH PRATHAP **Date: 12/06/2020**

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Abstract

The research topic ‘Stock Market Price Prediction using Time series models’ mainly aims to evaluate the time series model to predict the stock market price of four Indian Banks. The time series prediction can be applied into various fields especially in financial field. This thesis examined a study on the time series prediction of KERAS with LSTM (Long Short-Term Memory), ARIMA and PROPHET models. The past 10 years of data is collected from yahoo finance is utilized to develop the time series models. The prediction results show that all three-time series models have strong potential in time series prediction. Keras with LSTM is giving better result while compared to other two models in time series prediction. In addition, a web application is developed to help the investors to identify the predicted stock price of Banks. The application is made with the aid of Flask web framework in python.

Chapter 1. Introduction

"The Stock Market is a device for transferring money from the impatient to the patient."- Warren Buffet (American Investor & CEO of Berkshire Hathaway)

"The four most dangerous words in investing are: This time it's different."- Sir John Templeton (British Investor)

1.1 Terms and Definition

What is Stock and Stock Market?

The Stock market is a prediction of buying and selling by a company on a given business day. The stock exchange is like an auction where the investors can sell and buy the shares of stocks and the investors who hold the share of these stocks in a company or organization are called as shareholders or stockholders. A stock exchange is an exchange where traders and stockbrokers buy and sell shares. The stock market mainly deals with the securities and these securities are involved in such a way that it is a fixed interest security and the trade in stock exchange means transfer of a security or stock from buyer to seller [1].

The financial activities of the stock market are carried through institutionalized formal exchanges or Over the Counter (OTC) marketplace which will be mainly operated under a regular set of regulations. The stock market and the stock exchange, both the term is used interchangeably in business but the latter is subset of the former (example: If one trades in share market that means that they can buy and sell shares on one of the stock exchange that is part of entire stock market.

The stock market which is primarily used for trading stocks can also be helpful to other financial securities like corporate bonds, exchange traded funds and some other basic derivatives such as commodities, currencies and bonds that is traded in the stock market. In today's world most of the people can do the purchase in online but some stuff can only be bought outside the online for which the stock market plays a crucial role in which it is designated in a similar fashion of market for various trading securities in a controlled, secure and managing environment. The main factor of the stock market is even though it brings hundreds of thousands of participants together who wish to buy or sell shares making them to have a fair pricing and transparency in transactions [2].

The working of the stock market is quite simple as it allows general public to take a choice whether or not to invest their shares in a particular organization, by allowing them to buy or sell an organization shares to the public through the process of initial public offerings. This activity will help an organization to deal with its investors. In order to initiate these processes an organization needs a marketplace where it can sell its shares and the place of this required marketplace is called as stock market.

What is Stock Market Prediction?

The future value of an individual stock, a market or the whole market can be aimed to be predicted, this is known as stock market prediction. It generally uses technical analysis of charts or the fundamental analysis of a company or combination of two. Since all investors wants to predict the value of stocks there will be more stock market prediction by self-styled experts in media and published by investment advisors and brokers [3].

In short, the stock market prediction is all about determining the future value of a company with which the company's financial instrument traded on an exchange. The success of the stock market price of the future will give a significant profit in the field of stock market. There are various aspects of the stock market prediction which are as follows: Fundamental analysis, Technical analysis, and the Machine learning.

Fundamental Analysis is mainly based on the past performance of the company which gives the credibility of its accounts and it is mainly done with the use of performance ratio which is mainly helpful for doing it.

Technical Analysis is not considered with the company's fundamental, here the techniques are used to predict the future price of the stocks and these techniques includes of the Exponential Moving Average (EMA), oscillators and volume indicators etc. Candle stick patterns developed by Japanese rice merchants are most used technical analysis nowadays.

Machine Learning is another way in which stock market can be predicted and it uses many algorithms with which all these algorithms are based on the Artificial Neural Networks (ANN) and Genetic Algorithms. The main aspect of the artificial neural network is the use of time series forecasting with which using this forecasting the anticipating trend changes of the numerous stock markets and time series datasets.

The predictive analysis is being utilized by organizations or companies, individuals everywhere throughout the world by extracting the historical data. The different techniques in executing the forecast framework like Machine Learning, Technical Analysis, Fundamental Analysis, and Time series Forecasting. By advancing the innovation, the Artificial Intelligence includes the man-made consciousness which enables the framework to prepare and improve as a matter of fact [4].

What is Time series forecasting?

The most important aspect of machine learning involves with the time series forecasting and it is important because most of the prediction problems including time component are dealt here. Before we see time, series forecasting let us see more about the time series. The time series is modelled through a stochastic process and mainly constituted with the four components which are: Level, Trend, Seasonality and Noise.

Level is a value for baseline in the series if it is straight line.

Trend is linear increasing or decreasing behavior of the series over time.

Seasonality is cycles of behavior or repeat patterns over time.

Noise is a change in observations which cannot be explained for the given model.

The time series forecasting is all about making predictions about the future and the process of predicting future is called as extrapolation in statistical handling of the time series. The modern field mainly focus on the topic and hence refer to it as a time series forecasting. Forecasting mainly involves with taking the historical data that fits the model and using them to predict future observations and important aspect which has to be considered is future cannot happen and it can be predicted only with estimation of already happened events.

The purpose of time series forecasting involves with mainly two folds which are: to understand or model the stochastic mechanisms which leads to an observed series and to predict or forecast the future values of the series based on the already known historical data of that series. The time series forecasting is mainly used in R and Python and it has many kind of models which are as follows: Naïve, SNaïve, Exponential smoothing, ARIMA, Dynamic linear models, FBProphet, LSTM. Out of which ARIMA, FBProphet and LSTM are mainly used in this paper.

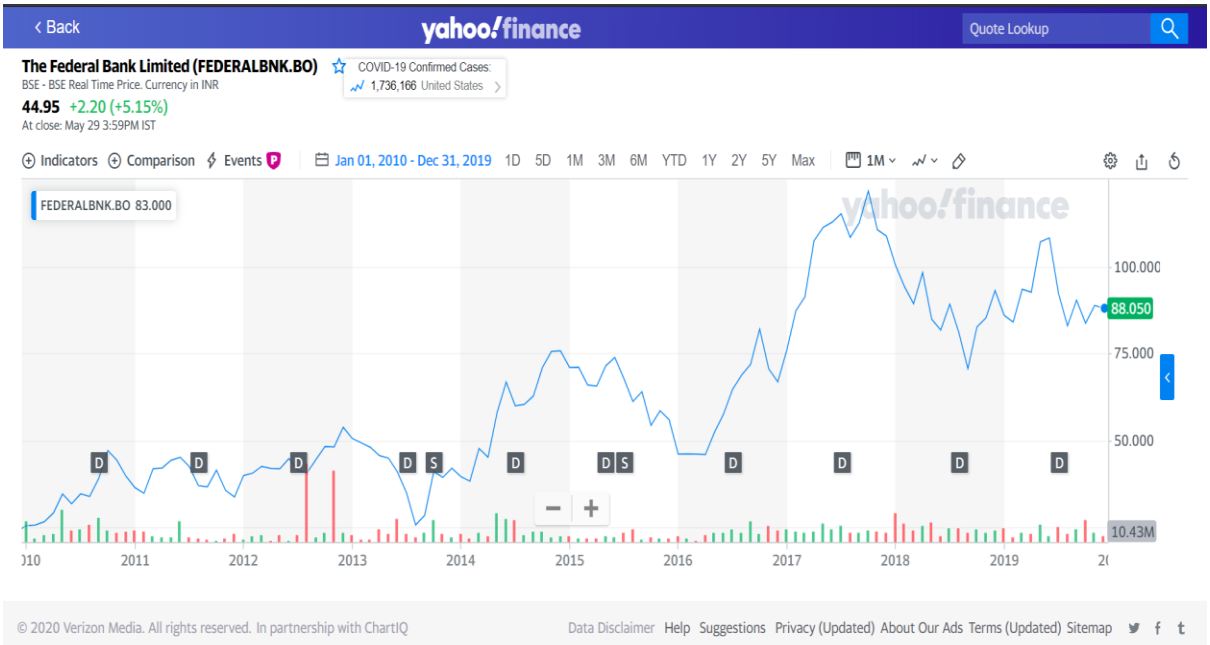


Figure 1 : The Federal Bank Limited stock price representation in Yahoo Finance. [5]

The figure 1.1 shows an example of time series data representation of a Federal Bank in India over a period of 10 years.

1.2. Overview of approach

This thesis primarily centered around the stock market price prediction of top four (Federal Bank, ICICI Bank, Canara Bank and Axis Bank) Indian banks by using time series models. Yahoo Finance is utilized for gathering 10 years of data. Close price value in the dataset is used for the future price prediction. For this KERAS with LSTM (Long Short Term-Memory), Prophet and ARIMA algorithms are used.

Python version 3 programming language is used for doing the time series analysis. Jupyter Notebook is used for the processing and visualization of data in the primary stage import libraries and python packages for the functioning of the model. Data is split for training and testing purpose. Time series models are developed in the subsequent stage. Data is predicted and forecasted in the final stage. By calculating the RMSE value of each algorithm efficiency and accuracy of each algorithm is identified and Visualized with the help of a Bar diagram. A web application is also developed. Flask and Python are used for developing back end and HTML(Hyper Text Markup Language) and CSS (Cascading Style Sheet)are used for designing the application.

List of Technologies used for implementation

1. Programming Language - Python Version 3.
2. Libraries – Pandas, NumPy, Sklearn, TensorFlow, Keras.
3. IDE – Jupyter Notebook, PyCharm
4. Web Framework – Flask
5. Python Package Manager – Anaconda 3

1.3 Document Structure

The document contains eight chapters. In chapter one it includes problem definition, overall view of the project. In chapter two it highlights about the project motivation and research problem. In chapter three it describes the detail study of time series models, analysis and forecasting in existing research papers. In chapter four it deals with the CRISP DM Approach and defines about algorithm used. In chapter five it defines about the Core Structure - Hardware and Software, Artefact Diagram. In chapter six it defines data Collection, Pre-Processing etc. In chapter seven express the deployment of time series models - testing and evaluation. In chapter eight describes the conclusion and future work of the project.

1.4 Dissertation Roadmap

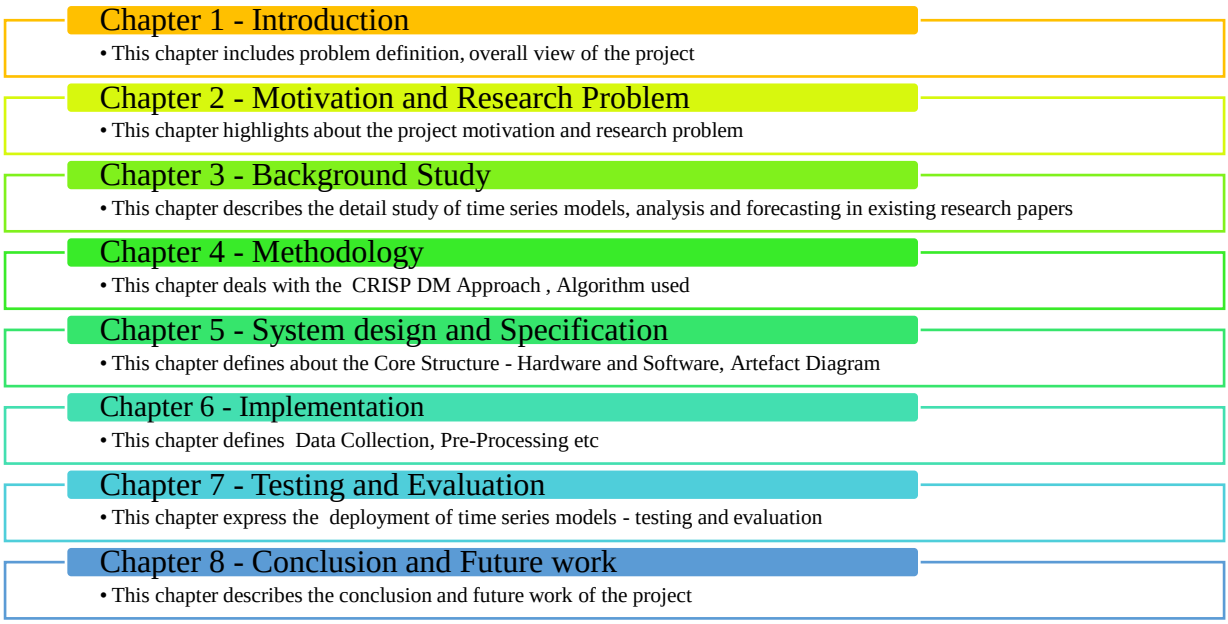


Figure 2: Dissertation Roadmap

Chapter 2. Motivation and Research Problem

Time series helps with understanding the past conduct and would be useful for future expectations. It assists with looking at the exhibition of two diverse arrangement of an alternate kind for a similar time length. The investigation of time arrangement causes us to think about the current execution of the arrangement with that of the past [6]. By Predicting Stock Market Price in Banking sector that which helps to develop the economy of a nation.

2.1 Research Question

1. Identifying which is the most suitable time series model for Stock Market Price Prediction in the field of Banking Sector in India?

2. How the prediction of Stock Market Price of Banks in India helps the development of Indian Economy?

India is a country which have a growing economy. One of the world's 7^{th} largest country in the world which have a mixed economy system. Prediction of Stock Market Price in the Banking Sector which helps to identify the stock rates of coming dates that which helpful for the investors to invest their capital in financial sector, especially in banks. The main advantage of investing money in the banking sector that will rapidly increase the development of Indian Economy by introducing new banks. If the number of bank accounts is increased, it would also mean that stock prices are steadily rising. [7]

Predicting day by day stock market price helps the investors to identify the which bank is more suitable for the investing their money. By predicting the Stock Market Price Prediction, Government can also identify What are the factors that influencing the rise and falls of Stock Price?

2.3 Time Series Models

1. KERAS with LSTM (Long Short Term-Memory).

2. Prophet model.

3. ARIMA (Autoregressive integrated moving average) model.

Chapter 3. Background Study

This chapter discussed about the background study of the research papers that are related to the project.

3.1 Literature Review

3.1.1 Stock Exchange: The Birth

Stock is a word which is used for symbolizing an investor's ownership in a company and those who hold the stock are called as shareholders. The concept of modern stock world began in the late 16th century. When merchants want to start the huge business they don't have a single great investor so they decided to collect savings from all the investors who are interested to give their particular share and contribute to the large business and hence become business partners. This all started back in 1602, when Dutch East India Company issued the first paper of shares, which allowed the shareholders to conveniently buy, sell and trade their stock with other shareholders [8].

3.1.2 Stock Market Price Prediction system – Modular Neural Network

It is based on the buying and selling time prediction system for the stocks on Tokyo stock exchange and it concentrates mainly on the modular neural networks. A number of learning algorithms and prediction methods were developed for the prediction system which is also called as TOPIX (Tokyo Stock Exchange Prices Indexes) and this prediction system gave an accurate prediction, simulation on stocks trading [9].

3.1.3 Stock Price Prediction using ARIMA(Auto-regressive Integrated Moving Average) Model

In terms of economics and finance the stock price prediction plays a crucial role and which gives more interests towards the better development of the predictive models. That is where the Auto-regressive Integrated Moving Average (ARIMA) models playing an important role in the time series prediction. This paper mainly concentrates on the stock price prediction using the ARIMA model and it mainly takes the data from the New York Stock Exchange (NYSE) and Nigeria Stock Exchange (NSE) used with stock predictive models and the result obtained

from this paper states that ARIMA model is strong for short term prediction and it also favors the existing techniques for the stock price prediction [10].

3.1.4 Stock price prediction using RNN, CNN, and LSTM

The rise and fall in share market price decide the fate of the investor's profit. The existing algorithms which are linear and non-linear focus on predicting the stock index movement for the single company but on the other hand the proposed method is a model independent approach and the data is not fitted to a specific model rather identifying the latent dynamics in the data using deep learning. This performs the price predictions for the NSE (Nigeria Stock Exchange) listed companies and compares their performance and applied a sliding window approach for predicting the future values on short term basis [11].

3.1.5 Stock price prediction using time series data

Researchers have taken some time to predict the data with algorithms fast and accurate enough to make stock prices prediction. Investor's mainly want their stock prices to forecast with much smarter techniques and this method worked well for them. In this paper mainly concentrates on the three main time series forecasting algorithms which are LSTM (Long Short-Term Memory), Auto-regressive Integrated Moving Average (ARIMA), Facebook prophet time series algorithms [12].

3.1.6 Stock Market Trend Prediction

A trend analysis of the stock market is useful for an appreciation of the changes in the stock market attributes over time. The predictions can be made with a certain level of accuracy, but the objective of the predictions is to reduce the risk. Linear regression, FBProphet, Bayesian Regression are used to predict and compare the stock price. A new risk feature for long-term stock market prediction is developed using the forecasting models [13].

3.1.7 Neural Networks for Stock Price Prediction

This research focuses primarily on how previous information and neural networks can be used to enhance predictive ability. The daily stock pricing is a complex problem in the real world, considering political and world events, so we have to derive information and thus event awareness is derived mainly from the headlines. This paper also takes many economic measures and uses the neural networks to input them along with event information. This method also gives us a less predictive error than the multiple regression analysis [14].

3.1.8 Comparison of Neural Networks and ARIMA Models

This calculates the forecasting performance of ARIMA, and artificial neural networks model published for the New York Stock Exchange. The prominent techniques used here are fall into two categories mainly which are statistical and computing techniques. In which the ARIMA falls into the statistical computing techniques and the artificial neural networks falls into the category of computing techniques and that too soft computing technique. The use of ARIMA as a time series forecasting is very essential but the use of artificial neural network is most accurate, and this paper mainly predicts the use of these and compares which is good for the stock market prediction [15].

3.1.9 Stock Price Prediction and Trend Prediction – Neural Networks

This mainly constitutes on the analyzing the feed forward network using back propagation learning algorithm with early stopping and the radial basis neural network is used to predict the trend of the stock price. In this research, Fundamental data or Technical indicators are not used as a basic objective of the research to predict the uses of artificial neural networks for future prices based on past prices [16].

3.1.10 Comparisons of Artificial Neural Networks Architecture in Stock

The up's and downs of the stock market is predicted with the artificial neural networks in this paper and it provides a numerical analysis of concrete financial time series. This concept consists of algorithms such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) and Multi-Layer Perceptron (MLP) recurrent neural techniques. This paper mainly shows that neural networks are there to predict financial time series movements when trained on plain time series data [17].

3.1.11 Stock Price Prediction Using LSTM

The forecast of the stock market price prediction is complex task for many researchers but however the investors are highly interested in the research of the stock market price prediction and even many investors are keenly interested in the future situation of the stock market prices and considering all these in the mind, this paper mainly represent the Long Short Term Memory

(LSTM) and Recurrent Neural Network (RNN) approach to predict the stock market prices for the future [18].

Chapter 4. Methodology

This chapter discussed about three topics

1. CRISP-DM methodology.

2. Tools and technology used in this project.

3. Time series models - KERAS with LSTM , PROPHET, and ARIMA

4.1 CRISP DM Diagram

The CRISP DM represents cross industry process for data mining. It is a strong and very much demonstrated system. Its adaptability and handiness when examining to gruesome business issues. It is the brilliant line that almost every customer engagement goes through.

This model is a glorified sequence of times. Many individuals of the companies can act in an alternative way and it is important to track back past tasks and retrace certain activities on a regular basis. The model does not try to take every imaginable path through the information mining process. This is a 6-phase model. [19].

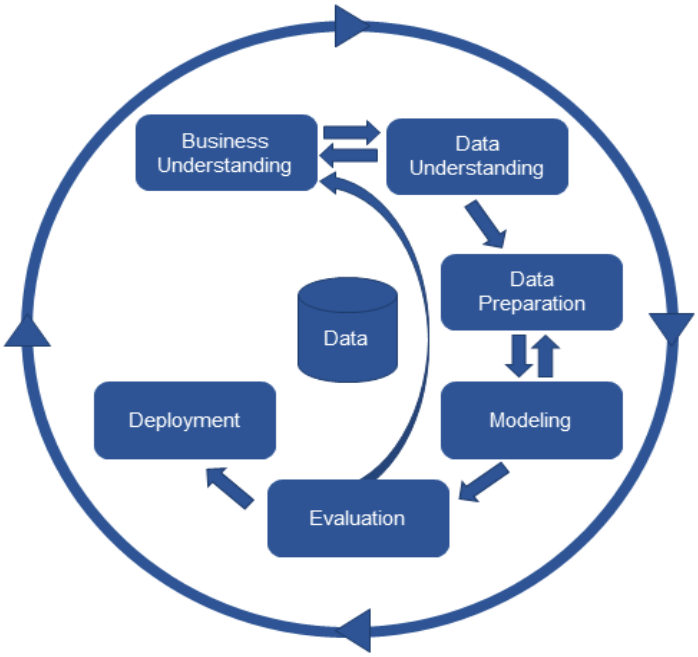


Figure 3 : CRISP – DM Diagram. [20].

1. Business Understanding: To identify the business objectives and data mining goals.
2. Data Understanding: Collecting of data from sources, exploring and verifying the quality of data.
3. Data preparation: This phase is the time-consuming phase. Data selecting, cleaning, constructing, integrating are takes place in this phase.
4. Modelling: Selecting the techniques for the modelling, creating the test design building and accessing of models.
5. Evaluation: Evaluation of results.
6. Deployment: Planning of deployment and monitoring.

William Vorhies, one of the makers of CRISP-DM, contends that since all information science ventures start with business understanding, have information that must be accumulated and cleaned, and apply information science calculations, "Fresh DM gives solid direction to even the most exceptional of the present data science exercises" [19].

4.2 Tools and Technologies

4.2.1 Python Programming Language

Python is used in this project because Python is an interpreted, object oriented and high-level programming language. It was created by Guido Van Rossum in the year 1990. It is cross platform programming language. This programming language is freely usable for commercial purposes. Python is easy to use and very powerful. Also, this language is versatile in nature. The companies like Google, Facebook, Netflix etc. are using python.

Advantage of Python:

Python is a object oriented programming language the we can used for scientific and nonscientific programming. Simple high-level language with lots of libraries. Python is a platform independent programming language. We can use python in servers to create web applications. It is used in database systems because it can read and modify the data very easily. One of the major advantages of the python is we can used to handle big data for performing complex mathematics.

Python can work on different platforms. Python has a simple syntax that is very similar to English language. Prototyping of the python code is very fast. The recent version of the python is python version 3 [21].

4.2.2 Pandas

Pandas package is one of the most fast and powerful packages in python programming language. It is very flexible and easy to use in open source data analysis. It is also using for visualizing the data. That is why pandas are called the backbone of data science projects. By using pandas, we can clean, transform, and analyze the data. Pandas can extract data from csv file into data frames. We can calculate statistics such as average, mean, max and min etc. Visualizing the data with the aid of matplotlib is another feature of pandas. We can plot line graph, bar diagram, histogram etc. [22].

The main essential data structure pandas are Panel. Panel is data structure which helps to manipulate the data sets and time series.

We can install pandas using pip command and import the panda's library with the help of import function. Pandas have two core components.

1. Series
2. DataFrame

Series:

One dimensional array is called series in pandas. The function 'pd. Series' is used to create constructor which can include lot of arguments. The commonly used argument name is called data that specifies the all elements in the series. For the manual casting panda's series also used dtype keyword. The series of elements collectively called as Index of the series [23].

The parameters in panda series are data, index, dtype and copy.

DataFrame:

DataFrame is the two-dimensional array in pandas. The function 'pd. DataFrame' is used to create a DataFrame. The DataFrame is not scalar. The index is rows in DataFrame. Column is another label [23].

The parameters in panda DataFrame are data, index, columns, dtype and copy.

Advantage of Pandas

1. It can present the data in Series or DataFrame data structures.
2. Panadas package contain multiple methods for data filtering.
3. It handles the data very efficiently.
4. It can create the data flexible.

Disadvantages of Pandas

1. Learning slope is very steeper in pandas.
2. It has difficult syntax.
3. It has bad documentation.
4. Pandas cannot used for three-dimensional arrays [24].

4.2.3 NumPy

NumPy stands for numerical python. NumPy is a library used in python programming. It is fast and versatile. It is used to process powerful N dimensional arrays. NumPy consist of functions that which can work in the field of linear algebra, Fourier transform and metrices. NumPy data structures performed in

1. Size – It needs only less space.
2. Performance – It is faster than lists
3. Functionality – SciPy and NumPy are the main functions for linear algebra [25].

4.2.4 Sklearn

Scikit Learn also known as Sklearn is a simple and efficient tool using for predictive analytics. It is free accessible and reusable. It is also an open source library package [26].The main features of Sklearn are Preprocessing, Model selection, Regression, Classification, Clustering.

4.2.5 TensorFlow

TensorFlow is a prominent framework used in machine learning and deep learning. The word TensorFlow is combined from two words.

1. Tensor – Multi dimensional array
2. Flow – the flow of data

It is a free and open source library. It is released on 9 November 2015. It is developed by Google Brain Team. To increase the speed TensorFlow is totally developed on the python programming language. TensorFlow can train and run neural network programs. It supports platforms such as Windows, MacOS, Linux and Android [27].

Advantages of TensorFlow

1. Graphs: When comparing to other libraries It has a better graph visualization.
2. Library Management: Google developed TensorFlow. It has the advantages of quick updates and frequent releases with new features and libraries.
3. Debugging, Scalability and pipelining
4. It has excellent community support [27].

Disadvantage of TensorFlow

1. Computation speed is very high.
2. It is very hard to find the errors because of its unique structure.
3. It does not need any super lower matter [27].

4.2.6 Keras

Keras is open source neural network library in python. It is a high-level framework. It can easily build a neural network model in a limited time. The main advantage of Keras are user friendly, Fast deployment, multiple back ends , modularity [28].

It runs on both CPU and GPU. It supports convolutional and recurrent neural networks. It is installed simply by using pip install keras.

4.2.7 Jupyter Notebook

Jupyter notebook is a web based open source interactive application. It allows to develop codes and documents in a single page. We can use Jupyter Notebook for cleaning, modelling,

training, and evaluating of data. The prominent feature of Notebook is we can visualize the data [29].

The main features of Jupyter Notebook are we can execute the code within the browser. We can display the outputs in multiple formats such as HTML, pdf etc. Markdown markup language helps the formatting of texts in the console. Notebook documents are saved internally in ipynb format. We can install Jupyter Notebook by using pip command in the command prompt [30].

4.2.8 PyCharm

PyCharm is a python IDE. It was developed by JetBrains. It was released in February 2010. It is a cross platform application compatible in Windows, Linux and macOS. PyCharm develops with variety of modules, tools, and packages [31].

Feature of PyCharm are follows

1. It is an intelligent and powerful code editor.
2. It supports google app engine.
3. It helps for integrated debugging and testing.
4. Python developers used PyCharm for creating web pages including HTML, CSS etc.
5. It helps for remote development.
6. It supports popular framework such as Flask, Django, Pyramid etc. [31].

4.2.9 Flask

Flask is a micro web framework application. It has wide varieties of tools and libraries for developing web application in python language. It is extremely flexible in nature. Flask is simple to learn and easy to implement. It is small core and easy to extensible. Code in flask is more explicit in nature [32].

4.2.10 Anaconda3

Anaconda is open source distributor of R and Python programming. It provides tools for doing data analysis and machine learning techniques. It includes various python libraries and hundreds of scientific packages. Navigator is the GUI of Anaconda where the user can open

various tools and applications. Another important factor of anaconda is anaconda cloud where we can save our code [33].

4.3 Time Series models

The prediction of stock market price id done with following Algorithms. Time series is sequence of numbers measured over a regular period. Based on the frequency, times series can be classified in to yearly, monthly and daily.

The Univariate time series forecasting that use previous values in the time series to estimate the future values. Multivariate time series forecasting type of forecasting which we use different predictors.

4.3.1 ARIMA Model

ARIMA is a prediction algorithm short for Auto Regressive Integrated Moving Average, built on the principle that the past time series values can be used for the purposes of predicting future values only. ARIMA is a class of models that describe such time series on the basis of their own past value , i.e. their own limitations and delayed forecasting errors. ARIMA models can be based on any non-seasonal time series which exhibits trends and which is not a white natural variability.There are 3 parameters in ARIMA model p, d, q [34].

1. p denotes Auto Regressive.
2. q denotes Moving Average.
3. d denotes the number of differences required to station the time series

When a time series is seasonal, the seasonal patterns must be introduced and SARIMA – Seasonal ARIMA. Auto Regressive means in ARIMA a linear regression model that uses its own lag predictors. Linear models of regression work well if the predictors are not interrelated or independent. Differences are the most popular approach and difference may be required depending on the nature of the sequence. Therefore, the value of d is the minimum number of differences required to stabilize the series. And if the time series is still, then d = 0. "p" is a "Regressive Automatic Term" (AR) order. The number of Y deficiencies to be used as predictors is mentioned. "q" is the order of the term "moving average." It refers to the amount of late prediction mistakes that the ARIMA model will produce [34].

Auto Regressive model (AR) is one in which Yt only relies on its own deficiencies. Yt is a 'yt lagging' element.

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + .. + \beta_p Y_{t-p} + \epsilon_1$$

Equation 1 – Equation of AR [34].

The moving average model (MA only) is one in which Yt only depends on lagging prediction error.

$$Y_t = \alpha + \epsilon_t + \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + .. + \phi_q \epsilon_{t-q}$$

Equation 2 – Equation of MA [34].

An ARIMA model is a model that differs the time series to make it stationary, at least once, and combines the terms AR and MA. So, the equation is

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + .. + \beta_p Y_{t-p} \epsilon_t + \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + .. + \phi_q \epsilon_{t-q}$$

Equation 3 – Equation of ARIMA [34].

Now, Equation of ARIMA in words

Predicted Yt = constant + Linear Y-lag (up to p-lag) + Linear Lagged Forecast Combination (up to q lags) [34].

4.3.2 FB Prophet Model

Prophet is a Facebook open source library focused on decomposable models (trend + seasonality + holidays). It gives us the ability to predict time series with accuracy and supports custom seasonality and holidays. The Prophet package offers easy-to-tune, intuitive parameters. Those who have no experience in forecasting models can use this to make accurate predictions on a wide variety of business problems. The three main components of prophet model are trend, seasonality, and holidays [35].

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

Equation 4: components of prophet [35].

- g(t): linear curve in part for modeling non-periodic time series transition.
- s(t): daily changes (seasonality weekly / yearly).
- h(t): holidays effects of irregular timescales.
- **ε**t: error term is responsible for any unexpected alteration that is not suited to the pattern.

Trend:

Trend is formed by a linear piece curve that matches the pattern or non-periodic sections. The linear fitting method ensures that the spikes / missing data.

Seasonality:

The Prophet adapts and predicts the effect of seasonality to a scalable model using four sequences. The following method approximates the seasonal effects of s(t):

$$s(t) = \sum_{n=1}^{N} \left(a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right) \right)$$

Equation 5: Seasonality effect [35].

Holidays and Events:

Holidays and events contribute to predictable time series shocks. Prophet allows analysts to identify past and future events in a personalized manner. There is a window during certain days and parameters are used to model the impact of holidays and events [35].

4.3.3 Keras with LSTM

LSTM is a sort of recurring neural network. A recurrent neural network is a neural network which seeks to form time or sequence-based behavior for instance language, stock prices,

energy demand, etc. The output of the neural network is calculated by the input of same network layer at t+1 time [36].

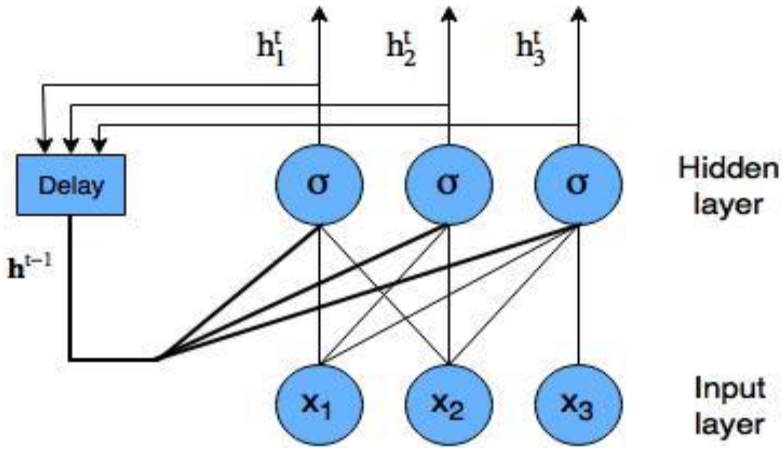


Figure 4: Recurrent Neural Network with nodes [36].

At the time of training of model and prediction, the recurrent neural network became unrolled.

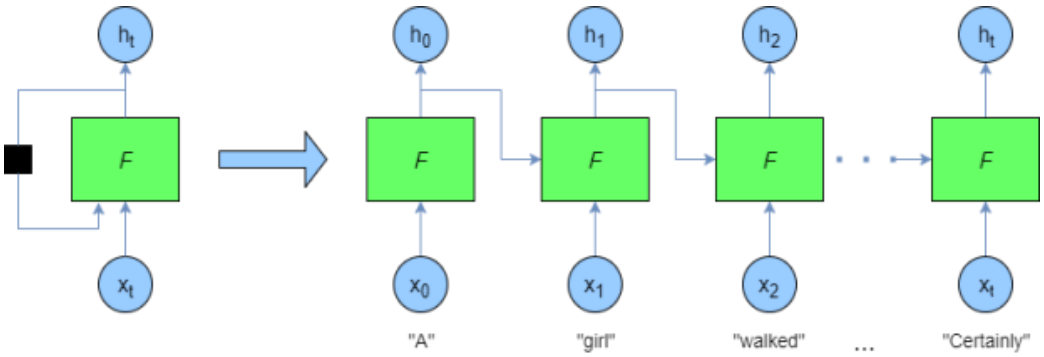


Figure 5: Unrolled recurrent neural network [36].

LSTM is a recurrent neural network with LSTM cellblocks replacing the neural network's regular layers. The different components of these cells are called the input gate, forget gate and the output gate [36].

1. Input layer: The activity of the data contraptions refers to the non-cooked data, which can enter the system.

2. Hidden layer: Determine every secret unit's endeavor. The exercises of the systems entered and the loads on the connections between the data and the components. At least one hidden layer may also be present.

3. Output layer: The output direct depends on the actions of the hinged units and the load between the secret and output devices.

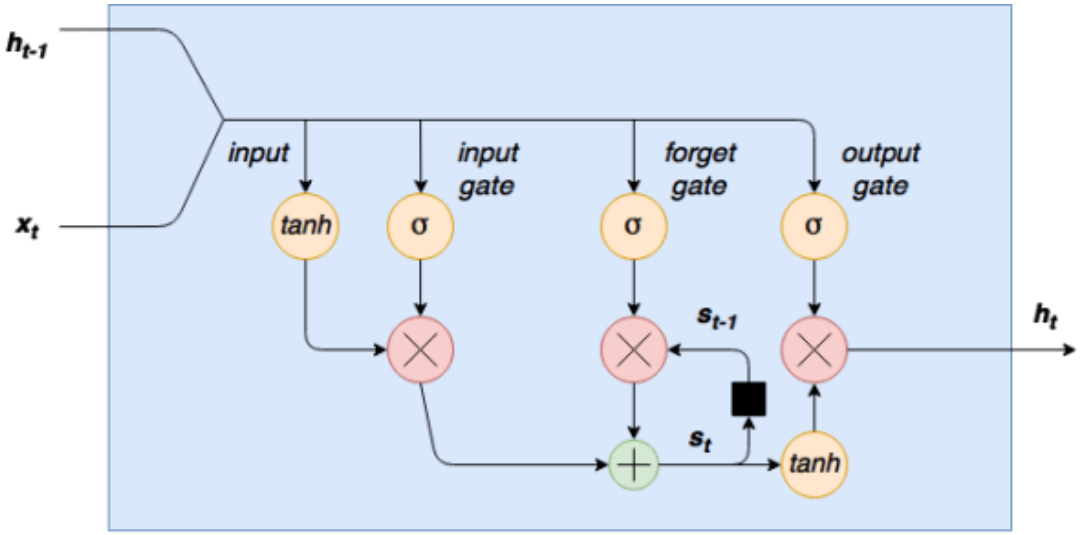


Figure 6: Cell diagram of LSTM [36].

LSTMs are designed explicitly to prevent the problem of long-term dependence. The long-term retention of knowledge is basically their automatic comportment, not something they try to understand. All repetitive neural networks are shaped like a chain of neural network repeating modules. This repeating module has a structure in standard RNNs, like a single layer of tanh [37].

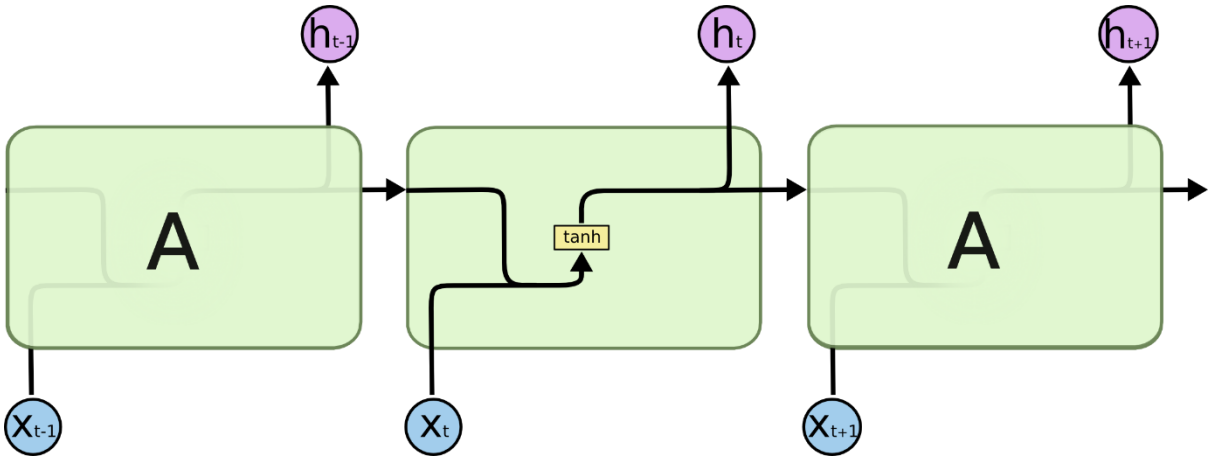


Figure 7: RNN contains Single layer [37].

LSTMs have a structure like this chain, but the repetitive module which have different structure. There are four, interacting very specifically, instead of making a single neural network layer.

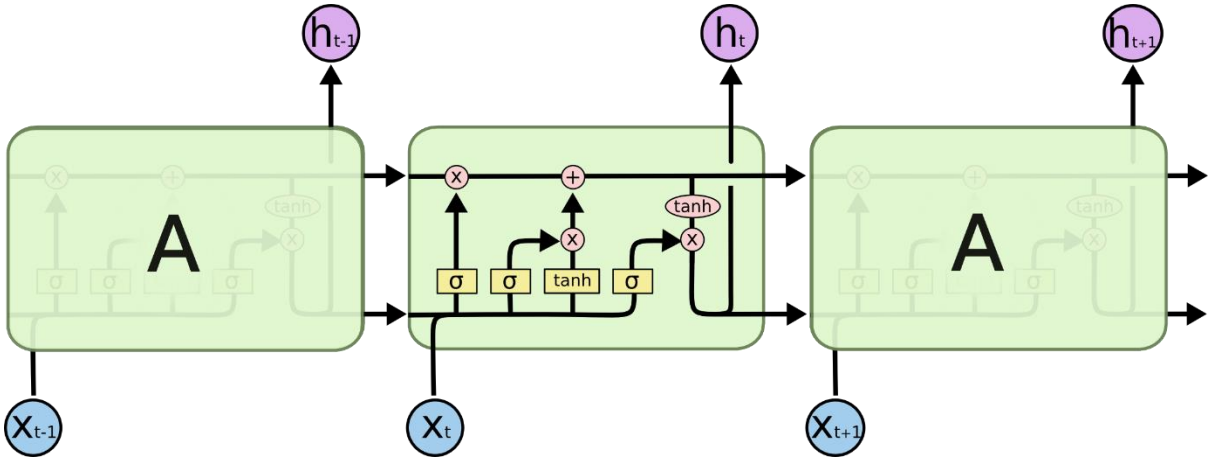


Figure 8: LSTM with interactive layers [37].

Due to its large-range and short-range data dependencies, LSTMs may help deal with disappearance and exploding gradients. LSTMs in many cases work a little better than GRUs, but due to the larger latent state size, they are more costly to train and operate. LSTMs are the prototypical, non-trivial state controlled latent autoregressive variable model [38].

Chapter 5. System Design and Specifications

5.1 Core Structure

In this section, we discuss different modules used in the program. Firstly 10 years of historical data is collected from the yahoo finance. Yahoo finance is a financial website that provide stock market data's, news, live updates etc. These data are processed and normalized for doing analysis. Time series analysis models are used to identify the performance of the processed data with the aid of Jupyter Notebook. Jupyter Notebook is an IDE which allows majority of python library functions. Python 3.8.2 version is used not only for processing the data but also it is used for the predicting and forecasting of stock market data. The project architecture is classified in to two phases.

5.1.1 Analysis Phase

The below figure shows the architecture of the analysis phase. The analysis phase is classified into preparation phase and experimental phase.

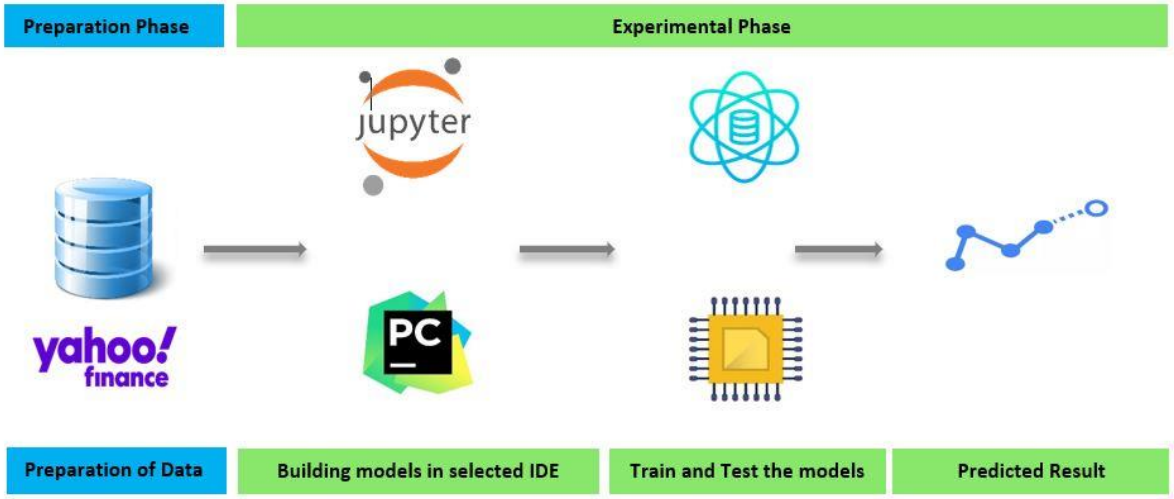


Figure 9: Architecture of Analysis Phase.

Preparation Phase:

Preparing of the data is the initial stage of the project. The raw data is collected from yahoo finance using python library fix yahoo finance. The collected data consist of seven attributes. Date attribute refers the date. Open attribute refers the opening value of the stock. Close attribute refers the closing value of the stock. High attribute refers the highest stock value in a

day. Low attribute refers the lowest stock value in a day. Adj Close attribute refers the closing price after adjustments. Volume is the amount of transactions made in a day. For pre-processing of data steps like cleaning, format and select the data which is suitable for the algorithms. In this project we collected the ten years of data from different banks.

Experiment Phase:

In this phase Jupyter Notebook is used to perform the training and testing of time series models. Different time series models are developed using ARIMA, PROPHET and KERAS with LSTM. For the predicting the stock price these models are used.

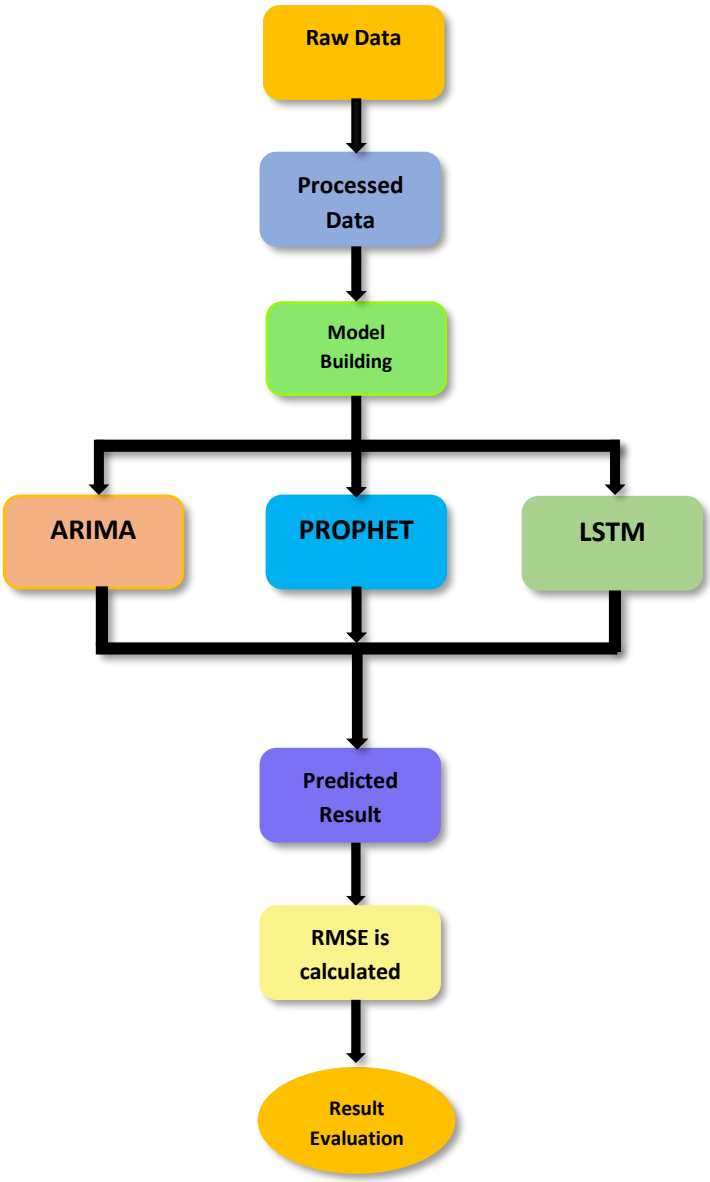


Figure 10: Step by Step procedure of Analysis Phase.

5.1.2 User Interface Phase

The user interface is developed with the aid of Flask web framework in Python programming language.

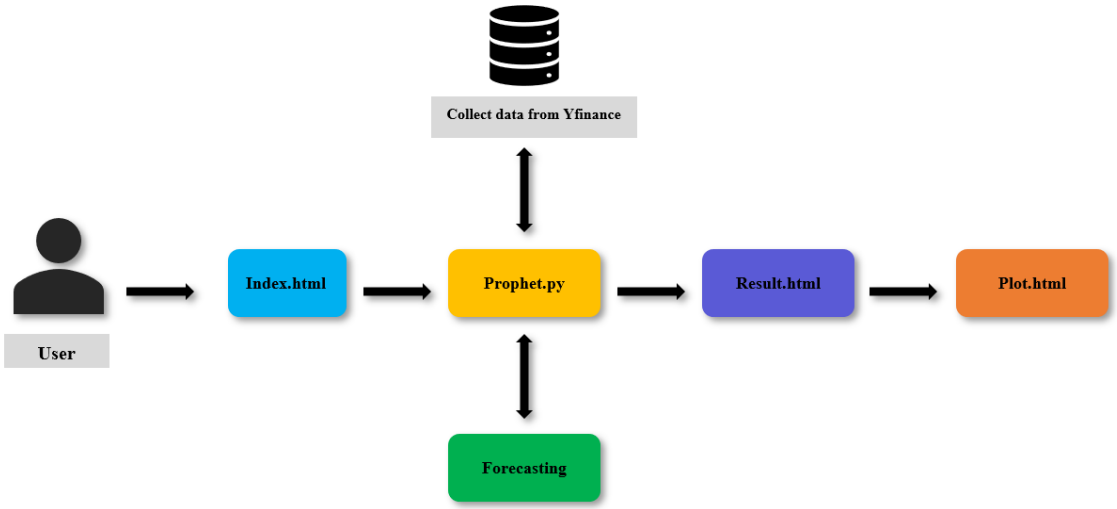


Figure 11: Working model of User Interface.

User can search forecasted price of any bank in India using the ticker symbol of Banks in the yahoo finance. Index.html is a html file that act as the front end of the web application. Prophet.py is the file act as the back end of the web application where all the process taking place. Data is collected from yahoo finance with the help of web reader and forecasting is done in prophet.py file. The forecasted data is drafted in the form of graphs using dygraphs. The output graph is displayed through result.html and plot.html files.

Chapter 6. Implementation

In this chapter we are going to discuss about the step by step procedure of Analysis phase.

6.1 Data Collection

The historical data of Banks are collected from yahoo finance using Yfinance library and saved into the directory in csv format.

```
#importing of libraries
import pandas
from pandas_datareader import data as pdr
from pandas.util.testing import assert_frame_equal
import yfinance as yf
import datetime
yf.pdr_override()

stocks = ["FEDERALBNK.BO"]
start = datetime.datetime(2010,1,4)
end = datetime.datetime(2020,1,1)

d = pdr.get_data_yahoo(stocks, start=start, end=end)

#file saved in the directory
d.to_csv('D://Dataset//FEDERALBNK.BO.csv')

d.head(5)
```

Figure 12: Collect and save data from yahoo finance.

After running the above code, the output is shown in figure 13

```
[**********100%**********]  1 of 1 completed
```

Out[7]:

Date	Open	High	Low	Close	Adj Close	Volume
2010-01-04	23.770000	23.795	23.379999	23.580000	8.429377	724800
2010-01-05	23.900000	24.170	23.650000	23.920000	8.550918	1556550
2010-01-06	24.190001	24.650	24.100000	24.379999	8.715360	1034000
2010-01-07	24.610001	24.990	24.405001	24.565001	8.781491	1360420
2010-01-08	24.790001	25.100	24.605000	24.760000	8.851200	1886220

Figure 13: Collected data.

6.2 Implementation of ARIMA model

For the implementation of ARIMA model, first we introduce the python packages and libraries.

```
import pandas as pd
import numpy as np
import itertools

import warnings
warnings.filterwarnings("ignore")

import statsmodels.api as sm
import matplotlib
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')

matplotlib.rcParams['axes.labelsize'] = 14
matplotlib.rcParams['xtick.labelsize'] = 12
matplotlib.rcParams['ytick.labelsize'] = 12
matplotlib.rcParams['text.color'] = 'k'
```

Figure 14: Importing Packages and libraries.

The above figure 14 represents the initial stage in which packages are imported. We import Pandas, NumPy and Itertools. Python Itertools is a module which offers different functions to produce complex iterators. Warnings are imported to avoid the future warnings at the time of execution. Matplotlib library is used to plot variables in graphical format. Stats models is a python module that contain classes and functions. These classes and functions are used to estimate the wide range of statistical model and testing.

```
In [3]: df = pd.read_csv('D://Dataset//FEDERALBNK.BO.csv')
        df.head(5)
```

Out[3]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2010-01-04	23.770000	23.795	23.379999	23.580000	8.429377	724800
1	2010-01-05	23.900000	24.170	23.650000	23.920000	8.550918	1556550
2	2010-01-06	24.190001	24.650	24.100000	24.379999	8.715360	1034000
3	2010-01-07	24.610001	24.990	24.405001	24.565001	8.781491	1360420
4	2010-01-08	24.790001	25.100	24.605000	24.760000	8.851200	1886220

Figure 15: Reading of data from the directory and its output.

The figure 15 shows the reading of dataset in csv format from the directory. This dataset is stored in a variable called df. After that we print the first 5 rows of the dataframe by using head().we can also use tail to print the last 5 rows of the dataframe.

```
In [5]:
#removing columns,sorted by date and checking the missing values
df.Date = pd.to_datetime(df.Date, format='%Y%m%d', errors='ignore')
cols = ['High', 'Low', 'Open', 'Volume', 'Adj Close']
df.drop(cols, axis=1, inplace=True)
df = df.sort_values('Date')
df.isnull().sum()

Out[5]: Date     0
        Close    0
        dtype: int64

In [6]:
df['Date'].min()

Out[6]: '2010-01-04'

In [7]:
df['Date'].max()

Out[7]: '2019-12-31'
```

Figure 16: Data preprocessing.

The figure 16 shows the checking of missing values, removing of columns and sort the data in date format. After that we are checking the minimum and maximum value of the date.

```
In [9]:
#creating Date coloumn as index
df = df.set_index('Date')
df.index

Out[9]: Index(['2010-01-04', '2010-01-05', '2010-01-06', '2010-01-07', '2010-01-08',
               '2010-01-11', '2010-01-12', '2010-01-13', '2010-01-14', '2010-01-15',
               ...
               '2019-12-17', '2019-12-18', '2019-12-19', '2019-12-20', '2019-12-23',
               '2019-12-24', '2019-12-26', '2019-12-27', '2019-12-30', '2019-12-31'],
              dtype='object', name='Date', length=2461)
```

Figure 17: Indexing with time series data.

```
In [10]:
df.index = pd.to_datetime(df.index)
monthly_mean = df.Close.resample('M').mean()

In [11]:
#Creating monthly mean from 2010
monthly_mean['2010':]

Out[11]: Date
         2010-01-31    25.496053
         2010-02-28    25.214211
         2010-03-31    26.134524
         2010-04-30    28.136500
         2010-05-31    30.180952
                           ...
         2019-08-31    84.662500
         2019-09-30    87.584210
         2019-10-31    84.005264
         2019-11-30    86.380000
         2019-12-31    86.176191
         Freq: M, Name: Close, Length: 120, dtype: float64
```

Figure 18: Creating monthly mean.

The figures 17 and 18 shows the indexing of date with the time series data. The current date time data is very difficult to work. So, we used the average close price value of the month and starting of every month as timestamp.

```
#Plotting the monthly mean
monthly_mean.plot(figsize=(15, 6), title = 'Federal Bank')
plt.show()
```

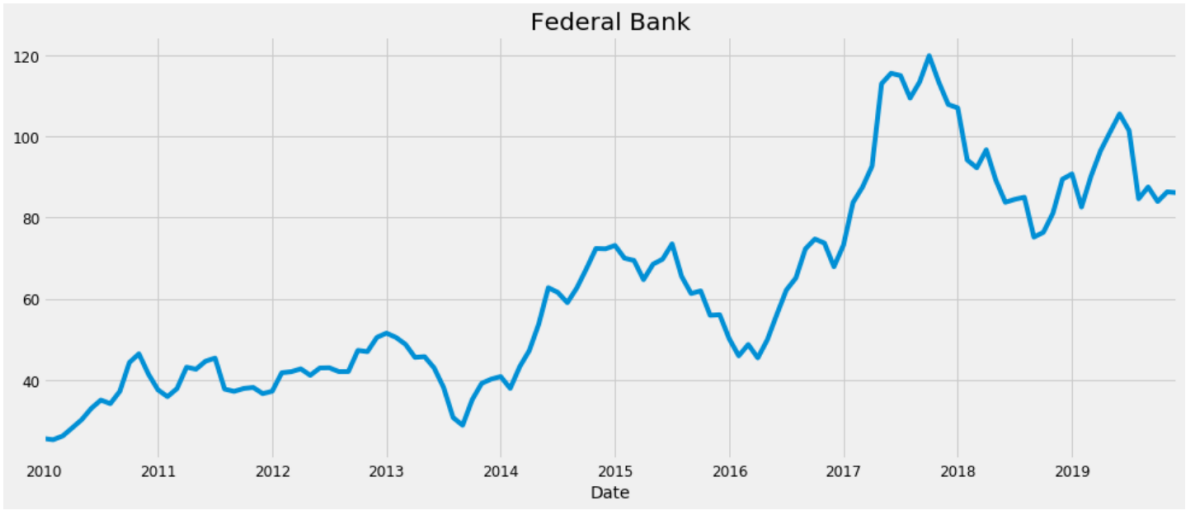


Figure 19: Visualizing Close time series data.

```
In [13]:  # Visualising the Distinct components: trend, seasonality, and noise.
          from pylab import rcParams
          rcParams['figure.figsize'] = 18, 8
          decomposition = sm.tsa.seasonal_decompose(monthly_mean, model='additive')
          fig = decomposition.plot()
          plt.show()
```

Figure 20: Code for implementing time series decomposition method.

The figure 20 describes the code for implementing the time series decomposition method which is used to decompose our data in to three components: trend, seasonal and noise. The below figure 21 shows the graph. The graph clearly showing the unstable nature of closing price.

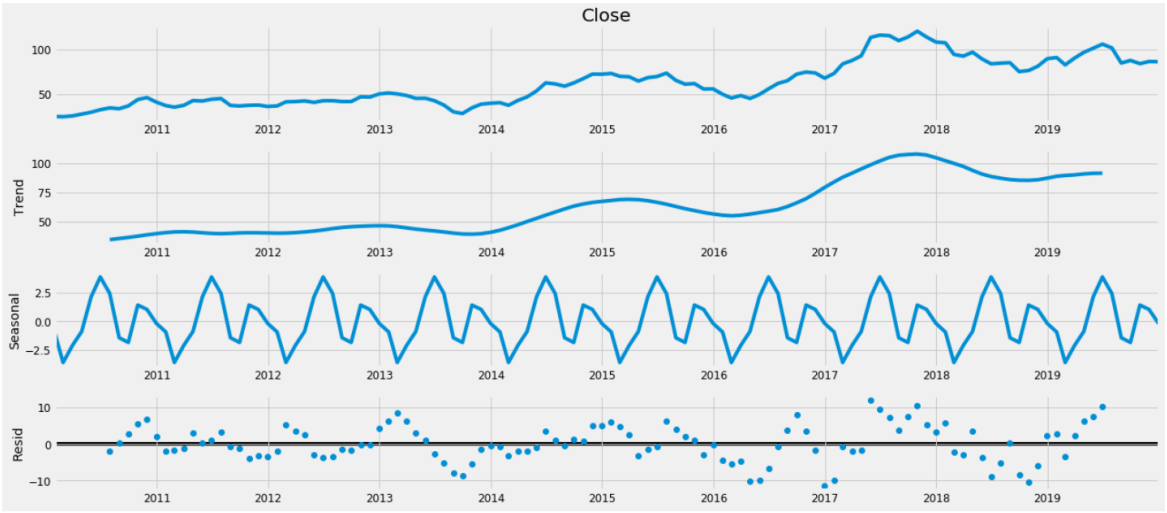


Figure 21: Time series decomposition graph.

Now we are going to predict the closing stock price by building the ARIMA model. For the initially we are selecting the p, d, q parameters. These three parameters reflect seasonality, trend, and noise.

```
In [14]:
# Define the p, d and q parameters to take any value between 0 and 2
p = d = q = range(0, 2)
# Generate all different combinations of p, q and q triplets
pdq = list(itertools.product(p, d, q))
# Generate all different combinations of seasonal p, q and q triplets
seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q))]
```

Figure 22: Code for Generating all Seasonal ARIMA Combinations.

Here p is the autoregressive part in the model. It enables us to include the effect of past values in our model. d is the integrated part of the model. It means the number of past time points deduct from the present value. q is the moving average part of the model which allows us to determine the error model. In seasonal ARIMA, defined as ARIMA(p, d, q)(P, D, Q)s, in relation to seasonal effects. The s denotes period of time series 4 in quarterly and 12 in annually. Now, we have to find the value of ARIMA(p, d, q)(P, D, Q)s. For that we used grid search to iteratively explore all the different combinations in parameters. For that SARIMAX() function is used.

```
import warnings
warnings.filterwarnings("ignore")

l_param = []
l_param_seasonal=[]
l_results_aic=[]
for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            mod = sm.tsa.statespace.SARIMAX(monthly_mean,
                                            order=param,
                                            seasonal_order=param_seasonal,
                                            enforce_stationarity=False,
                                            enforce_invertibility=False)

            results = mod.fit()

            print('ARIMA{}x{}12 - AIC:{}'.format(param, param_seasonal, results.aic))

            l_param.append(param)
            l_param_seasonal.append(param_seasonal)
            l_results_aic.append(results.aic)
        except:
            continue

minimum=l_results_aic[0]
for i in l_results_aic[1:]:
    if i < minimum:
        minimum = i
i=l_results_aic.index(minimum)

mod = sm.tsa.statespace.SARIMAX(monthly_mean,
                                order=l_param[i],
                                seasonal_order=l_param_seasonal[i],
                                enforce_stationarity=False,
                                enforce_invertibility=False)

results = mod.fit()
print("\n\n")
print(results.summary().tables[0])

print(results.summary().tables[1])

print(results.summary().tables[2])
```

Figure 23: Seasonal ARIMA Model.

The figure 23 shows the implementation of SARIMAX function to fit the seasonal ARIMA model.

```
                                SARIMAX Results
==========================================================================================
Dep. Variable:                             Close   No. Observations:                  120
Model:             SARIMAX(0, 1, 1)x(0, 1, 1, 12)   Log Likelihood                -286.610
Date:                            Sun, 07 Jun 2020   AIC                            579.220
Time:                                    10:46:13   BIC                            586.817
Sample:                                01-31-2010   HQIC                           582.287
                                     - 12-31-2019
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1          0.2491      0.109      2.290      0.022       0.036       0.462
ma.S.L12      -1.0000   2124.055     -0.000      1.000   -4164.072    4162.072
sigma2        22.7535   4.83e+04      0.000      1.000   -9.47e+04    9.47e+04
==============================================================================
==========================================================================================
Ljung-Box (Q):                       43.70   Jarque-Bera (JB):                 3.40
Prob(Q):                              0.32   Prob(JB):                         0.18
Heteroskedasticity (H):               3.89   Skew:                            -0.08
Prob(H) (two-sided):                  0.00   Kurtosis:                         3.92
==========================================================================================
```

Figure 24: SARIMAX Result.

The SARIMAX results suggested SARIMAX(0,1,1)×(0,1,1,12) with lowest AIC value of 579.220. The coef column describes the weight and effect on the time series in each function. The column P>|z| shows the value of each characteristic weight.

```
In [15]:
#Plotting the diagnostics results
results.plot_diagnostics(figsize=(20, 10))
plt.show()
```

Figure 25: Code for Plotting result diagnostics.

Now we are going to plot the diagnostics results with the help of plot diagnostics. This figure shows the Standardized residual, Histogram plus estimated density, Normal Q-Q and Correlogram. In figure 26, Histogram plus estimated density shows the red line of KDE follows closely with the N(0,1) where in stands for standard notation with standard deviation 1 and mean 0. In the Q-Q Plot shows that blue dots follow the trend of standard normal distribution. The standard residual does not show any obvious seasonality and it is confirmed by the correlogram plot. In the Correlogram plot time series residual have low correlation.

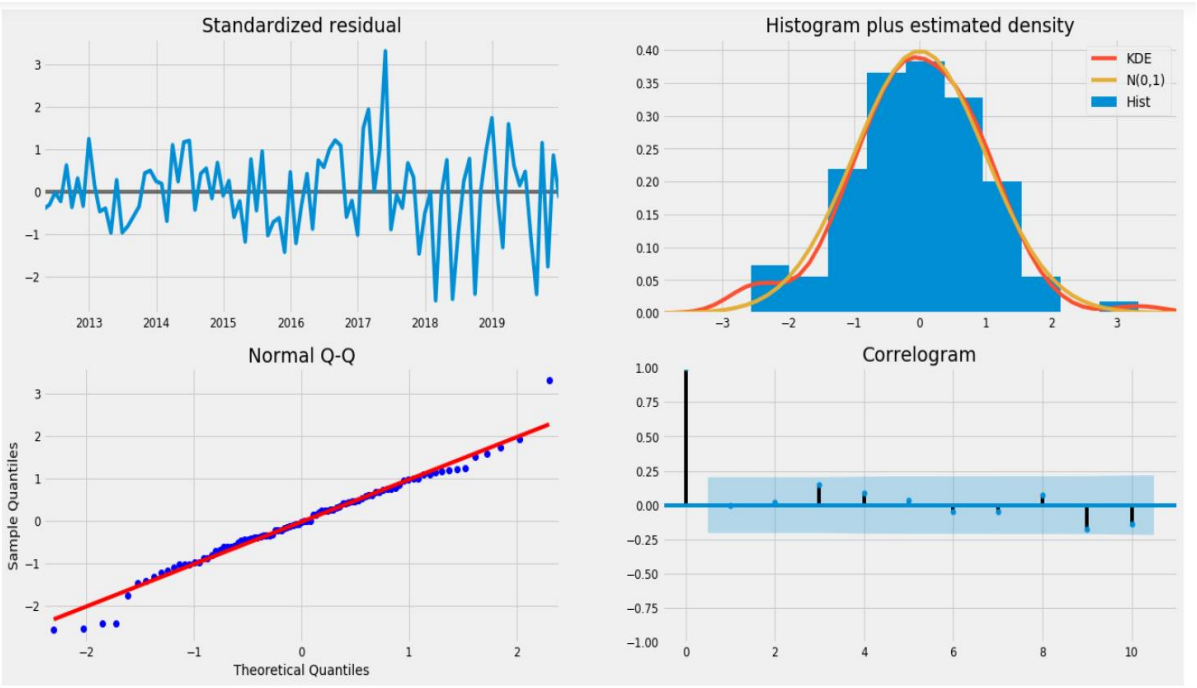


Figure 26: Result Diagnostics graph.

The above figure helps us to conclude that our model is good enough to forecast the future stock price values.

```
In [16]:
pred = results.get_prediction(start=pd.to_datetime('2011-12-31'), dynamic=False)
pred_uc = results.get_forecast(steps=24)
pred_ci = pred.conf_int()


ax = monthly_mean['2012':].plot(label='observed')
pred.predicted_mean.plot(ax=ax, label='Predicted', alpha=.7, figsize=(12, 7))
pred_uc.predicted_mean.plot(ax=ax, label='Forecast')

ax.fill_between(pred_ci.index,
                pred_ci.iloc[:, 0],
                pred_ci.iloc[:, 1], color='k', alpha=.2)

plt.title('Federal Bank')
ax.set_xlabel('Date')
ax.set_ylabel('close price')
plt.legend()

plt.show()
```

Figure 27: Code for plotting the graph of observed, predicted, and forecasting results.

For validating the forecast, we begin by comparing forecast values to real time series value. It helps us to understand the prediction accuracy. The attribute get_prediction() and coef_int() which helps to get the values and confidence interval for time series prediction. The dynamic = FALSE argument which means the forecast are generated at each point using the entire history.

The figure 27 explains the code for predicting and forecasting the closing price in the graph. We took start date as 31-12-2011 for prediction and 24 months for forecasting. Now first we are plotting the observed value. Then we are going to plot the predicted value and forecasted value. After all these we defined the title, y-label, and x-label of the graph.

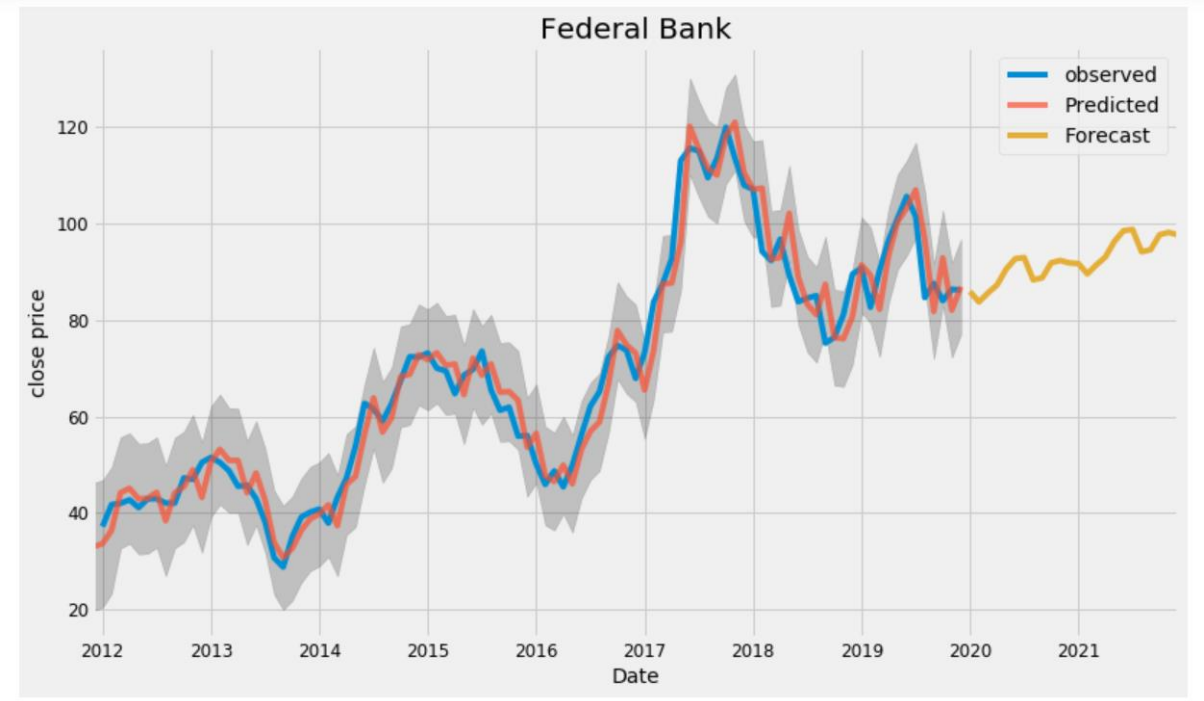


Figure 28: Visualizing of predicted and forecasting graph of Closing Price.

6.3 Implementation of Prophet model

For the implementation of Prophet model, first we introduce the python packages and libraries.

```
In [2]:
#imports
import pandas as pd
import numpy as np
from fbprophet import Prophet
import matplotlib.pyplot as plt
from functools import reduce

%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

import logging, sys
logging.disable(sys.maxsize)


pd.options.display.float_format = "{:,.2f}".format
```

Figure 29: Importing necessary libraries.

The figure 29 represents the importing of necessary libraries for building , predicting, and forecasting of Prophet model. We import prophet from the FBProphet. Warnings are imported to avoid the future warnings at the time of execution. Matplotlib library is used to plot variables in graphical format.

```
In [3]:
stock_price =  pd.read_csv('D:\Dataset\FEDERALBNK.BO.csv',parse_dates=['Date'])
```

```
In [4]:
stock_price.describe()
```

Out[4]:

	Open	High	Low	Close	Adj Close	Volume
count	2,461.00	2,461.00	2,461.00	2,461.00	2,461.00	2,461.00
mean	62.52	63.38	61.41	62.33	53.90	868,591.30
std	25.14	25.38	24.74	25.02	31.00	3,296,248.21
min	22.98	23.80	22.12	22.99	8.43	0.00
25%	41.60	42.19	40.81	41.54	23.83	249,270.00
50%	57.05	57.70	56.12	56.90	53.90	437,280.00
75%	82.50	83.65	80.95	82.35	80.69	807,687.00
max	126.70	127.75	125.65	126.30	123.23	112,236,160.00

Figure 30: Importing and describing of Data.

The figure 31 shows the reading of data from the directory and it stored in a variable. Describe function is used for describing the count, mean, std, min, max etc. of each attribute in the dataset. Parsing of date means creating the date column as index.

```
In [5]: stock_price = stock_price[['Date','Close']]

In [6]: stock_price.columns = ['ds', 'y']
        stock_price.head(10)
```

Out[6]:

	ds	y
0	2010-01-04	23.58
1	2010-01-05	23.92
2	2010-01-06	24.38
3	2010-01-07	24.57
4	2010-01-08	24.76
5	2010-01-11	25.25
6	2010-01-12	24.64
7	2010-01-13	24.69
8	2010-01-14	25.62
9	2010-01-15	26.22

Figure 31: Data Preparation.

The figure 32 shows the data preparation. For the working of prophet, we changed the names of Date and Close attributes into ds and y. y is the attribute that we are used to predict the future.

```
In [7]: #prophet
        stock_price.set_index('ds').y.plot(figsize=(15,8))
```

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x25d0daefac8>

Figure 32: Code for Visualizing the data.

The figure 33 describes the code for plotting the graph. We set the ds attribute which contains date as index and define the size of the plot. Matplotlib library is used for the plotting of graph. The output of the code is visualized in figure 34.

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x23f43c65bc8>

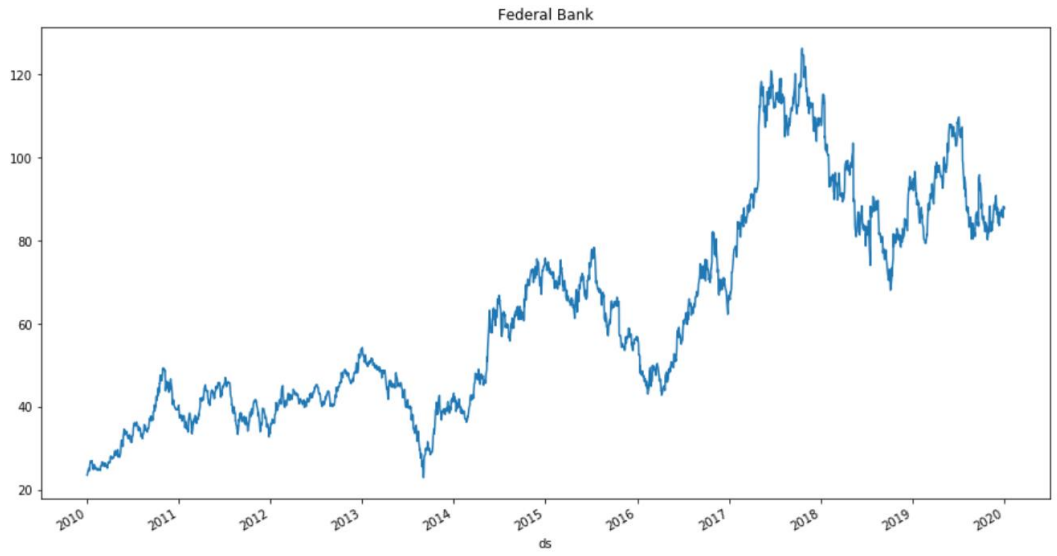


Figure 33: Visualization of Data.

After visualizing the data, we called prophet() for running the prophet model and assigned in a variable called model. By using fit method, we fit our stock price.

```
In [25]: model = Prophet()
         model.fit(stock_price)

Out[25]: <fbprophet.forecaster.Prophet at 0x1f288044088>
```

Figure 34: Code for implementing the model.

```
In [9]: future = model.make_future_dataframe(365, freq='d')

        future_boolean = future['ds'].map(lambda x : True if x.weekday() in range(0, 5) else False)
        future = future[future_boolean]

        future.tail()
```

Out[9]:

	ds
2819	2020-12-24
2820	2020-12-25
2823	2020-12-28
2824	2020-12-29
2825	2020-12-30

Figure 35: Predicting and forecasting the future stock price.

The figure 36 shows the prediction and forecasting of future variables. For the creation of future dates, we used a helper function in prophet called make_future_dataframe with the forecasting period of 365 days. Stocks are traded only in weekdays. So, we need to remove the weekends for that we used Boolean expression. The Boolean expression stating that Monday is 0 and Saturday is 5 and if a day is not equal to 0-4 then return as false.

```
In [10]: forecast = model.predict(future)

In [11]: forecast.tail()
```

Out[11]:

	ds	trend	yhat_lower	yhat_upper	trend_lower	trend_upper	additive_terms	additive_terms_lower	additive_terms_upper	weekly	weekly_lower
2474	2020-01-20	83.30	75.39	90.57	83.30	83.30	-0.41	-0.41	-0.41	0.41	0.41
2475	2020-01-21	83.28	74.86	90.07	83.28	83.28	-0.48	-0.48	-0.48	0.50	0.50
2476	2020-01-22	83.26	75.33	89.70	83.26	83.26	-0.79	-0.79	-0.79	0.37	0.37
2477	2020-01-23	83.24	75.17	90.16	83.24	83.24	-0.81	-0.81	-0.81	0.52	0.52
2478	2020-01-24	83.22	74.09	89.40	83.22	83.22	-1.10	-1.10	-1.10	0.41	0.41

Figure 36: Forecasting the stock price.

The figure 37 shows the forecasted value of stock price. For forecasting the price value, we created forecast and call the predict from the model and pass the predict in the future dataframe. After executing the program, we get the output with lot of attributes. Yhat is the attribute that denote the forecasted value.

```
In [13]: plt.figure(figsize=(16,6))
         model.plot(forecast);
```

```
<Figure size 1152x432 with 0 Axes>
```

Figure 37: Visualization of forecasted stock price using plot function.

After visualizing the forecasted graph. We visualized the components of the graph by using plot components.

```
In [14]: model.plot_components(forecast);
```

Figure 38: Code for displaying components.

The above code is used to visualize the components of the forecasted graph.

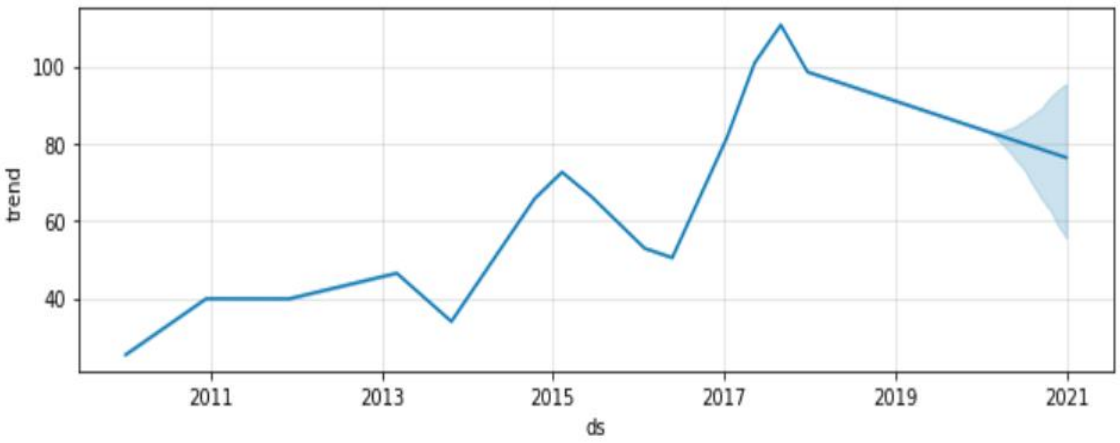


Figure 39: Trend component of the graph.

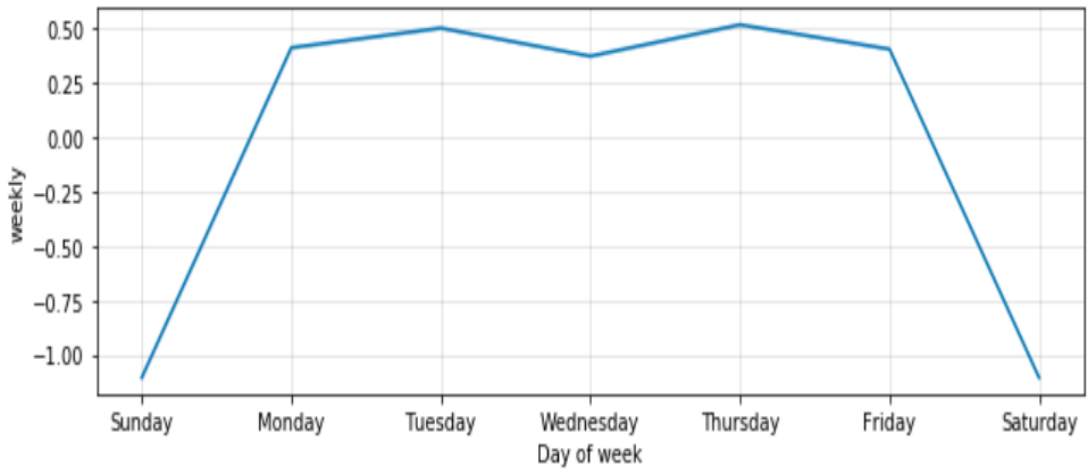


Figure 40: Weekly Component of the graph.

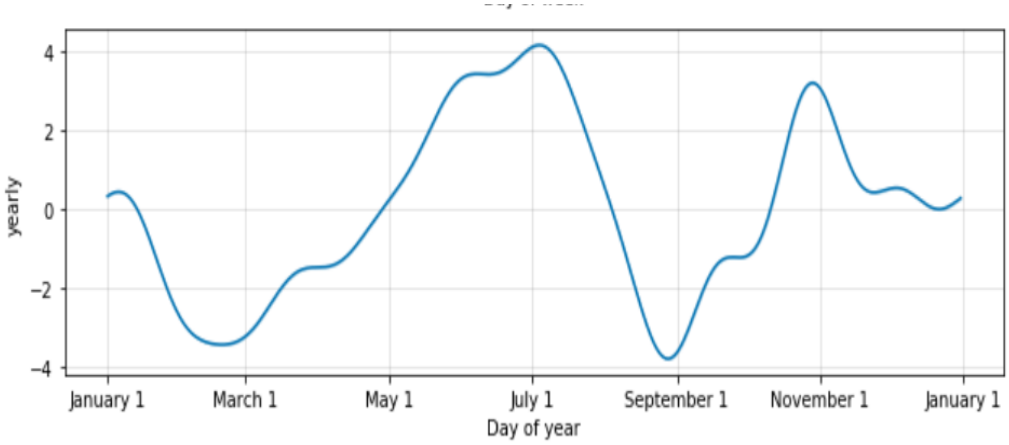


Figure 41: Yearly Component of the graph.

Now, we are going to visualize the forecasted graph. The figure 42 shows the code for visualizing the forecasted graph. In the graph we visualize ds, yhat, yhat_lowe and yhat_upper.

```
In [15]: stock_price_forecast = forecast[['ds','yhat', 'yhat_lower', 'yhat_upper']]
         df = pd.merge(stock_price, stock_price_forecast, on='ds', how='right')
         df.set_index('ds').plot(figsize=(16,8), color=['#F29F0E', "#000000", "#0EB6F2", "#0EB6F2"], grid=True);
```

Figure 42: Code for visualizing the Forecasted graph.

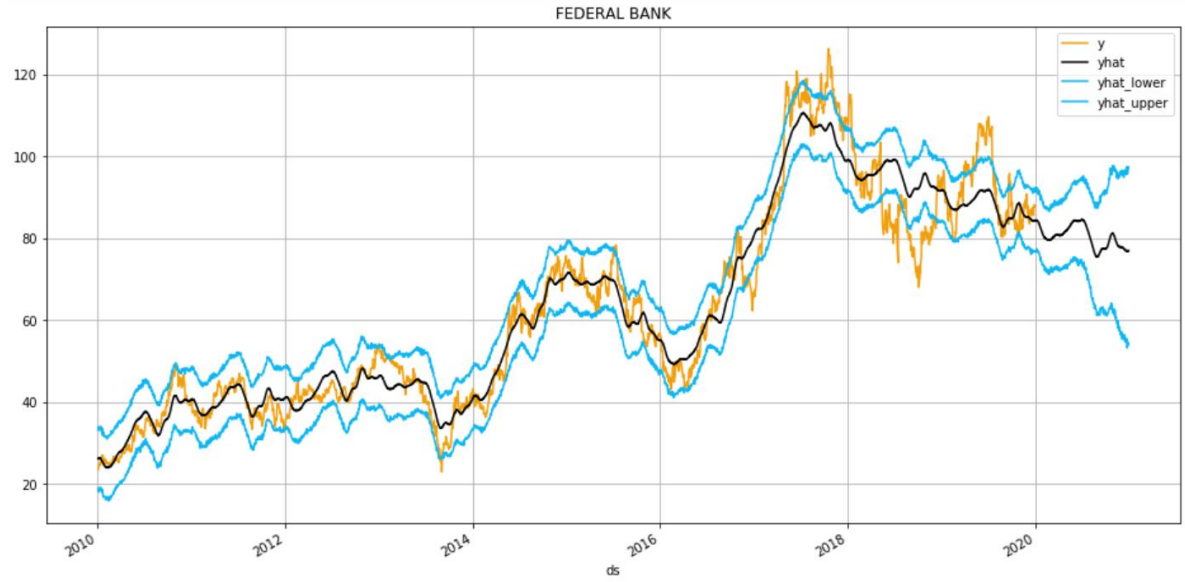


Figure 43: Forecasted Graph.

Y – Actual Stoke Price.

Yhat – Forecasted Stock Price.

Yhat_lower and Yhat_upper – Uncertainty interval of stock price.

6.4 Implementing the KERAS – LSTM model

For the implementation of LSTM model, we need to import the libraries initially. The main packages and libraries such as Pandas, NumPy, Matplotlib, Sklearn and keras. Layers. Matplotlib library is used to plot variables in graphical format.

```
In [2]: #importing libraries

import pandas as pd
import numpy as np

import matplotlib
import matplotlib.pyplot as plt
import matplotlib.dates as mdates

%matplotlib inline

from sklearn import linear_model
from keras.layers import LSTM,Dense,Dropout
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import TimeSeriesSplit

Using TensorFlow backend.
```

Figure 44: Importing of packages and libraries.

```
In [3]: df_final = pd.read_csv("D://Dataset//FEDERALBNK.BO.csv",na_values=['null'],index_col='Date',parse_dates=True,infer_datetime_f
        df_final.head()
```

Out[3]:

Date	Open	High	Low	Close	Adj Close	Volume
2010-01-04	23.770000	23.795	23.379999	23.580000	8.429377	724800
2010-01-05	23.900000	24.170	23.650000	23.920000	8.550918	1556550
2010-01-06	24.190001	24.650	24.100000	24.379999	8.715360	1034000
2010-01-07	24.610001	24.990	24.405001	24.565001	8.781491	1360420
2010-01-08	24.790001	25.100	24.605000	24.760000	8.851200	1886220

Figure 45: Reading the data from directory.

The figure 45 shows the reading of dataset which is in csv format from the directory and assigned to a variable. Parse date is used to create the date column as index. The output is printed using head(). In the figure we clearly see that date is transferred as index column.

The below figure 46 shows the Preprocessing steps. At first, we check the shape of the date that we import for the analysis. After that we describe the data using describe function. At last we check the missing values in the dataset.

```
In [4]: df_final.shape
Out[4]: (2461, 6)

In [5]: df_final.describe()
Out[5]:
```

	Open	High	Low	Close	Adj Close	Volume
count	2461.000000	2461.000000	2461.000000	2461.000000	2461.000000	2.461000e+03
mean	62.520234	63.378297	61.410343	62.334283	53.904860	8.685913e+05
std	25.137545	25.379739	24.740983	25.024562	31.001343	3.296248e+06
min	22.980000	23.795000	22.125000	22.985001	8.429377	0.000000e+00
25%	41.599998	42.189999	40.810001	41.540001	23.829430	2.492700e+05
50%	57.049999	57.700001	56.125000	56.900002	53.904865	4.372800e+05
75%	82.500000	83.650002	80.949997	82.349998	80.690247	8.076870e+05
max	126.699997	127.750000	125.650002	126.300003	123.230705	1.122362e+08

```
In [6]: df_final.isnull().values.any()
Out[6]: False
```

Figure 46: Preprocessing of Dataset

```
In [7]: df_final['Close'].plot(figsize=(14,6), title = 'Federal Bank')
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x27099dd4bc8>
```

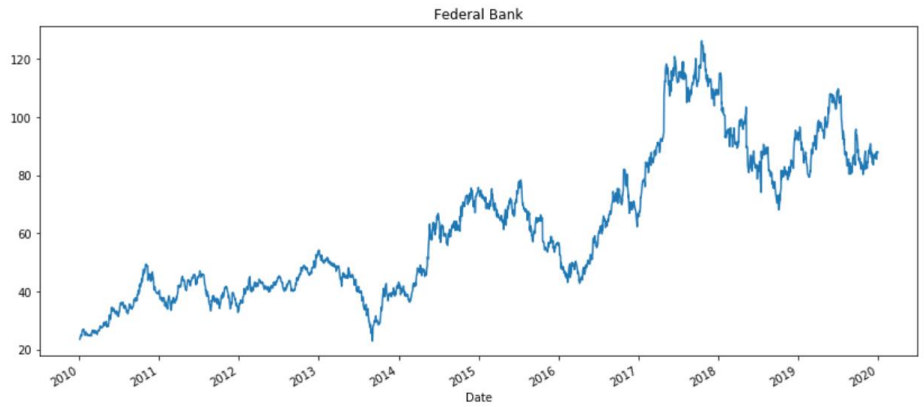


Figure 47: Visualizing the Graph with Close Price.

The figure 47 shows the graph of Closing stock price. Matplotlib library is used to plot the graph. Date is act as the x values and Closing stock price act as the y value of the graph.

```
In [8]: #Correlation Analysis
        X=df_final.drop(['Close'],axis=1)
        X=X.drop(['Adj Close'],axis=1)

        X.corrwith(df_final['Close']).plot.bar(
                figsize = (16, 6), title = "Correlation with Close", fontsize = 20,
                rot = 90, grid = True)
```

Figure 48: Correlation Analysis.

The figure 48 shows the correlation analysis of the data. For doing correlation analysis first we drop the close from df_final. After that correlation graph is plotted with all other attributes. The title of the graph is ‘Correlation with Close’. Having a font size of 20.

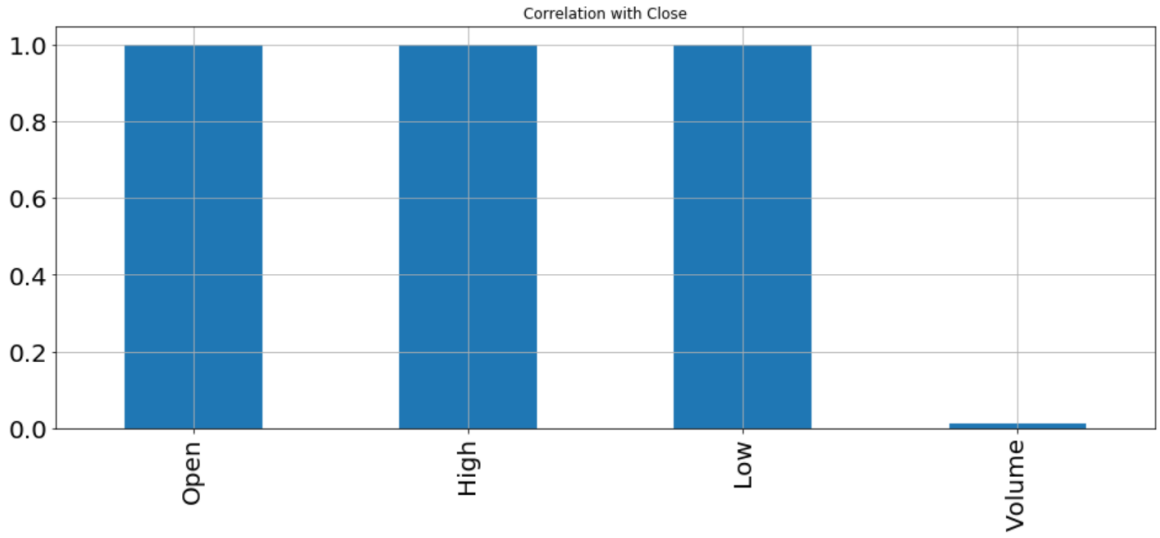


Figure 49: Correlation Graph.

```
In [11]: from sklearn.preprocessing import MinMaxScaler
         scaler = MinMaxScaler()
         feature_minmax_transform_data = scaler.fit_transform(test[feature_columns])
         feature_minmax_transform = pd.DataFrame(columns=feature_columns, data=feature_minmax_transform_data, index=test.index)
         feature_minmax_transform.head()
```

Out[11]:

Date	Open	High	Low	Volume
2010-01-04	0.007617	0.000000	0.012123	0.006458
2010-01-05	0.008870	0.003607	0.014731	0.013869
2010-01-06	0.011666	0.008225	0.019078	0.009213
2010-01-07	0.015715	0.011495	0.022024	0.012121
2010-01-08	0.017451	0.012554	0.023956	0.016806

Figure 50: Normalizing the data.

The figure 50 shows the process of normalizing the data. For normalizing the data first, we import MinMaxScaler from Sklearn. Preprocessing. After that define scalar is equal to MinMaxScaler.

The below figure 51 shows the code for displaying the shape of feature column and target column. After printing the shapes, we shift the target array because we want to predict n+1thday value. Then we took last 90 rows as validation set. Finally, we print the shape and the target close price.

```
In [12]:
display(feature_minmax_transform.head())
print('Shape of features : ', feature_minmax_transform.shape)
print('Shape of target : ', target_adj_close.shape)

# Shift target array because we want to predict the n + 1 day value


target_adj_close = target_adj_close.shift(-1)
validation_y = target_adj_close[-90:-1]
target_adj_close = target_adj_close[:-90]

# Taking last 90 rows of data to be validation set
validation_X = feature_minmax_transform[-90:-1]
feature_minmax_transform = feature_minmax_transform[:-90]
display(validation_X.tail())
display(validation_y.tail())

print("\n -----After process------ \n")
print('Shape of features : ', feature_minmax_transform.shape)
print('Shape of target : ', target_adj_close.shape)
display(target_adj_close.tail())
```

```
 -----After process------

Shape of features :  (2371, 4)
Shape of target :  (2371, 1)
```

	Close
Date	
2019-08-07	87.349998
2019-08-08	87.900002
2019-08-09	83.250000
2019-08-13	84.449997
2019-08-14	85.250000

Figure 51: Displaying dataset after Normalization.

```
In [13]:
ts_split= TimeSeriesSplit(n_splits=10)
for train_index, test_index in ts_split.split(feature_minmax_transform):
        X_train, X_test = feature_minmax_transform[:len(train_index)], feature_minmax_transform[len(train_index): (len(train_
        y_train, y_test = target_adj_close[:len(train_index)].values.ravel(), target_adj_close[len(train_index): (len(train_i

In [14]:
X_train.shape
Out[14]: (2156, 4)

In [15]:
X_test.shape
Out[15]: (215, 4)

In [16]:
y_train.shape
Out[16]: (2156,)

In [17]:
y_test.shape
Out[17]: (215,)
```

Figure 52: Train and Test Splitting of Data.

The figure 52 shows the splitting of training and testing data using timeseries split. Then we printed the shapes of xtrain, ytrain, xtest, ytest. After that we created a benchmark model.

```
In [19]:
from sklearn.tree import DecisionTreeRegressor

dt = DecisionTreeRegressor(random_state=0)

benchmark_dt=dt.fit(X_train, y_train)

validate_result(benchmark_dt, 'Decision Tree Regression')
```

Figure 53: Benchmark model.

The figure 53 shows the code for validating the benchmark model. Here we import DecisionTreeRegressor from Sklearn.tree.

```
RMSE:   3.1866692133420957
R2 score:   0.05098331945275958
```

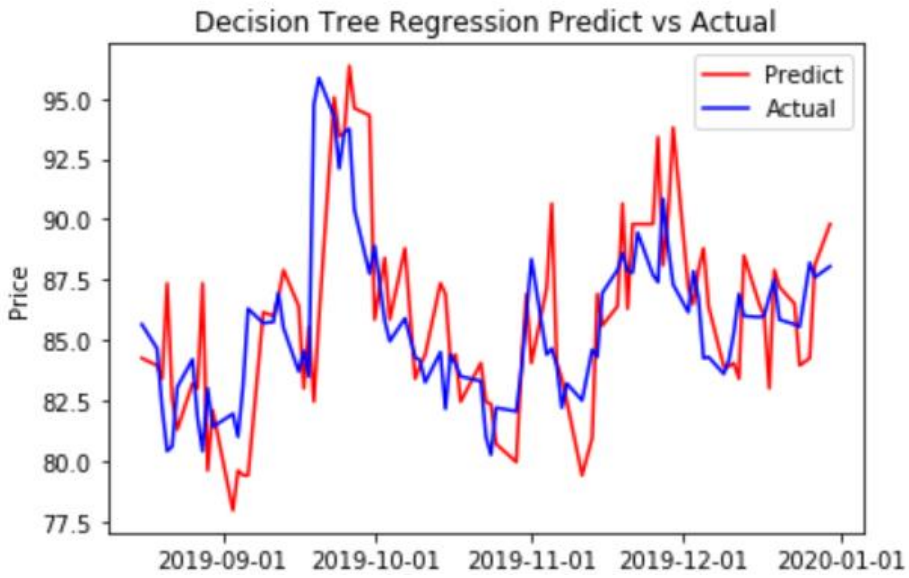


Figure 54: Output of Benchmark model.

```
In [21]:
from keras.models import Sequential
from keras.layers import Dense
import keras.backend as K
from keras.callbacks import EarlyStopping
from keras.optimizers import Adam
from keras.models import load_model
from keras.layers import LSTM
K.clear_session()
model_lstm = Sequential()
model_lstm.add(LSTM(16, input_shape=(1, X_train.shape[1]), activation='relu', return_sequences=False))
model_lstm.add(Dense(1))
model_lstm.compile(loss='mean_squared_error', optimizer='adam')
early_stop = EarlyStopping(monitor='loss', patience=5, verbose=1)
history_model_lstm = model_lstm.fit(X_tr_t, y_train, epochs=200, batch_size=8, verbose=1, shuffle=False, callbacks=[early_sto
```

Figure 55: LSTM Model Building.

After getting the benchmark model we started to process the data for building the LSTM model. For creating the models, we import Sequential from keras.models, Dense from keras.layers,

Keras.backend, Early stopping from keras.callbacks, Adam from keras.optimizer, Loadmodel from keras.models and LSTM from keras.layers.

```
In [22]:
y_pred_test_lstm = model_lstm.predict(X_tst_t)
y_train_pred_lstm = model_lstm.predict(X_tr_t)
print("The R2 score on the Train set is:\t{:0.3f}".format(r2_score(y_train, y_train_pred_lstm)))
r2_train = r2_score(y_train, y_train_pred_lstm)

print("The R2 score on the Test set is:\t{:0.3f}".format(r2_score(y_test, y_pred_test_lstm)))
r2_test = r2_score(y_test, y_pred_test_lstm)

The R2 score on the Train set is:       0.995
The R2 score on the Test set is:        0.957
```

Figure 56: Evaluation of model using R2 Score.

R2 score is regression score function. It is statistical measure that which is used to describe the proportion of variance of a dependent variable that is explained in regression model. It can be negative or positive. Here the R2 score for train set is 0.995 and R2 score for test set is 0.957.

```
In [25]:
y_pred_test_LSTM = model_lstm.predict(X_tst_t)

In [26]:
plt.figure(figsize=(12,6))
plt.plot(y_test, label='True')
plt.plot(y_pred_test_LSTM, label='LSTM')
plt.title("LSTM's_Prediction")
plt.xlabel('Observation')
plt.ylabel('INR_Scaled')
plt.legend()
plt.show()
```

Figure 57: Code for Visualizing of LSTM Prediction

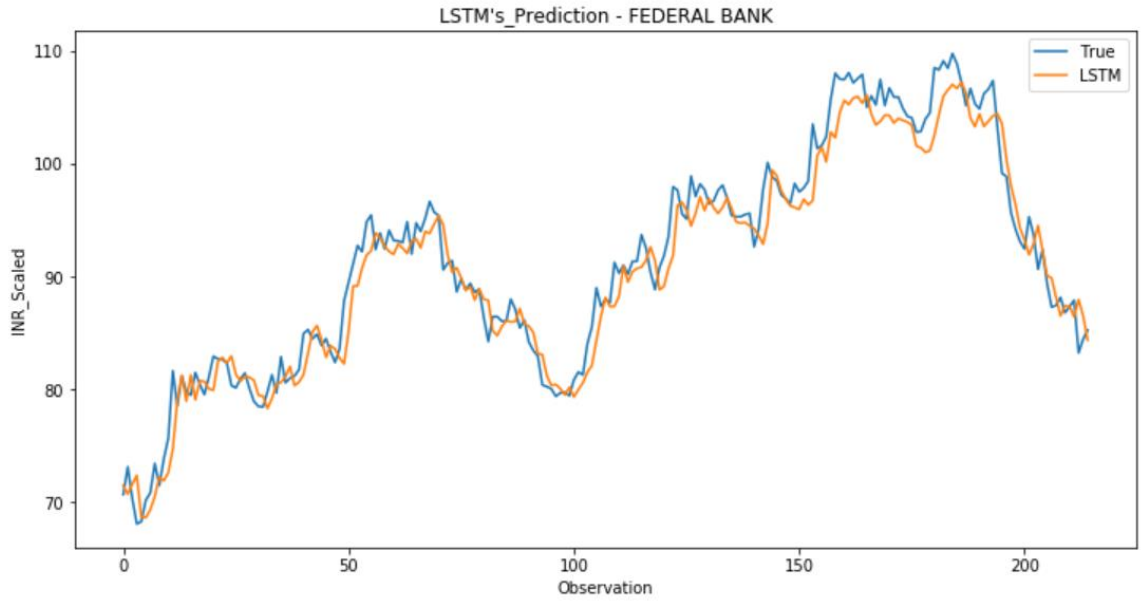


Figure 58: Predicted Graph.

6.5 Predicted Graphs of all banks – ARIMA model

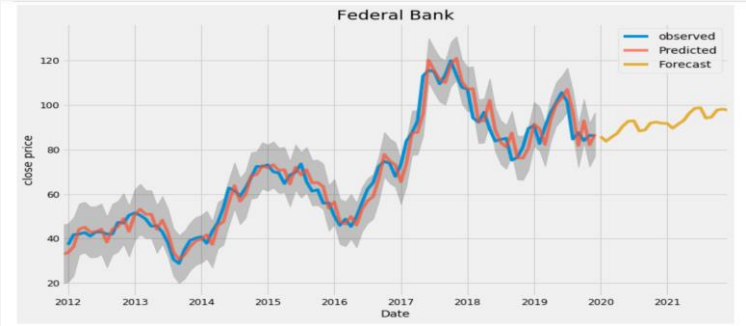
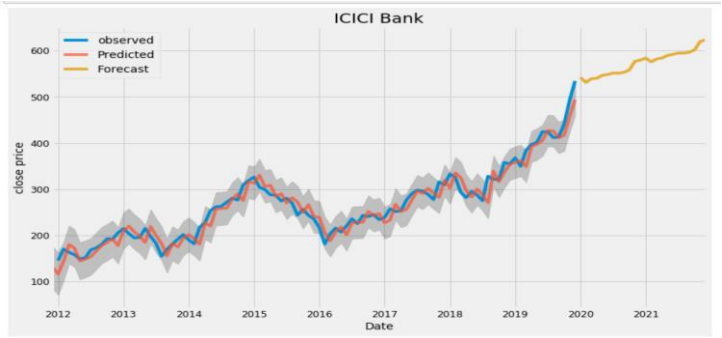
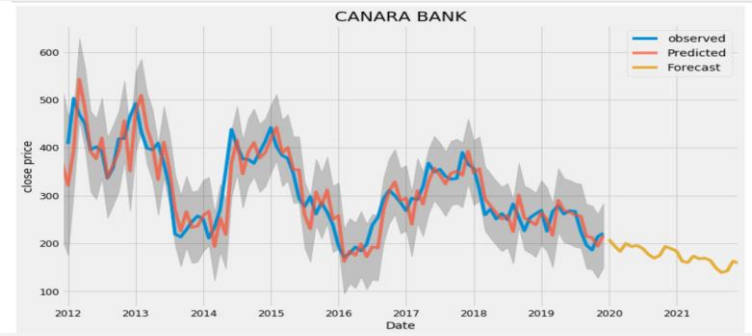
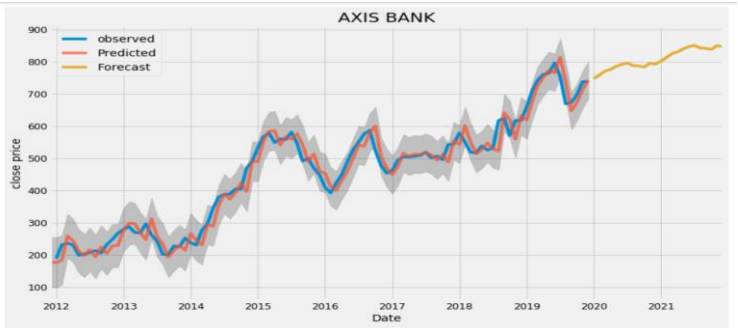
Sl.No	Bank Name	Predicted Graphs
1	Federal Bank	
2	ICICI Bank	
3	Canara Bank	
4	AXIS Bank	

Table 1: Predicted Graphs - ARIMA.

6.6 Predicted Graphs of all banks – Prophet

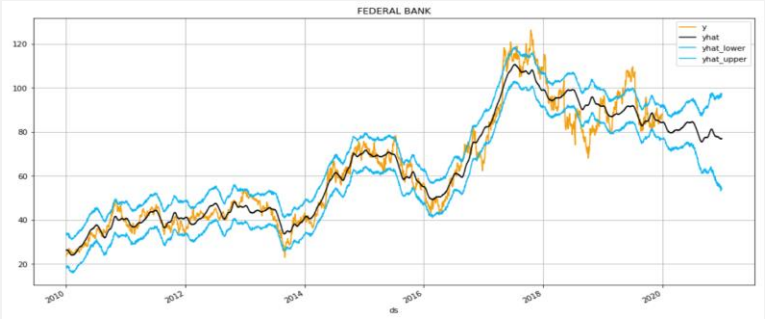
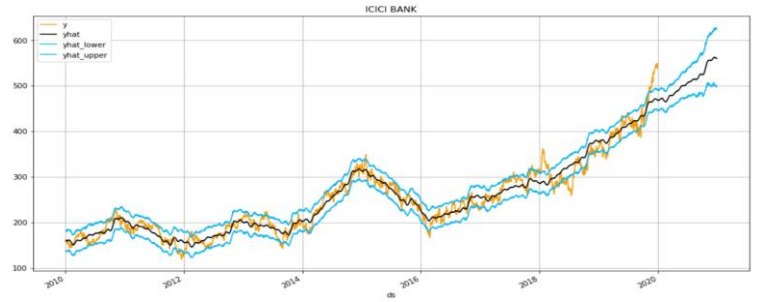
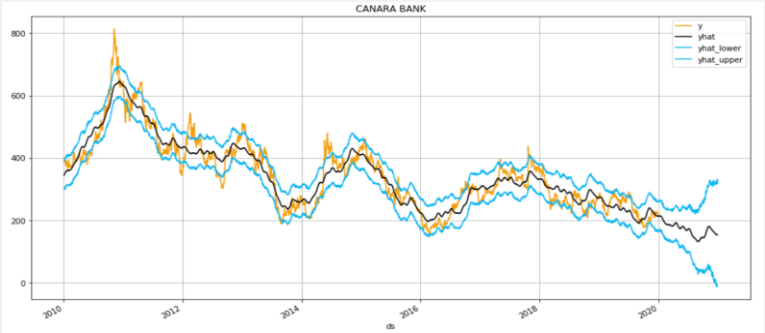
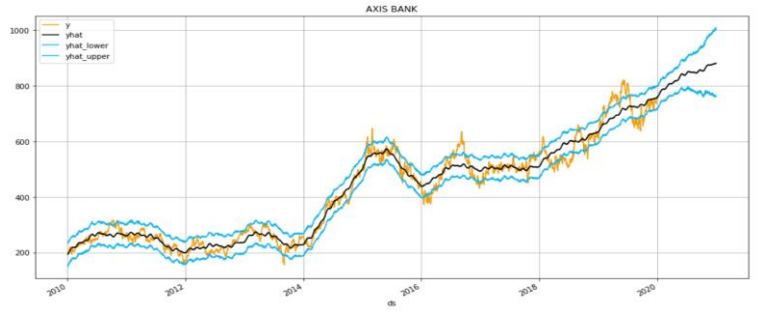
Sl.No	Bank Name	Predicted Graphs
1	Federal Bank	
2	ICICI Bank	
3	Canara Bank	
4	AXIS Bank	

Table 2: Predicted Graphs - Prophet.

6.7 Predicted Graphs of all banks – Keras-LSTM model

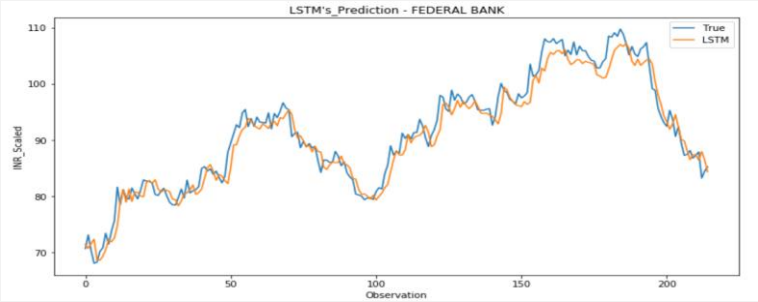
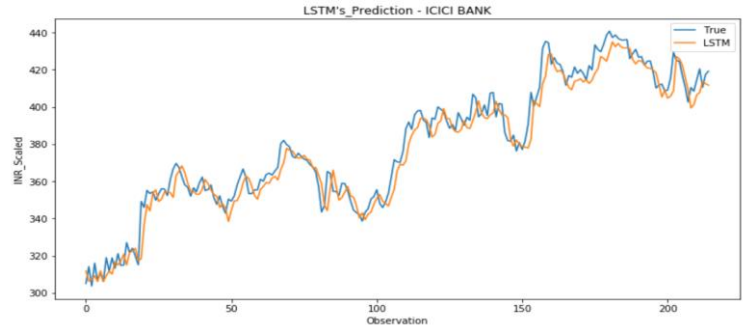
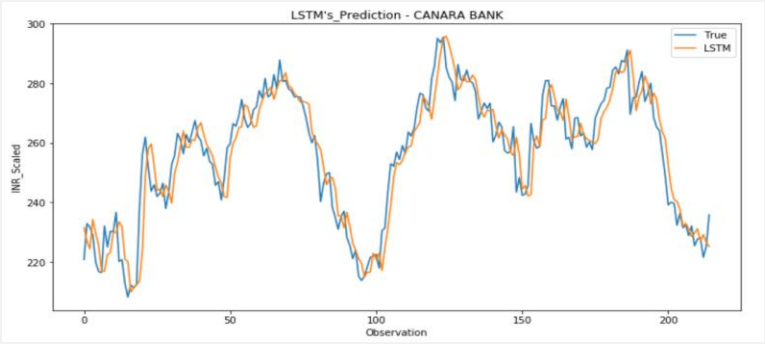
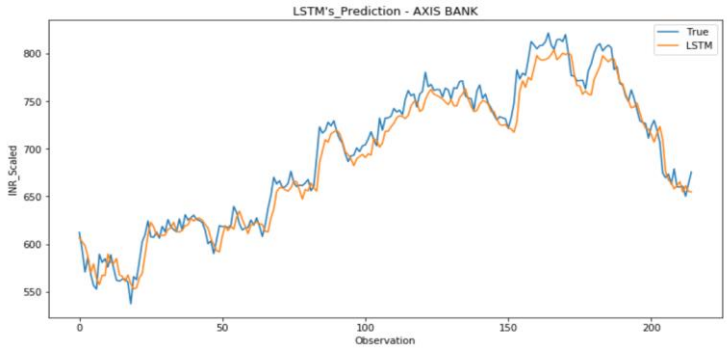
Sl.No	Bank Name	Predicted Graphs
1	Federal Bank	
2	ICICI Bank	
3	Canara Bank	
4	AXIS Bank	

Table 3: Predicted Graphs - Keras with LSTM.

Chapter 7. Testing and Evaluation

7.1 RMSE – Root Mean Square Error Value

The RMSE value is the square root of Mean Square Error. RMSE measures the difference between predicted value and the original value. We know that lower RMSE value gives the better performance in time series models. The RMSE value is calculated for three time series models and compared between each of them. The final phase of the project is the execution of evaluated result.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (P_i - O_i)^2}{n}}$$

Equation 6: Formulae for RMSE.

The Equation 6 is the formulae for calculating the RMSE value. Here n stands for positive integer, P_i for ideal distance and O_i for the performance.

7.2 RMSE value – ARIMA Model

7.2.1 Federal Bank

```
In [17]:
y_forecasted = pred.predicted_mean
y_truth = monthly_mean['2011-12-31':]

from sklearn import metrics
print('Mean Absolute Error:', metrics.mean_absolute_error(y_truth, y_forecasted))
print('Mean Squared Error:', metrics.mean_squared_error(y_truth, y_forecasted))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_truth, y_forecasted)))

Mean Absolute Error: 4.014757690134823
Mean Squared Error: 26.10177673992103
Root Mean Squared Error: 5.108989796419741
```

Figure 59: Validation Report of Federal Bank.

The figure 59 shows the Validation report of Federal Bank. Here we import metrics from Sklearn for calculating the errors between the predicted model and actual model. We also calculated RMSE , MAE, and MSE.

RMSE of Federal Bank = 5.10.

7.2.2 ICICI Bank

```
In [33]:
y_forecasted = pred.predicted_mean
y_truth = monthly_mean['2011-12-31':]

from sklearn import metrics
print('Mean Absolute Error:', metrics.mean_absolute_error(y_truth, y_forecasted))
print('Mean Squared Error:', metrics.mean_squared_error(y_truth, y_forecasted))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_truth, y_forecasted)))

Mean Absolute Error: 14.500844790493142
Mean Squared Error: 329.98612643763096
Root Mean Squared Error: 18.1655202633349
```

Figure 60:Validation Report of ICICI Bank.

The figure 60 shows the Validation report of ICICI Bank. Here we import metrics from Sklearn for calculating the errors between the predicted model and actual model. We also calculated RMSE , MAE, and MSE.

RMSE of ICICI Bank = 18.16.

7.2.3 Canara Bank

```
In [49]:
y_forecasted = pred.predicted_mean
y_truth = monthly_mean['2011-12-31':]

from sklearn import metrics
print('Mean Absolute Error:', metrics.mean_absolute_error(y_truth, y_forecasted))
print('Mean Squared Error:', metrics.mean_squared_error(y_truth, y_forecasted))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_truth, y_forecasted)))

Mean Absolute Error: 30.111556884594464
Mean Squared Error: 1557.0224462191634
Root Mean Squared Error: 39.45912373861289
```

Figure 61: Validation Report of Canara Bank.

The figure 61 shows the Validation report of Canara Bank. Here we import metrics from Sklearn for calculating the errors between the predicted model and actual model. We also calculated RMSE , MAE, and MSE.

RMSE of Canara Bank = 39.45.

7.2.4 AXIS Bank

```
In [65]: y_forecasted = pred.predicted_mean
         y_truth = monthly_mean['2011-12-31':]

         from sklearn import metrics
         print('Mean Absolute Error:', metrics.mean_absolute_error(y_truth, y_forecasted))
         print('Mean Squared Error:', metrics.mean_squared_error(y_truth, y_forecasted))
         print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_truth, y_forecasted)))

         Mean Absolute Error: 23.812250802812173
         Mean Squared Error: 933.8209108428855
         Root Mean Squared Error: 30.558483451291973
```

Figure 62: Validation Report of AXIS Bank.

The figure 62 shows the Validation report of AXIS Bank. Here we import metrics from Sklearn for calculating the errors between the predicted model and actual model. We also calculated RMSE , MAE, and MSE.

RMSE of AXIS Bank = 30.55.

7.3 RMSE Value – PROPHET Model

7.3.1 Federal Bank

```
In [18]: from sklearn.metrics import mean_squared_error,mean_absolute_error
         print('Mean Absolute Error:',mean_absolute_error(metric_stock_price.y,metric_stock_price.yhat))
         print('Mean Squared Error:',mean_squared_error(metric_stock_price.y,metric_stock_price.yhat))
         print('Root Mean Squared Error:',np.sqrt(mean_squared_error(metric_stock_price.y,metric_stock_price.yhat)))

         Mean Absolute Error: 4.261437592532773
         Mean Squared Error: 34.566624952913465
         Root Mean Squared Error: 5.879338819366805
```

Figure 63: Validation Result of Federal Bank.

The figure 63 shows the Validation report of Federal Bank. Here we import mean squared error and mean absolute error from Sklearn for calculating the errors between the predicted model and actual model. We also calculated RMSE , MAE, and MSE.

RMSE of Federal Bank = 5.87.

7.3.2 ICICI Bank

```
In [35]: from sklearn.metrics import mean_squared_error,mean_absolute_error
         print('Mean Absolute Error:',mean_absolute_error(metric_stock_price.y,metric_stock_price.yhat))
         print('Mean Squared Error:',mean_squared_error(metric_stock_price.y,metric_stock_price.yhat))
         print('Root Mean Squared Error:',np.sqrt(mean_squared_error(metric_stock_price.y,metric_stock_price.yhat)))

         Mean Absolute Error: 13.422718757084994
         Mean Squared Error: 312.7684667503777
         Root Mean Squared Error: 17.685261285895034
```

Figure 64: Validation Report of ICICI Bank.

The figure 64 shows the Validation report of ICICI Bank. Here we import mean squared error and mean absolute error from Sklearn for calculating the errors between the predicted model and actual model We also calculated RMSE , MAE, and MSE.

RMSE of ICICI Bank = 17.68.

7.3.3 Canara Bank

```
In [52]: from sklearn.metrics import mean_squared_error,mean_absolute_error
         print('Mean Absolute Error:',mean_absolute_error(metric_stock_price.y,metric_stock_price.yhat))
         print('Mean Squared Error:',mean_squared_error(metric_stock_price.y,metric_stock_price.yhat))
         print('Root Mean Squared Error:',np.sqrt(mean_squared_error(metric_stock_price.y,metric_stock_price.yhat)))

         Mean Absolute Error: 29.62579450309121
         Mean Squared Error: 1364.4655818650347
         Root Mean Squared Error: 36.93867325534357
```

Figure 65: Validation Report of Canara Bank.

The figure 65 shows the Validation report of Canara Bank. Here we import mean squared error and mean absolute error from Sklearn for calculating the errors between the predicted model and actual model. We also calculated RMSE , MAE, and MSE.

RMSE of Canara Bank = 36.93.

7.3.4 AXIS Bank

```
In [70]: from sklearn.metrics import mean_squared_error,mean_absolute_error
         print('Mean Absolute Error:',mean_absolute_error(metric_stock_price.y,metric_stock_price.yhat))
         print('Mean Squared Error:',mean_squared_error(metric_stock_price.y,metric_stock_price.yhat))
         print('Root Mean Squared Error:',np.sqrt(mean_squared_error(metric_stock_price.y,metric_stock_price.yhat)))

         Mean Absolute Error: 23.84139140625334
         Mean Squared Error: 996.300804425197
         Root Mean Squared Error: 31.5642329928227
```

Figure 66: Validation Report of AXIS Bank.

The figure 66 shows the Validation report of AXIS Bank. Here we import mean squared error and mean absolute error from Sklearn for calculating the errors between the predicted model and actual model. We also calculated RMSE , MAE, and MSE.

RMSE of AXIS Bank = 31.56.

7.4 RMSE Value – KERAS with LSTM Model

7.4.1 Federal Bank

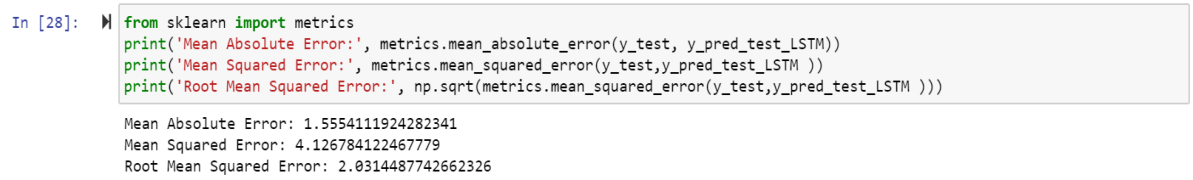


Figure 67: Validation Report of Federal Bank.

The figure 67 shows the Validation report of Federal Bank. Here we import metrics from Sklearn for calculating the errors between the predicted model and actual model. We also calculated RMSE , MAE, and MSE. After all we print all the values.

RMSE of Federal Bank = 2.03.

7.4.2 ICICI Bank

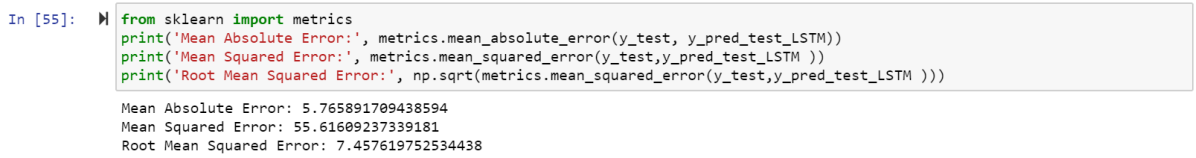


Figure 68: Validation Report of ICICI Bank.

The figure 68 shows the Validation report of ICICI Bank. Here we import metrics from Sklearn for calculating the errors between the predicted model and actual model. We also calculated RMSE , MAE, and MSE. After all we print all the values.

RMSE of ICICI Bank = 7.45.

7.4.3 Canara Bank

```
In [82]: from sklearn import metrics
         print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred_test_LSTM))
         print('Mean Squared Error:', metrics.mean_squared_error(y_test,y_pred_test_LSTM ))
         print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,y_pred_test_LSTM )))

         Mean Absolute Error: 5.67011399379996
         Mean Squared Error: 55.34085014545746
         Root Mean Squared Error: 7.439143105590688
```

Figure 69: Validation Report of Canara Bank.

The figure 69 shows the Validation report of Canara Bank. Here we import mean squared error and mean absolute error from Sklearn for calculating the errors between the predicted model and actual model. We also calculated RMSE , MAE, and MSE. After all we print all the values.

RMSE of Canara Bank = 7.43.

7.4.4 AXIS Bank

```
In [109]: from sklearn import metrics
          print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred_test_LSTM))
          print('Mean Squared Error:', metrics.mean_squared_error(y_test,y_pred_test_LSTM ))
          print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,y_pred_test_LSTM )))

          Mean Absolute Error: 11.15367204533067
          Mean Squared Error: 210.49221545650173
          Root Mean Squared Error: 14.508349852981272
```

Figure 70: Validation Report of AXIS Bank.

The figure 70 shows the Validation report of AXIS Bank. Here we import mean squared error and mean absolute error from Sklearn for calculating the errors between the predicted model and actual model. We also calculated RMSE , MAE, and MSE. After all we print all the values.

RMSE of AXIS Bank = 14.50.

The above figures clearly show the testing and evaluation of time series models of different banks. Now we are comparing the models in bar diagrams

7.5 Comparison of Time Series Models

We drafted the data in the form of a bar diagram in Jupyter Notebook. For the comparison of RMSE value we import NumPy and Matplotlib libraries. NumPy is python library that deals with arrays. Matplotlib is a visualizing library in python.

Comparison of Time Series Models Using RMSE value

```
In [1]:
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

Figure 71: Importing libraries.

```
In [2]:
Models=['ARIMA','PROPHET','KERAS with LSTM']
RMSE=[5.10,5.87,2.03]
graph = np.arange(len(Models))
plt.style.use('fivethirtyeight')
plt.figure(figsize=(10,6))
plt.bar(graph,RMSE, label="RMSE")
plt.xticks(graph,Models)
plt.ylabel("Value of RMSE")
plt.title('Comparison Report Graph - Federal Bank')
plt.legend()
```

Figure 72: Code for Developing Bar Diagram.

The figure 72 describes the code for the developing the Comparison bar diagram. First, we initialize the model names in a variable called Models. Then we store RMSE values in an array variable called RMSE. We use the plot style as fivethirtyeight. Figure size of the graph is 10,6. Title of the graph is given using plt.title.

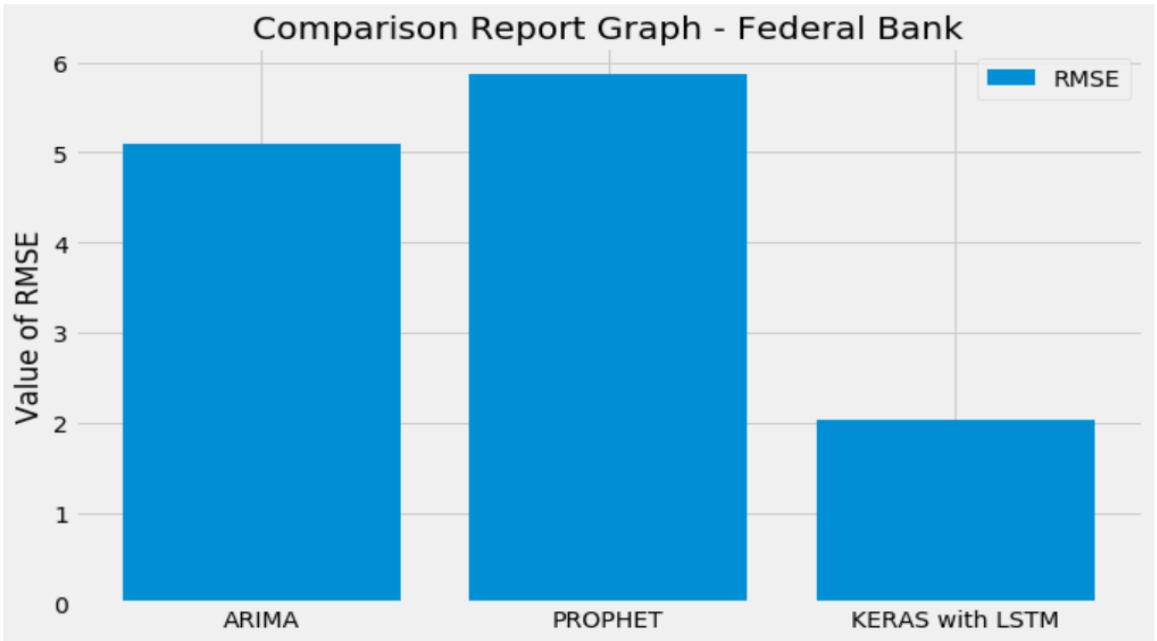


Figure 73: Comparison Report Graph - Federal Bank.

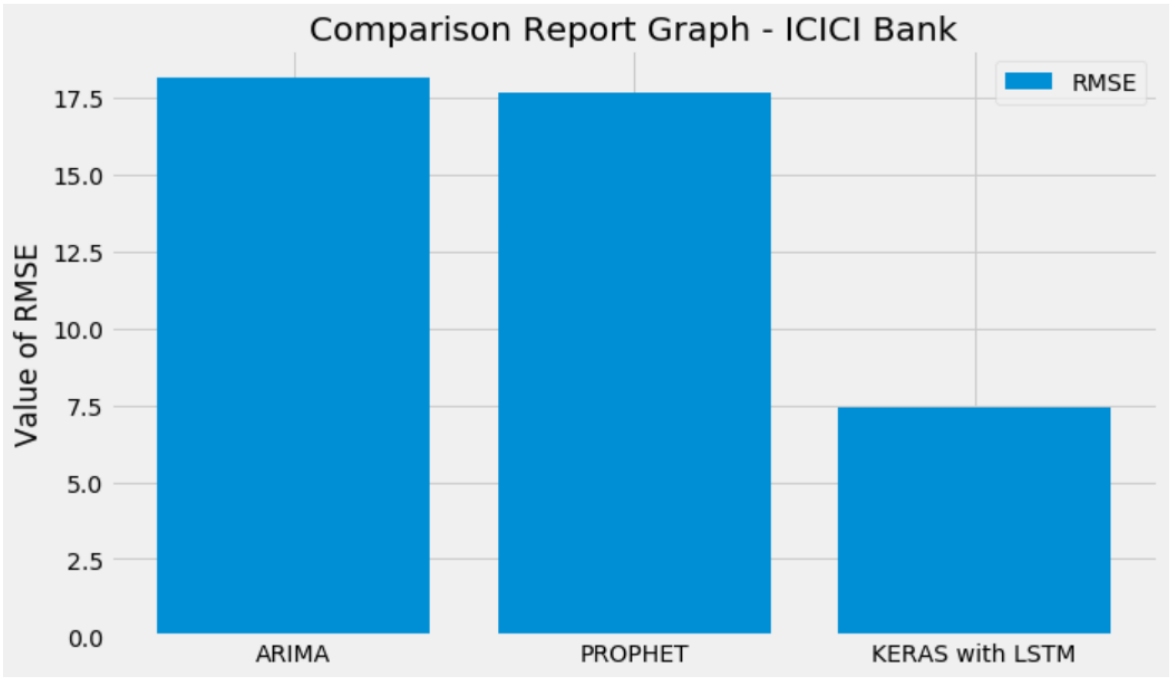


Figure 74: Comparison Report Graph - ICICI Bank.

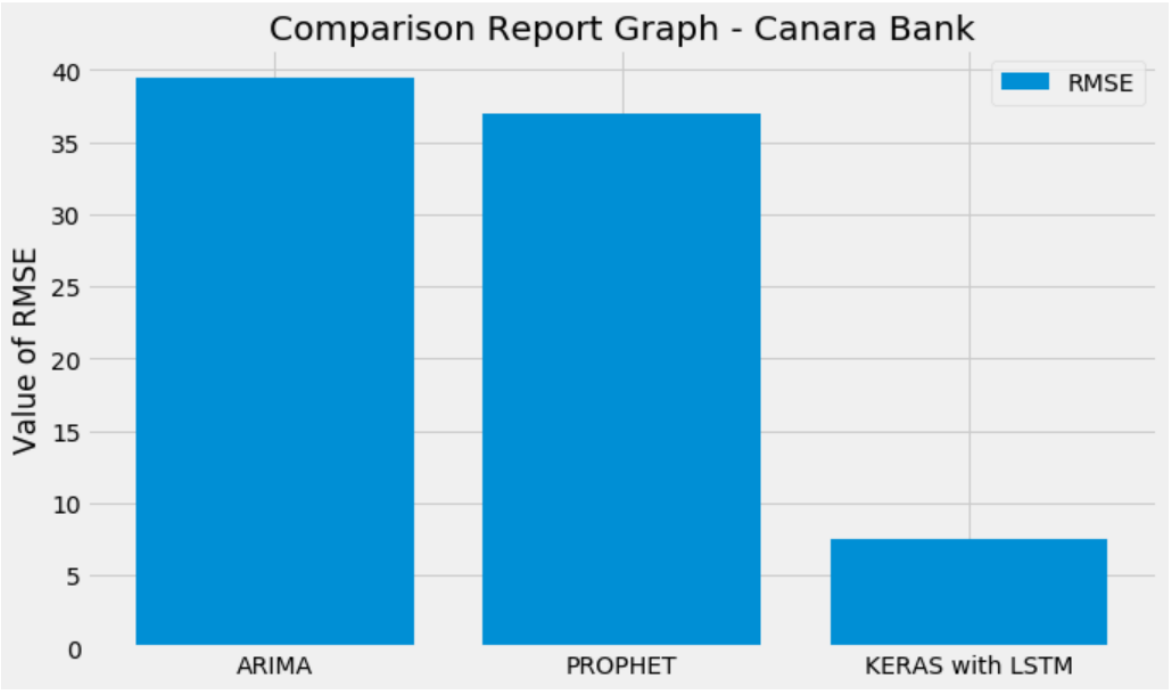


Figure 75: Comparison Report Graph - Canara Bank.

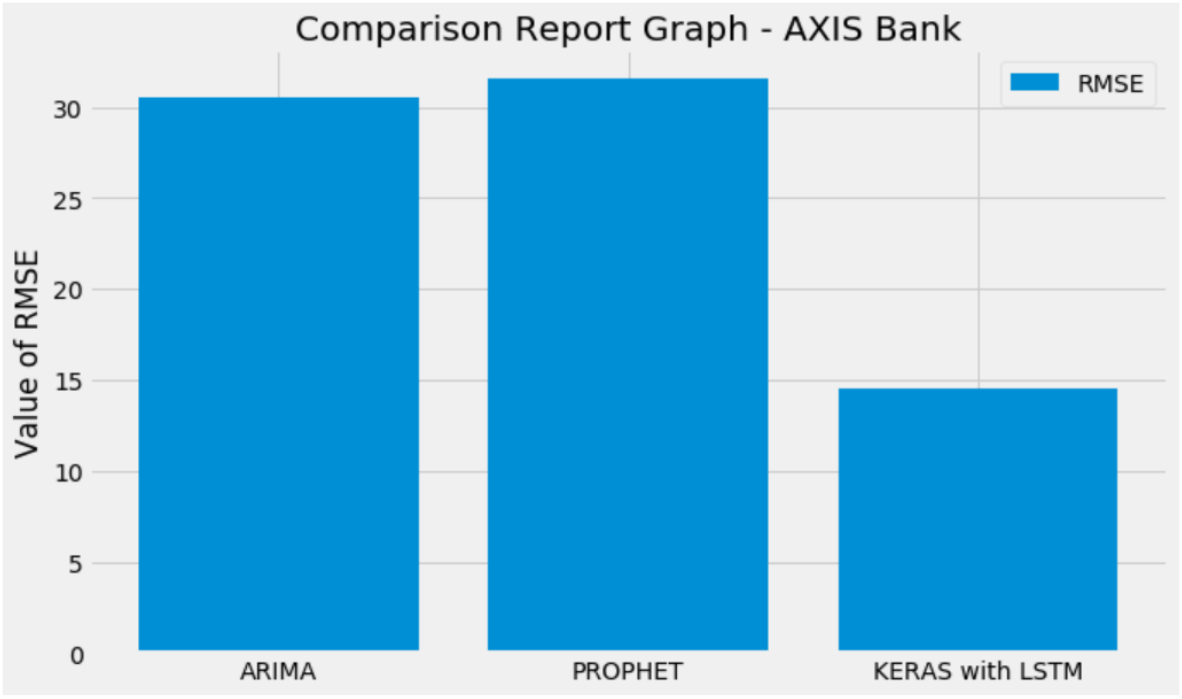


Figure 76: Comparison Report Graph -AXIS Bank.

In all above graphs it is clearly identified that KERAS with LSTM time series model having the least RMSE value. Lower RMSE value have the better performance model.

7.6 User Interface Testing

User Interface is developed just for Investors to identify the future stock price value of the Banks. For developing the UI, we used flask web framework. Algorithm used for the prediction of Prophet because for the easy development of the back end. For testing of the UI, first we must run the python file.

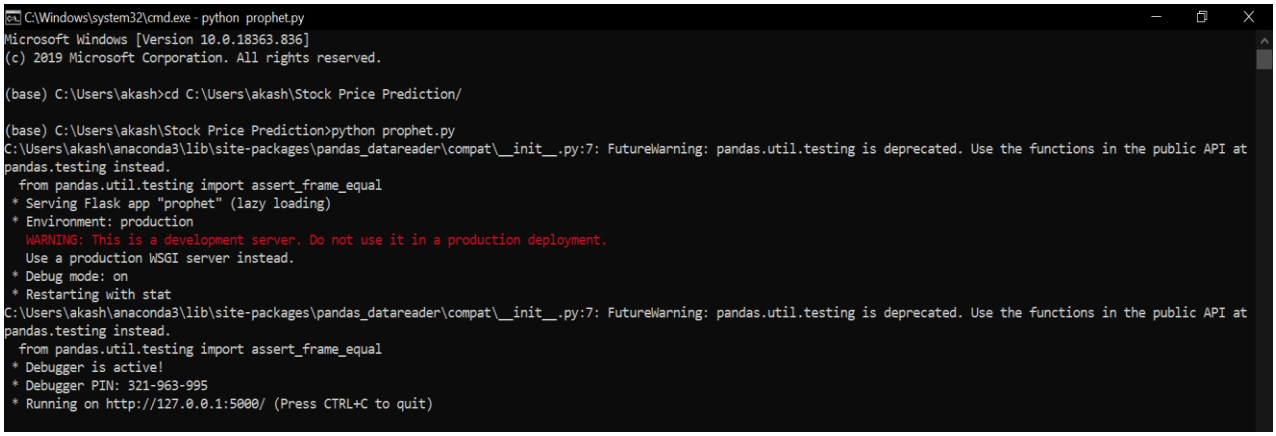


Figure 77: Python File running using Command Prompt.

After running the program, homepage of the web application is opened in the browser.

Figure 78: Home Page of the UI

In the web page we need to enter the ticker symbol of the bank in the submit box. When we are submitting the bank ticker symbol it fetches the real time data from yahoo finance wit the help of yahoo finance api.

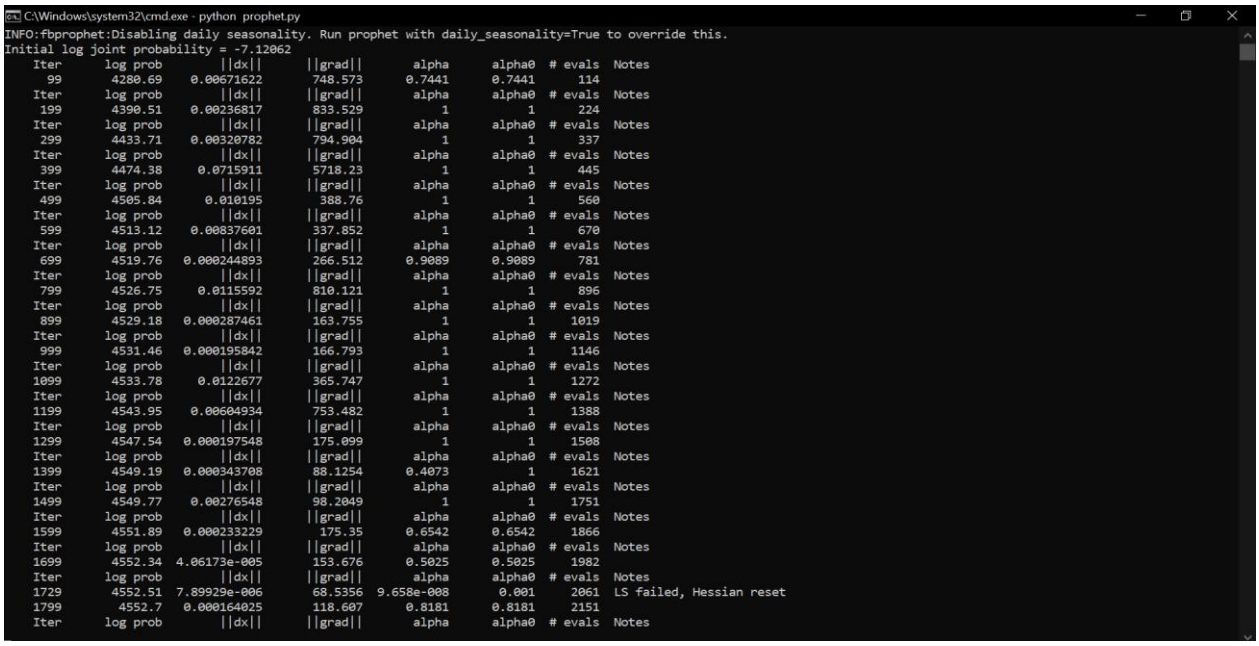


Figure 79: Real time data fetching.

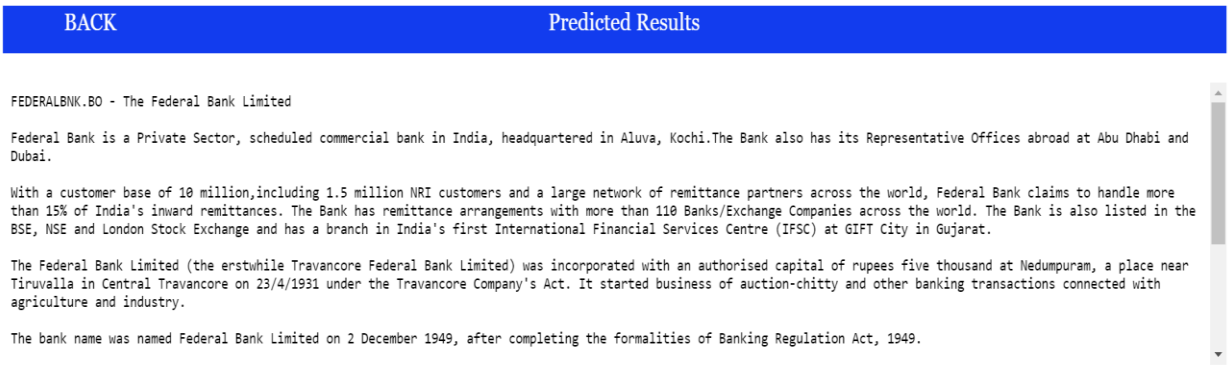


Figure 80: Bank Information.

Figure 81: Forecasted Result.

The figure 81 shows the forecasted result of the federal bank. By analyzing the graph investor can decide whether need to buy the stock or not of this bank. It is very easy to understand the predicted values and original values ,if we develop a UI.

Chapter 8. Conclusion and Future Work

8.1 Conclusion

In this project the study of time series models such as ARIMA, PROPHET and KERAS with LSTM for predicting stock price is successfully completed. The objective of the project is achieved. By comparing with the RMSE value KERAS with LSTM is giving the best time series model for the prediction of stock price. ARIMA and PROPHET also generated strong predicted graph with the stock price. UI is developed and predicted successfully for the stock market price. UI will help the investors to identify the best predicted value in the banking sector. By the increasing of investors in the banking sector that leads to the development of the economy of the country. Government will initiate to introduce more banking schemes. The small-scale banks will be developed also. They can also identify the factors affecting for the stock price.

8.2 Future Work

The future scope of the project is listed below

1. Stock Price prediction can be used not only in banking sector but also in various fields.
2. The accuracy of the stock prediction depends on marketplace, interest rates, dividends, economic fluctuations, political climate. So, need to focus on the external factors as well.
3. Introduce more algorithms for the stock price prediction.
4. Not only using Prophet Algorithm But also, we can use all the algorithms for developing the web application of stock prediction.
5. Investors can identify the accuracy of the predicted result within the application by using more algorithms for a single stock
6. Make the application more user friendly by defining about the algorithms, daily stock news, factors affecting the stock predictions etc.

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