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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
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SPECIAL TOPIC-2 REPORT

ON

"Visualizing and Forecasting Of Stocks Using Historical Data "

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CERTIFICATE

This is to certify that MOHAMMED TAHEER - (ENG19CS0186), P SAI KIREETI - (ENG19CS0215), PRARTHAN P - (ENG19CS0228), N SHAIK SAFI - (ENG19CS0195) has satisfactorily completed his/her Special Topic - 2 Project Report as prescribed by the University for the 6^{TH} semester B.Tech. program in Computer Science & SPECIAL TOPIC - 2 course during the year 2021-22 at the School of Engineering, Dayananda Sagar University., Bangalore.

Date: ______________

Signature of the faculty in-charge

Max Marks	Marks Obtained

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Signature of Chairman

Department of Computer Science & Engineering

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ABSTRACT

The goal of the project is to accurately estimate the values of a basket of equities on the NSE/BSE. This study investigated and analysed a range of neural network prediction approaches, and ultimately chose the LSTM (Long Short-Term Memory, LSTM) neural network, based on the need for stock price prediction and the practical issues it encounters. The practicality of the procedure and the applicability of the model are then assessed, and a conclusion is reached after an in-depth examination of how to predict stock price using the LSTM. It has been discovered that historical data is particularly significant to investors when making investing decisions. Opening and closing prices have previously been employed as significant new financial market forecasters, but severe maxima and minima may provide extra information regarding future price behaviour. As a result, the opening price, closing price, lowest price, highest price, date, and daily trading volume of three representative stocks in the stock market are chosen as research objects, and the key data collected from them includes the opening price, closing price, lowest price, highest price, date, and daily trading volume. The results reveal that, while the LSTM neural network model has several drawbacks, such as prediction time lag, it can forecast stock values when combined with an attention layer. Its primary idea is to find the role of time series by analysing historical stock market data, and to extensively investigate its underlying laws using the LSTM neural network model's selective memory advanced deep learning function, in order to anticipate stock price trends.

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CHAPTER 1

INTRODUCTION

The stock market has an air of unpredictability about it. A stock market, also known as an equity market or a share market, is a collection of buyers and sellers (a loose network of economic transactions, not a physical facility or discrete entity) of stocks (also known as shares), which represent ownership claims on businesses; these may include securities listed on a public stock exchange as well as private stock. Shares of private enterprises are sold to investors through equity crowdfunding platforms as an example of the latter. Shares of common stock, as well as other asset kinds such as corporate bonds and convertible bonds, are traded on stock exchanges.

Small individual stock investors to huge institutional investors, which can be headquartered anywhere in the world and include banks, insurance firms, pension funds, and hedge funds, all participate in the stock market. A stock exchange trader may execute their buy or sell orders on their behalf.

1.1 Complex platform and multifaceted problem

Small individual stock investors to huge institutional investors, which can be headquartered anywhere in the world and include banks, insurance firms, pension funds, and hedge funds, all participate in the stock market. A stock exchange trader may execute their buy or sell orders on their behalf.

1.2 Predictions – challenging, great financial potential

The ability to make accurate stock market predictions is not only beneficial financially, but it is also difficult academically. The act of attempting to anticipate the future value of a business stock or other financial instrument traded on an exchange is known as stock market prediction. A successful forecast of a stock's future price could result in a large profit. Insider trade data is available on stock exchange websites and can be used to forecast future prices.

One of the most difficult things to do is to predict how the stock market will perform. Physical vs. psychological causes, rational vs. irrational behaviour, and so on are all elements in the forecast. All of these factors combine to make stock values extremely volatile and difficult to anticipate accurately. Is it possible to apply machine learning to change the game in this domain? Machine learning techniques have the potential to find patterns and insights we didn't perceive previously, and they can be utilised to make unerringly precise forecasts, using features such as an organization's newest announcements, quarterly revenue statistics, and so on.

1.3 Relevance of the Project

One of the most compelling arguments for forecasting market movement is that many investors believe that the only time to invest in the market is when it is rising. Such investors would prefer to stay away from the market while it dips, returning only when they are convinced that the market would recover again.

To predict stock market prices, machine learning fundamentals are utilised, and some algorithms additionally incorporate social sentiment as well as historical data to make predictions.

Predicting short-term market movement necessitates not only the capacity to correctly predict all of these criteria, but also the ability to predict how the majority of investors will react to each of these events. Almost all investors lack the ability to correctly and consistently foresee these events.

1.4 Scope of the Project

The goal of the project is to accurately estimate the values of a basket of equities on the NSE/BSE. We will know which stock to purchase and make a profit if we have an idea of the price of a stock in the market prior to its sale. A successful forecast of a stock's future price could result in a large profit. Stock prices, according to the efficient-market theory, represent all currently accessible information, and any price fluctuations that are not based on newly revealed information are thus fundamentally unpredictable.

CHAPTER 2

PROBLEM DEFINITION

The phrase "buy low, sell high" is well-known among investors, yet it does not provide enough context to make sound investing decisions. Before investing in any stock, an investor must understand how the stock market works. Investing in an excellent stock at the wrong moment can be devastating, whilst investing in a mediocre stock at the appropriate time can provide returns.

Today's financial investors have a trading dilemma since they don't know which stocks to buy or which stocks to sell in order to maximize profits.

Predicting long term value of the stock is relatively easy than predicting on day-to-day basis as the stocks fluctuate rapidly every hour based on world events.

CHAPTER 3

LITERATURE SURVEY

By incorporating memory cells and gate units into the neural network design, long-short term memory addresses the difficulty of learning to recall information over a time interval. Memory cells, each of which has a cell state that stores previously encountered information, are used in a typical formulation. The output is determined by a combination of the cell state (which is a representation of the prior information) and the cell state is updated every time an input is sent into the memory cell.

The updated cell state and the new input can be used to compute the new output when another input is passed into the memory cell.

3.1 Analysis of Investor sentiment and its effect on stock market volatility

The focus of this paper is on the specific mechanism of investor mood as it relates to stock market volatility. It performs a comparative study based on big data approach and sources using Pollet and Wilson's theory of volatility decomposition.

This study compiles data from the web news emotion index, web search volume, social network emotion index, and social network heat index to create an analysis index. It extracts the variables that have a substantial link with the financial market and incorporates them into forecasting analysis after correlation analysis and Granger causality tests.

The model calculates the market volatility index and examines the relationship between investor sentiment and stock price fluctuations. The deviation between stock price and value is employed as an explanatory variable in empirical studies, and the logarithmic return of stock is utilised to assess stock price volatility.

The stock market volatility index is a metric for determining how volatile the stock market is. It is an essential statistic that indicates investor mood since it reflects the number of investors prepared to pay to hedge investment risk based on the stock market's trend, volume, and price.

The market volatility index can accurately evaluate market risk and serve as a useful benchmark for government agencies and financial institutions when assessing risks and making macroeconomic decisions.

At the same time, derivatives based on volatility indexes can provide investors with a variety of investment and hedging tools.

• Mechanism of investors affecting stock market volatility.

• Collection of data to form indexes.

• Web news emotion index, web search volume, social network emotion index, social network heat index, corresponding analysis index.

3.2 Using Social Media Mining Technology to Assist in Price Prediction of Stock Market

The rise and fall of financial market activity is caused by a variety of causes. Stock market price and direction predictions are tough to make.

Statistical analysis approaches have a fair likelihood of identifying the primary cause influencing short-term stock volatility. While data mining techniques have proven to be profitable in predicting stock price movement with great accuracy.

Many financial experts and stock market investors believe that by using one of the technical analysis methodologies to forecast the stock market, they can make money.

3.3 An Ensemble stock predictor and Recommender System

The suggested model considers historical stock price time series data for a specific firm, tweets regarding that company, and the country's overall business news headlines. These characteristics are specified using a time series.

A time series of observations for a given variable can be defined as a chronological succession of observations.

In this situation, the variable is the closing stock price. Non-linear time-series forecasting models can be used to classify the suggested model.

The model aspires to improve upon some of the past work in this field. SVM and ANN algorithms have been used in the past to analyse stock market patterns. Investor sentiment, in addition to historical time series data, may cause prices to diverge from underlying fundamentals.

To classify the sentiment as positive, negative, or neutral, the sentiment analysis employs the Naive Bayes method. This investor sentiment is provided into the LSTM model as an input.

The model is built on data that was collected from three main sources. Historical stock price data on various companies over a period of 20 years was acquired from the official National Stock Exchange, India website. Tweets were scraped from www.twitter.com website using tweet-scraper module and filtered based on the company name. Historical news dataset was obtained from www.kaggle.com.

3.3.1 GENERIC SOLUTION

The system is based on a vast dataset gathered from a variety of sources, including the website of the National Stock Exchange of India (nseindia.com), the company's Twitter account, and numerous news sites. As the application's backbone, an ensemble machine learning model is developed using this data.

The model contains 3 modules:

- LSTM module for capturing trends in historical closing stock prices.
- LSTM module for capturing sentiments in news headlines.
- Multivariate regression to combine LSTM (stock) + LSTM (news) + LSTM (tweets) into a single prediction module.

3.4 Stock Tracking : A New Multi-Dimensional Stock Forecasting Apporach

3.4.1 Stock model

We assume that the stock market is merely weak because the price includes enough historical information, based on the EMH (Efficient Market Hypothesis). This assumption allows only historical data to be used to predict future prices. Every moving object of interest, with the exception of the stock, can be regarded a target. Stock forecasting is treated as a unique target tracking. We call it unique because all of the predicting data can be collected at the end, implying that the state space and observer space are same.

3.4.2 Methodology

- Problem formulation
- Stock forecasting
- Transition matrix computation
- Stock tracking process
- Stock forecasting
- State vector construction and model training
- Forecasting result

Attempt to apply information fusion theory to an economic application: stock forecasting. Such attempts can be seen in the application of a multiresolution filter to a typical macroeconomic or microeconomic system. The Stock Tracking method treats the fluctuating stock as a moving target, and predicts its value using a recursive process. This strategy is straightforward and easy to implement. Its predicted outcome is fascinating. Using vectors to represent stock data makes dealing with multi-dimensional data more easier and increases the versatility of this technique significantly.

CHAPTER 4

REQUIREMENTS

This chapter provides an overview of the proposed system, as well as the system architecture and UML diagrams such as use-case and class diagrams. A UML diagram is a diagram based on the UML (Unified Modelling Language) that is used to visually describe a system, including its major players, roles, actions, artefacts, or classes, in order to better understand, edit, maintain, or document system information.

4.1 Functional Requirements

- In the United States and India, stockbrokers are licensed professionals who buy and sell securities on behalf of investors. Brokers function as go-betweens for investors and stock exchanges, buying and selling equities on their behalf. To get access to the markets, you'll need a retail broker account.
- Portfolio managers are individuals who manage customer portfolios, or groupings of securities. Analysts provide suggestions to these managers, and they decide whether to buy or sell the portfolio. Portfolio managers are employed by mutual fund firms, hedge funds, and pension plans to make investment decisions and develop investment strategies for the money they hold.
- Investment bankers serve corporations in a variety of capacities, including private companies seeking to go public through an initial public offering (IPO) or companies involved in upcoming mergers and acquisitions. They handle the listing procedure in accordance with the stock market's regulatory standards.
- Custodian and depot service providers, which are institutions that hold customers' assets for safekeeping to reduce the risk of theft or loss, also work in tandem with the exchange to move shares to and from the accounts of transacting parties based on stock market trading.
- A market maker is a broker-dealer who facilitates the trading of stocks by posting bid and ask prices as well as keeping a stock inventory. He maintains adequate market liquidity for a certain (set of) share(s) and benefits on the spread between the bid and ask prices he quotes.

4.2 Non-Functional Requirements

Non-functional requirements are those that aren't directly related to the system's unique function. They define the criteria that can be used to assess a system's performance rather than specific behaviours. They might have anything to do with emergent system properties.

Non-functional requirements for this system are specified as follows:

- Data should be taken from authorized sources.
- Data retrieved through api should be accurate.
- Predictions made should be useful and worthwhile.

4.3 Hardware Requirements

- Dedicated GPU
- 64 bit quad core processor
- 16 GB RAM

4.4 Software Requirements

- Python
- Streamlit

CHAPTER 5

DESIGN

5.1 Overview of System Design

The method we're presenting will use a training algorithm that we'll develop to train a model, and depending on the results of that prediction, an individual can select whether or not to buy a stock. The closing price of a stock for the day is commonly used to calculate profit or loss; so, we will use the closing price as the target variable.

Fundamental and technical analysis are the two main components of stock market analysis.

- Fundamental Analysis involves analysing the company's future profitability on the basis of its current business environment and financial performance.
- Technical Analysis, on the other hand, includes reading the charts and using statistical figures to identify the trends in the stock market.

Stock market forecasting appears to be a difficult subject to solve since there are numerous variables that have yet to be considered, and it does not appear to be statistical at first. However, with the proper use of machine learning techniques, it is possible to link historical data to current data and train the system to learn from it and make suitable assumptions.

5.2 System Architecture

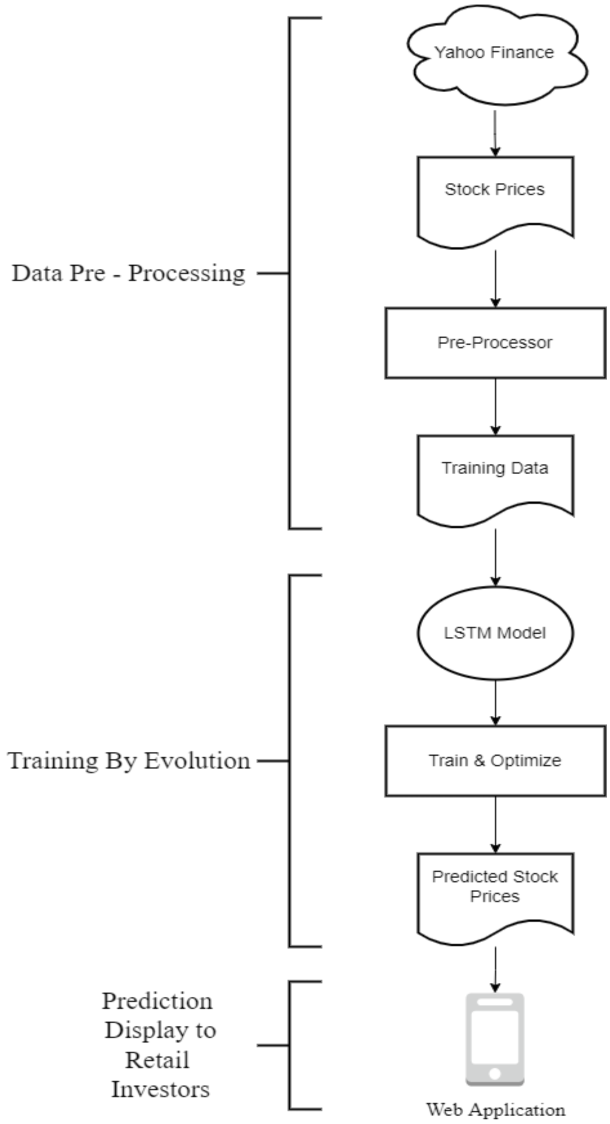


Fig. 5.1 System architecture

Data is automatically obtained from a stock market API and stored in a repository after the software has been started. The data that arrives through the API has previously been cleaned and filtered; now, using Python visual representation libraries, this clean data is displayed visually through graphs.

The data normalisation process is the next critical step. Normalization is a data preparation technique that is frequently used in machine learning. Normalization is the process of converting the values of numeric columns in a dataset to a similar scale without distorting the ranges of values.

Following normalisation, the training method begins, in which we train the model using the training algorithm and data, and then we visualise the predictions and real-time data side by side to cross-verify our results.

5.3 Use-Case Diagram

The primary form of system/software requirements for an undeveloped software programme is a UML use case diagram. The intended behaviour (what) is specified in use cases, not the actual technique of achieving it (how). Once defined, use cases can be represented both textually and visually (i.e. use case diagram). A major concept in use case modelling is that it assists us in designing a system from the standpoint of the end user. It's a good way to communicate system behaviour to users in their own words by defining every externally apparent system behaviour.

A use case diagram is usually simple. It does not show the detail of the use cases:

- It only summarizes some of the relationships between use cases, actors, and systems.
- It does not show the order in which steps are performed to achieve the goals of each use case.

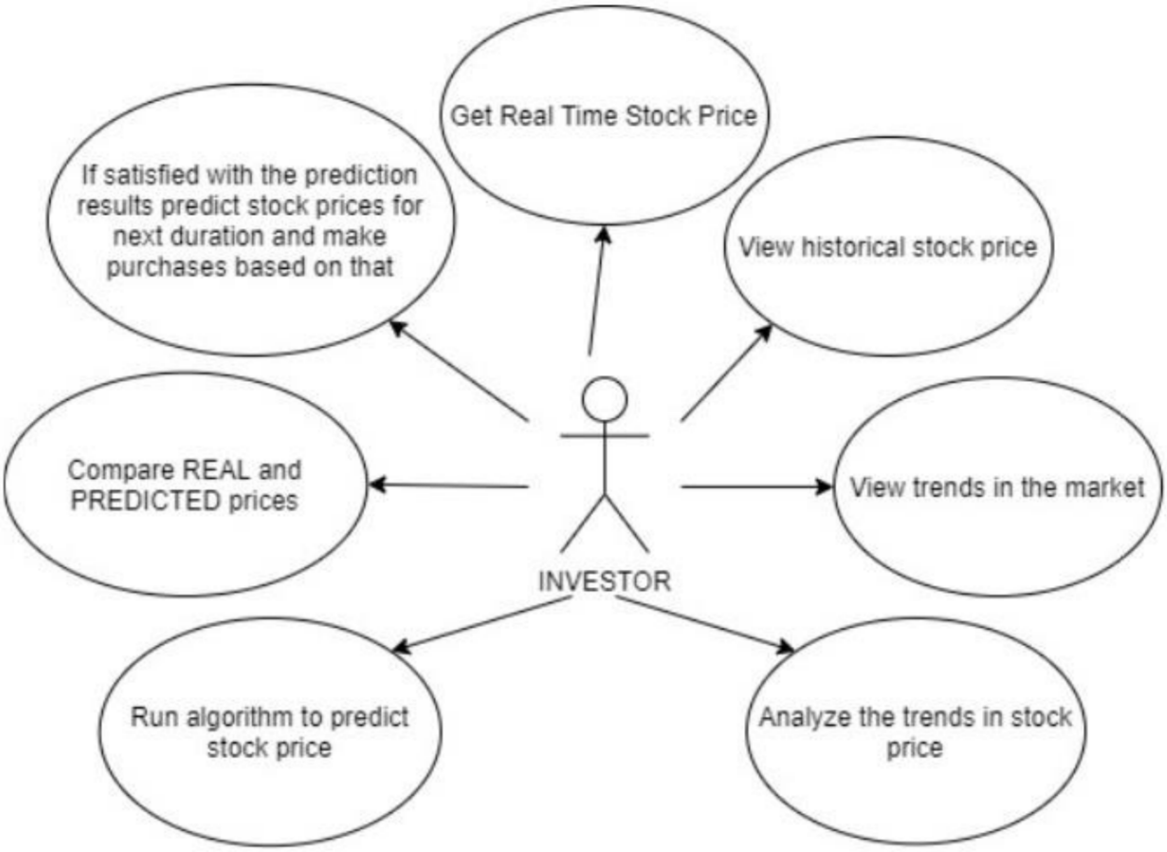


Fig. 5.2 Use case diagram

5.4 Research Design

5.4.1 Problem Framing

The project's goal is to forecast the stock price for the next ten business days. Short-term price movements are more influenced by trend momentum and price pattern, whereas long-term price movements are influenced by the fundamentals of a stock (e.g. firm management competencies, revenue model, market demand, macroeconomic considerations, and so on).

The mean squared error of the 10 projected stock prices is the training algorithm's loss function. The main performance metric for comparing different models is the training algorithm or optimizer, which is chosen to minimise its value.

Other ratings are defined to provide investors with further in-depth insights into a model's predictability performance and finance-domain-based model comparisons.

Forecasting stock prices for the next 10 days directly and predicting stock prices for the next day 1 at a time are the two main prediction methodologies that are being tried. It's thought that the two ways to problem framing will provide distinct abstractions learned, and thus performance for different use-cases.

Individual models will be constructed for each stock because various stocks have highly diverse properties and stock prices follow different trends.

S&P 500 equities from several industries were chosen for the project. When selecting stocks, a variety of parameters are evaluated, including stock price volatility, the absolute magnitude of the price, the respective industries, firm size, and so on, and stocks with various characteristics are chosen. The stocks are listed as below:

- Alphabet Inc., GOOGL

- Amazon.com Inc., AMZN

- Apple Inc., APPL

- AT&T Inc., T

- Boeing Co., BA

- Caterpillar Inc., CAT

- Facebook Inc., FB

- Microsoft Inc., MSFT

- Tesla Inc., TSLA

- Walmart Inc., WMT

- Nvidia Inc., NVDA
- Taiwan Semiconductor Inc., TSM
- Adobe Co., ADBE
- Intel Inc., INTC
- Qualcomm Inc., QCOM
- Twitter Inc., TWTR
- VMware Inc., VMW

5.4.2 Robust Design

The system is meant to be as robust as possible for model testing on the research side. This speeds up the process of experimenting with a model andr input configuration combinations.

5.4.3 Data Pre-processing

Before being fed into machine learning models, raw stock price data is pre-processed. Pre-processing is converting raw data into a format that models can understand and use, most commonly a feature matrix. It also tries to manually extract some features, particularly those relevant to the financial domain, in order to improve results and allow the model to learn additional abstractions.

As input, two important features are chosen. The first is a fixed-length list of raw historical data such as stock price and percentage change over time. When projecting future stock values, the fixed length determines the duration of the historical period to look back from today. Because the stock price reflects all important information, a technical analyst would focus on the stock's trading pattern rather than economic fundamentals and corporate fundamentals, according to the technical analysis principle. As a result, using a period of historical stock prices as the input for the training model could be a useful piece of information in identifying trade patterns and, as a result, predicting future stock price trends. Given a fixed lookback period, it is assumed that the predictive price movement patterns would occur during that time period.

Arithmetic moving averages are the second feature input. Moving averages are one of the most obvious ways for ordinary investors to determine the market's trend. Different periods of moving averages might be utilised as input into the model for stock price prediction with the robust system architecture, for example, a set of 22, 50, 100, and 200 day moving averages, which are often employed by investors.

5.4.4 Prediction Output

As stated in 4.4.1, two alternative prediction approaches are being tried, each with its own set of results. There will be 10 output units for 10-day projections, resulting in a one-dimensional vector of 10 stock prices, with the i-th element representing the i-th day stock price prediction.

There will be one output unit for a 1-day prediction, which is the stock price the next day. The anticipated stock price will then be used as the input for the next forecast, which will predict the stock price for the following day, and so on until all ten predictions have been created.

CHAPTER 6

IMPLEMENTATION

This chapter covers the stages of implementation for the proposed system to predict the stock price and movement of stocks.

6.1 Dataset

The following five variables make up this dataset: open, close, low, high, and volume.

Different bid prices for the stock at different times with virtually direct names are known as open, close, low, and high. The volume refers to the number of shares that have transferred from one owner to the next. During the historical period, from one person to another. The dataset can be obtained in a variety of ways.

6.1.1 Getting data from Yahoo Finance

Because the projections are based on Apple stock market prices, the ticker is set to "AAPL." Furthermore, a url string is defined that will return a JSON file containing all stock market data for Apple for the previous 40 years, as well as a file to save, which will be the file to which the data is saved.

Then there's a condition: if the data hasn't already been saved, it'll be retrieved from the URL supplied in the url string. The date, low, high, volume, close, and open values are recorded in a file as a pandas Data Frame df. If the data is already there, it is simply loaded from a CSV file.

7.1.2 Getting data from Kaggle

Data found on Kaggle is a collection of csv files and you don't have to do any preprocessing, so you can directly load the data into a Pandas DataFrame.

6.2 Introducing LSTM

Long Short-Term Memory models are time-series models with a lot of power. They have the ability to forecast any number of steps in the future. An LSTM module (or cell) consists of five basic components that enable it to represent both long and short-term data.

- Cell state (c_t) - This represents the internal memory of the cell which stores both short term memory and long-term memories.
- Hidden state (h_t) - This is output state information calculated w.r.t. current input, previous hidden state and current cell input which you eventually use to predict the future stock market prices. Additionally, the hidden state can decide to only retrive the short or long-term or both types of memory stored in the cell state to make the next prediction.
- Input gate (i_t) - Decides how much information from current input flows to the cell state.
- Forget gate (f_t) - Decides how much information from the current input and the previous cell state flows into the current cell state
- Output gate (o_t) - Decides how much information from the current cell state flows into the hidden state, so that if needed LSTM can only pick the longterm memories or short-term memories and long-term memories

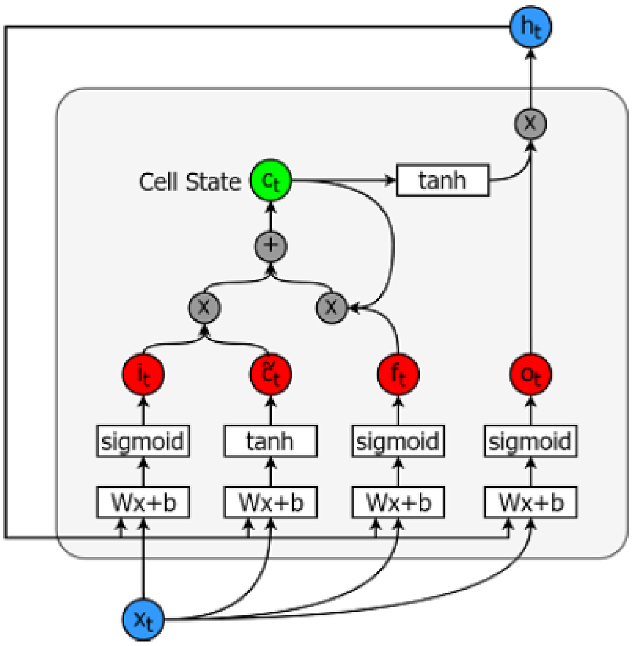


Fig 5.1 Cell state in LSTM

CHAPTER 7

METHODOLOGY

7.1 Research Implementation

Python is used to write all machine learning code. Keras is used to create neural networks, while scikit-learn is used to implement linear regression models.

7.1.1 Stock Price Data Collection

The information was gathered using the Alpha Vantage Stock Price API. It provides daily stock price information for S&P500 stocks for up to 20 years. A Python script is created to automatically retrieve stock prices for several stocks. During development and testing, the received stock prices are saved as .csv files in a local folder. The downloaded stock price data will be converted into a 2D JavaScript array and quickly uploaded to Firebase Cloud Storage during deployment. After the NYSE and NASDAQ have closed, a cron job that initiates the data-fetching and data-uploading script is set to run every 8 p.m. (EDT).

8.1.2 Data Pre-processing

For training, forecasting, and testing, Python scripts are built to convert raw stock prices (.csv files) into feature vectors. The scripts take the input options and raw stock prices as inputs and generate the lookback arrays and moving averages to produce the correct features. It joins the features together to create the final feature vectors, which are then sent to the model for training or testing. Except for the output size and the range of dates to build from, the three scripts have common procedures in building a dataset, therefore common functions are built to centralise the logic rather than repeating the same index-calculation-intensive work across functions.

The datasets are built with NumPy and Pandas. Numpy is a package that offers efficient n-dimensional array data structures and array manipulation methods. NumPy arrays are implemented as densely packed lists, rather as a dynamic array where the items are not stored contiguously, hence they are substantially more performant than Python lists for machine learning applications.

Pandas is a popular pre-processing framework for time series data. It comes with a number of programmes for reading raw input files like.csv and converting time series data to the proper format.

Pandas leverages NumPy as its underlying data structure, making interoperability between the two a breeze.

7.1.3 Model

All machine learning models employ a model base class as a common interface. All models then have their own model class, which specifies model-specific features such as methods for building, training, using, and saving the model.

The model options describe which machine learning model to employ as well as model hyperparameters such as the number of hidden layers, hidden units, activation functions, optimization techniques, and loss functions.

Aside from model setups, the input can also be customised, as there are numerous features that can be added to or removed from the feature vectors. The input variables define the types of features that should be expected by a model, such as the amount of prior stock prices as features and different moving averages. In terms of input format, the input options are linked to a model.

For layer shape inference during model development, all neural networks generated in Keras require the input tensor shape. To determine the input shape for a particular input option, a Python function is written.

7.1.4 Predicting Stock Price

The saved model will be loaded first when predicting stock price. The construct predict dataset script, which is similar to the build training dataset script but returns a flatten 1D feature vector, is then used to create a feature vector provided by the input choices. To anticipate stock price, the feature vector is fed into the model. The predictions are directly outputted for 10-day predict.

For 1-day predict, the projected stock price is attached to the raw dataset as if it had already happened, then a new feature vector is constructed for predicting the stock price for the next day, and so on for the next ten days.

7.1.5 Performance Evaluation

The test set is used to evaluate each model. The create test dataset script can generate a test set for predicting the last 100 days stock price in 1-day or 10-day disjoint intervals, or it can generate a comprehensive test set for predicting the last 100 days stock price in 1-day or 10-day disjoint intervals.

7.1.6 Model Score, Buy/Sell Score

There are three functions built to calculate distinct scores for users: one to calculate model trend score, one to calculate model accuracy score, and one to calculate buy/sell score. Helper functions are designed to separate the primary calculation function from the repeated steps for parts that have the same computation but with different offsets.

CHAPTER 8

TESTING

This chapter gives an overview of the various types of testing incorporated during the entire duration of the project.

8.1 Unit Testing

Unit testing is the process of testing a single software component or module. It is usually done by programmers rather than testers because it requires a thorough understanding of the internal programme design and code. It might also necessitate some research. Driver modules or test harnesses are used to test drivers.

8.2 Component Testing

Developers typically perform component testing once unit testing is completed. Component testing entails evaluating numerous functionalities as a single code, with the goal of determining whether any defects exist after connecting those functionalities.

9.3 Integration Testing

Integration testing is the process of testing all integrated components to ensure that the combined functionality after integration is correct. Code modules, standalone apps, client and server applications on a network, and so on are examples of modules. Client/server and distributed systems benefit greatly from this form of testing.

8.4 System Testing

The complete system is tested according to the requirements using the System Testing approach. It's a form of Black-box testing that's based on overall requirement requirements and includes all of a system's components.

8.5 Interface Testing

The goal of this Interface Testing is to ensure that the interface meets the requirements of the business. In the full design document and interface mock-up screens, the desired application interface is described. Checks sure the application connects to the server correctly.

8.6 Compatibility Testing

Compatibility testing determines whether the programme is compatible with the software and hardware specifications and performs as expected.

8.7 Performance Testing

Performance testing is done to ensure that the system is providing suitable and efficient performance in accordance with the criteria. To achieve efficient performance evaluation, the connection requirements must be met.

8.8 Usability Testing

User-friendliness is checked during Usability Testing. The application flow is checked to see if a new user can easily comprehend the application, and if a user gets stuck at any point, adequate help is documented. In this examination, the system navigation is primarily examined.

CHAPTER 9

RESULT

9.1 Stock Information Page

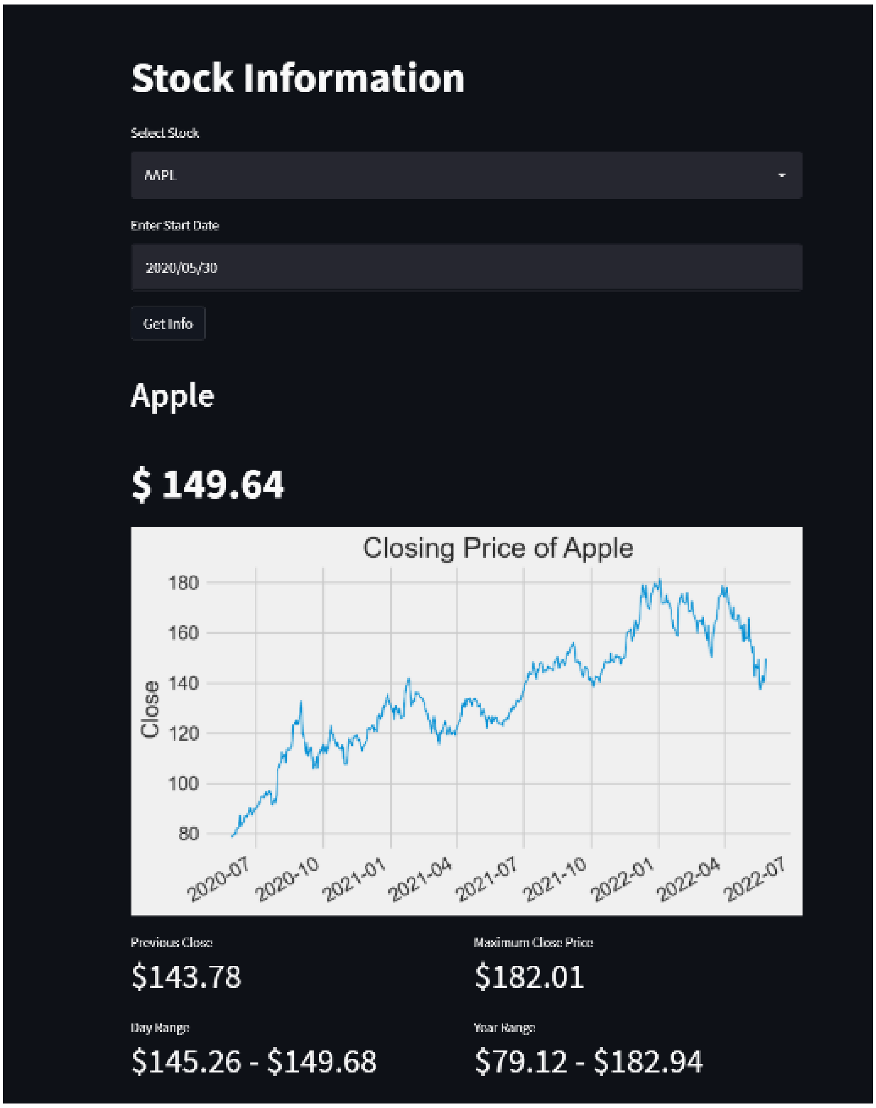


Fig: 9.1 General Stock Information

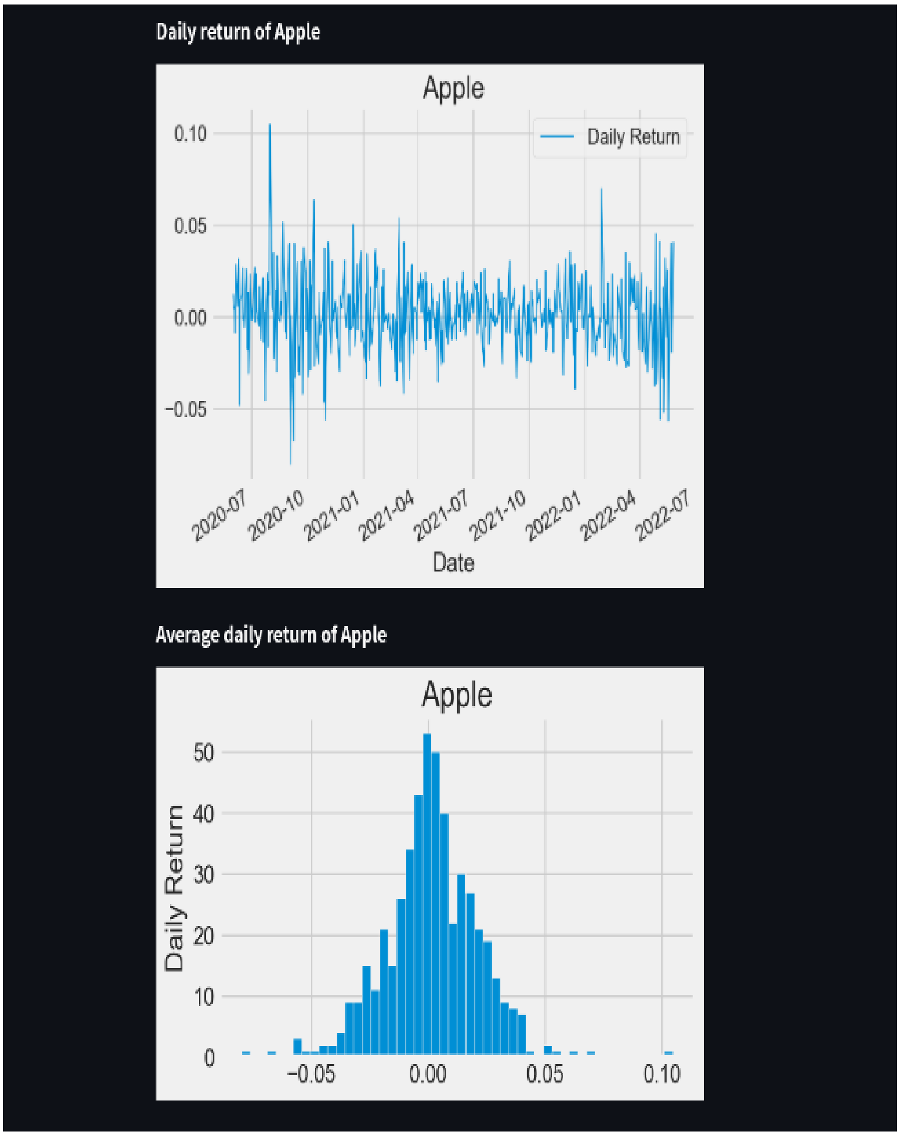


Fig: 9.2 Daily and Average Returns Of a Stock

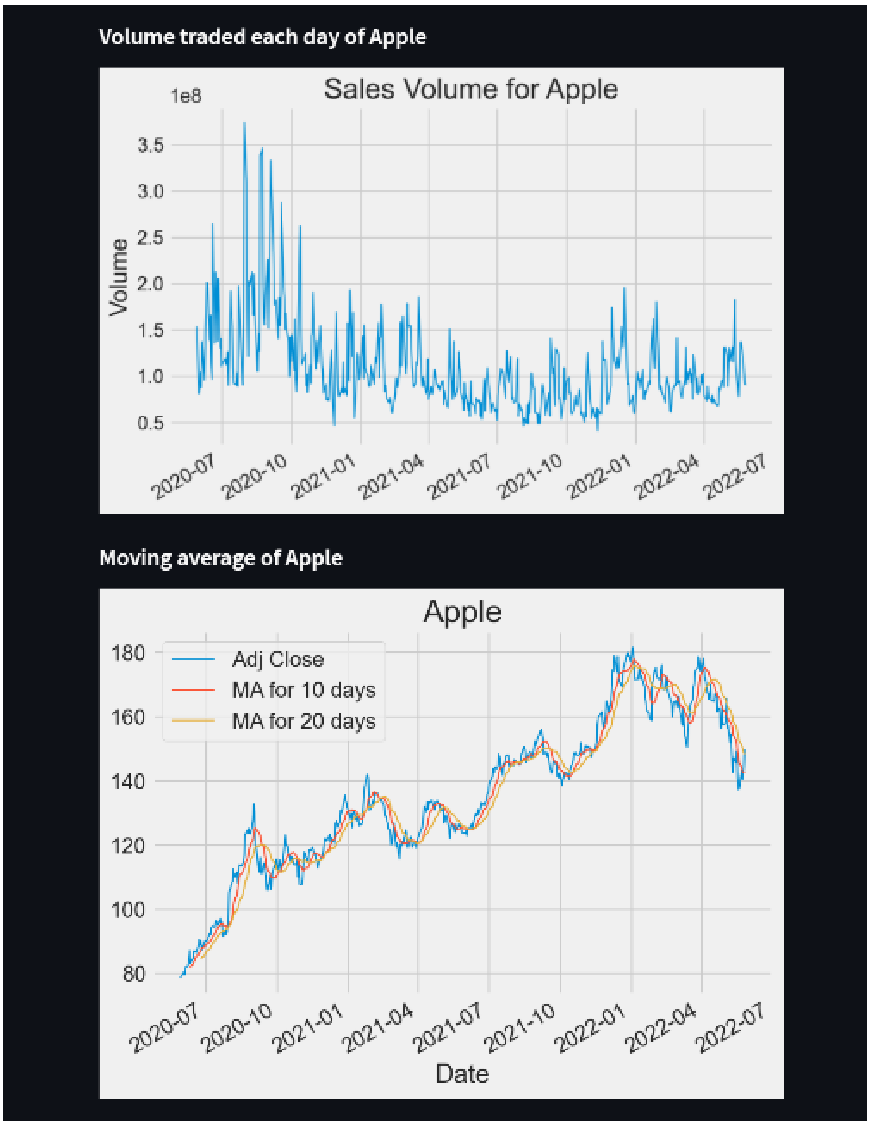


Fig: 9.3 Volume Trade and Moving Average Of a Stock

9.2 Stock Comparing Page

Fig: 9.4 Comparing Stocks

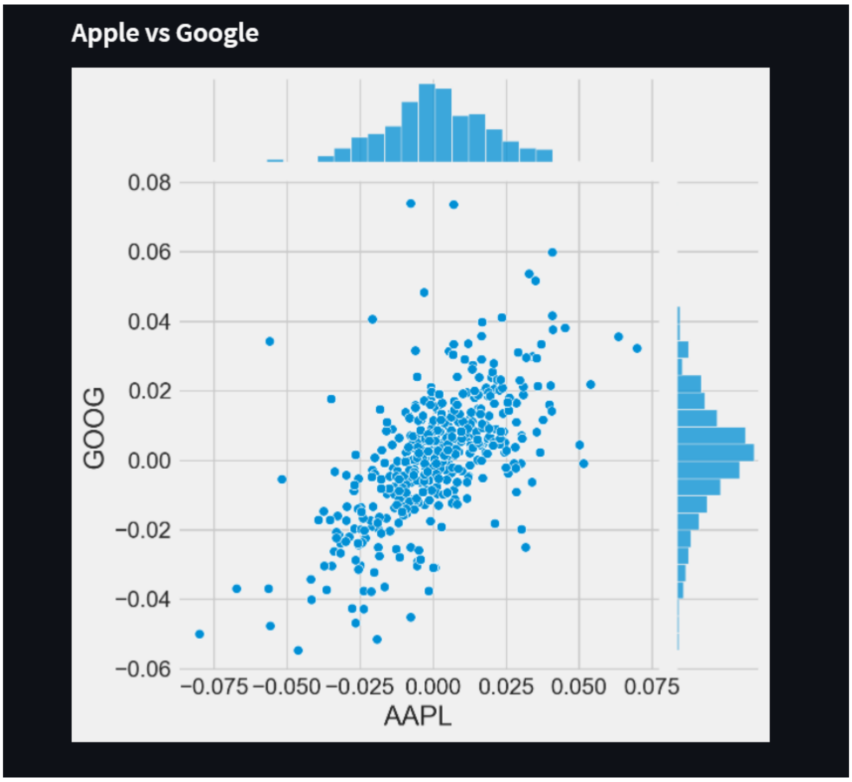
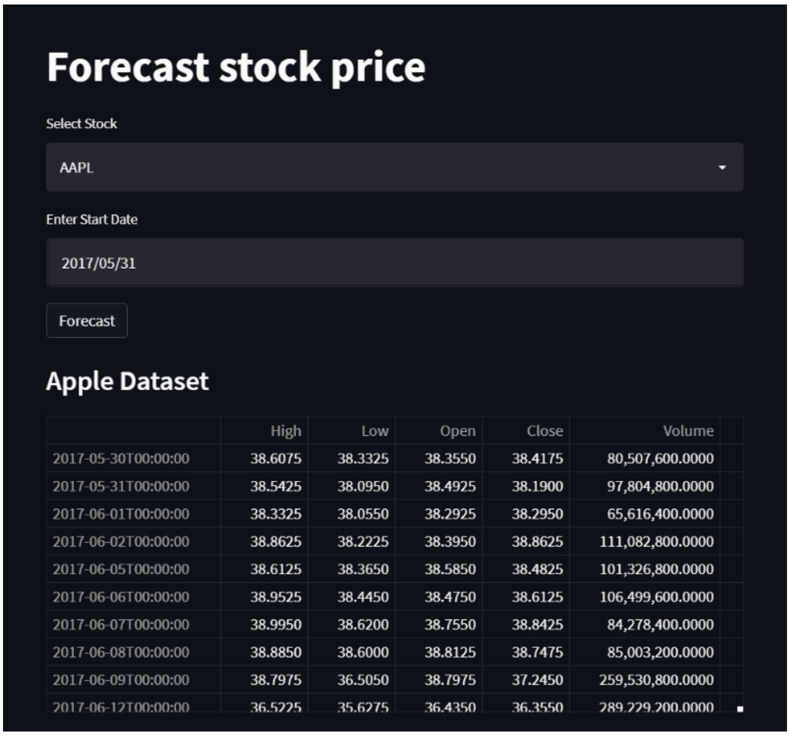


Fig: 9.5 Comparition Between AAPL and GOOG

9.3 Forecast Stock Page



	High	Low	Open	Close	Volume
2017-05-30T00:00:00	38.6075	38.3325	38.3550	38.4175	80,507,600.0000
2017-05-31T00:00:00	38.5425	38.0950	38.4925	38.1900	97,804,800.0000
2017-06-01T00:00:00	38.3325	38.0550	38.2925	38.2950	65,616,400.0000
2017-06-02T00:00:00	38.8625	38.2225	38.3950	38.8625	111,082,800.0000
2017-06-05T00:00:00	38.6125	38.3650	38.5850	38.4825	101,326,800.0000
2017-06-06T00:00:00	38.9525	38.4450	38.4750	38.6125	106,499,600.0000
2017-06-07T00:00:00	38.9950	38.6200	38.7550	38.8425	84,278,400.0000
2017-06-08T00:00:00	38.8850	38.6000	38.8125	38.7475	85,003,200.0000
2017-06-09T00:00:00	38.7975	36.5050	38.7975	37.2450	259,530,800.0000
2017-06-12T00:00:00	36.5225	35.6275	36.4350	36.3550	289,229,200.0000

Fig: 9.6 Stock Forecast

	Close	Predictions
2022-03-01T00:00:00	163.2000	159.73947143554688
2022-03-02T00:00:00	166.5600	157.68978881835938
2022-03-03T00:00:00	166.2300	161.47586059570312
2022-03-04T00:00:00	163.1700	160.48129272460938
2022-03-07T00:00:00	159.3000	157.46168518066406
2022-03-08T00:00:00	157.4400	154.13502502441406
2022-03-09T00:00:00	162.9500	152.90823364257812
2022-03-10T00:00:00	158.5200	158.7203826904297
2022-03-11T00:00:00	154.7300	153.14845275878906
2022-03-14T00:00:00	150.6200	150.04893493652344

Fig: 9.7 Closing Price History and Predicted Close price

CHAPTER 10

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