A

Project Report

on

Stock Price Prediction

submitted as partial fulfillment for the award of

BACHELOR OF TECHNOLOGY DEGREE

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Computer Science and Engineering

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May, 2023

DECLARATION

We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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ABSTRACT

In our Major Project we are building a Flutter based Mobile Application (APP) through which user can analyze and predict prices of stock and based upon that they can decide whether they should buy the stock or not and if they want to buy then for how many days, they should hold it in order earn maximum profit. Our goal is to build a user-friendly Mobile Application so that we can reach to maximum audiences and serve them with our product. We are using Machine Learning Techniques to do the prediction of prices of stock our prediction is basically based upon two factors the Conventional method and Modern Perspective.

India's stock market is extremely variable and indeterministic, which has a limitless number of aspects that regulate the directions and trends of the stock market; therefore, predicting the uptrend and downtrend is a complicated process. This project aims to demonstrate the use of recurrent neural networks in finance to predict the closing price of a selected stock and analyze sentiments around it in real-time. By combining both these techniques, the proposed model can give buy or sell recommendations.

The proposed system has been implemented as a mobile app using Flutter. The App displays all live prices. Additionally, the machine learning algorithm built with Keras and further enhanced with TensorFlow. It will analyze each stock individually with use of its past performance and that when the user should buy a particular stock in future so as to gain maximum profit from it. Also, it tells stocks in user portfolio that the user should sell to book profit or to reduce future losses.

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LIST OF ABBREVIATIONS

LSTM	Long Short-Term Memory
ML	Machine Learning
SEBI	Securities and Exchange Board of India
SVM	Support Vector Machine
EMH	Efficient Market hypothesis
AI	Artificial Intelligence
NN	Neural Networks
ARMA	Autoregressive Moving Average
DRL	Deep Reinforcement Learning
LMS	Least Mean Square
UML	Unified modelling Language
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
MV	Moving Average

CHAPTER 1
INTRODUCTION

1.1 INTRODUCTION

The purpose of our software is to predict future stock price based on the current stock price and after analyzing the past trend for a particular stock.

In our Major Project we are building a Flutter based Mobile Application (APP) through which user can analyze and predict prices of stock and based upon that they can decide whether they should buy the stock or sell it for intraday trading to make maximum profit from a particular stock. Our goal is to build a user-friendly Mobile Application so that we can reach to general public which are not very well versed with trends of stock market and serve them with our product so that everyone can invest in stock market. We are using Machine Learning Techniques to do the prediction of prices of stock.

India's stock market is extremely variable and indeterministic, which has a limitless number of aspects that regulate the directions and trends of the stock market; therefore, predicting the uptrend and downtrend is a complicated process. This project aims to demonstrate the use of recurrent neural networks in finance to predict the closing price of a selected stock. By using this technique, the proposed model can give buy or sell recommendations.

In many practical applications, including forecasting the weather and the financial markets, time-series prediction is a frequent and widely utilized approach. To forecast the outcome for the following time unit, it makes use of continuous data collected over a period of time. The effectiveness of numerous time series prediction algorithms has been demonstrated in real-world settings. These days, Recurrent Neural Networks (RNN), as well as its specific types Long-Short Term Memory (LSTM) and Gated Recurrent Unit (GRU), form the foundation of the majority of algorithms. The stock market is an example of a setting where time-series data are presented, and many scholars have investigated it and offered numerous models. In this project, LSTM model is used to predict the stock price.

1.2 WHAT IS THE STOCK MARKET?

The share market, also known as the stock market, is a platform where buyers and sellers come together to trade publicly listed shares of companies. The market is regulated by the Securities and Exchange Board of India (SEBI), which oversees the functioning of stock exchanges and ensures that listed companies comply with regulations and disclosure requirements.

We all understand that a share in market parlance is part ownership in a company. So if a company has issued 100 shares and you own 1 share then you own 1% stake in the company. Share market is where shares of different companies are traded.

Fig:1- Stock Market

Importance of Stock Market

- Stock markets help companies to raise capital.
- It helps generate personal wealth.
- Stock markets serve as an indicator of the state of the economy.
- It is a widely used source for people to invest money in companies with high growth potential.

Market Structure and Instruments

- Stock Classification: Stocks are categorized based on market capitalization, such as large-cap, mid-cap, and small-cap.
- Sector Classification: Companies are grouped into sectors like banking, technology, healthcare, and energy.
- Trading Instruments: The stock market offers equities, derivatives (futures and options), and other financial instruments.

Regulation and Investor Protection

- Securities and Exchange Board of India (SEBI): SEBI regulates the stock market and ensures fair practices, transparency, and investor protection.
- Listing Requirements: Companies must meet SEBI's criteria to list their shares on the stock exchanges.
- Investor Education: SEBI promotes investor education and awareness to enable informed investment decisions.

Factors Influencing the Stock Market

- Economic Indicators: GDP growth, inflation rates, interest rates, and government policies impact investor sentiment and market movements.
- Global Factors: International economic trends, geopolitical events, and foreign institutional investments influence the Indian stock market.
- Market Psychology: Market sentiment, news events, and investor behavior can cause volatility and affect stock prices.

Investment Strategies and Analysis

- Fundamental Analysis: Evaluating a company's financial health, including its revenue, earnings, and debt levels.
- Technical Analysis: Studying historical price patterns and market trends to predict future price movements.

- Research and Expert Opinions: Investors rely on research reports, news updates, and expert opinions for investment decisions.

Risk and Rewards

- Volatility: Stock prices can be volatile and subject to sudden fluctuations due to various factors.
- Diversification: Investors should diversify their portfolios to spread risk across different stocks and sectors.
- Long-Term Perspective: Having a long-term investment horizon helps mitigate short-term market volatility.

1.3 WORKING OF STOCK MARKET

The stock market is a marketplace where individuals and institutions can buy and sell shares of publicly listed companies. It operates through stock exchanges, such as the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE), which provide the infrastructure for trading. Companies can raise capital by issuing shares through an initial public offering (IPO) in the primary market. Once shares are listed, they can be traded in the secondary market, where investors can buy and sell shares among themselves. Investors place orders to buy or sell shares, with market orders executed at the prevailing market price and limit orders executed when the market reaches a specified price. Stock prices are influenced by factors such as economic indicators, company performance, and news events. Regulatory bodies, like the Securities and Exchange Board of India (SEBI), oversee the functioning of the stock market to ensure fairness, transparency, and investor protection.

Investing in the stock market carries risks, including price volatility and potential loss of capital. However, it also provides opportunities for capital appreciation and dividend income. Investors analyze company financials, industry trends, and market conditions to make informed investment decisions. Market participants, such as investors, brokers, and market makers, play crucial roles in facilitating trading and maintaining liquidity in the stock market. Market indices, such as the Nifty 50 and Sensex, provide benchmarks for overall market performance. Overall, the stock market serves as a mechanism for companies to raise capital and for investors to participate in the growth of businesses and the economy as a whole.

Stock Exchanges and Listing

- Stock exchanges, such as the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE), provide the infrastructure for trading.
- Companies seeking to raise capital can list their shares on these exchanges through an initial public offering (IPO).

Primary Market and IPOs

- In the primary market, companies issue new shares to the public through IPOs.
- Investors can subscribe to these shares and become shareholders in the company.

Secondary Market and Trading

- Once shares are listed, they can be traded in the secondary market.
- Investors buy and sell shares among themselves, with stock exchanges facilitating the transactions.

Market Participants

- Investors: Individuals and institutions who buy and sell shares for various reasons, such as capital appreciation and dividend income.
- Brokers: Intermediaries who execute trades on behalf of investors and provide market information.
- Market Makers: Participants who facilitate liquidity by continuously quoting buy and sell prices for specific stocks.

Order Types and Price Determination

- Market Orders: Investors can place market orders to buy or sell shares at the prevailing market price.
- Limit Orders: Investors can specify a desired price for buying or selling shares and wait for the market to reach that price.
- Bid and Ask Prices: The highest price at which buyers are willing to purchase shares (bid price) and the lowest price at which sellers are willing to sell (ask price) determine the market price.

Role of Market Indices

- Market indices, such as the Nifty 50 and Sensex, track the performance of a specific group of stocks.
- These indices provide an overview of the market's direction and serve as benchmarks for investment performance.

Regulation and Investor Protection

- Regulatory bodies, like the Securities and Exchange Board of India (SEBI), oversee the functioning of the stock market.
- They establish rules and regulations to maintain fairness, transparency, and investor protection.

Market Influences

- Economic Factors: Economic indicators, such as GDP growth, inflation rates, and interest rates, impact investor sentiment and stock prices.
- Company Performance: Financial results, business strategies, and industry trends influence individual stock prices.
- News and Events: Corporate announcements, political developments, and global events can affect market sentiment and stock prices.

1.4 PROJECT DESCRIPTION

In this study, data from Alpha Vantage is used to apply supervised machine learning. Close, Open, Low, High, and Volume are the five variables—make up this dataset. Close, open, high, and low comprise several of the stock's bid prices at various moments with essentially plain labels. It is the volume of the total block of shares that were transferred from one proprietor to the next within the deadline. Next, the prototype is evaluated using the test results.

We have compared different methods to predict the price of stocks so the more accurate method can be analyzed. The methods we used for comparison are 100 days simple moving average (100ma), 200 days simple moving average (200ma) and LSTM (Long Short-Term Memory). We have also analyzed the predicted results and compared it by plotting graph.

A. Data-set Generation (Alpha Vantage)

Alpha Vantage is a financial data provider that offers access to various financial market data, including stock prices, cryptocurrencies, foreign exchange rates, technical indicators, and more. Here's a brief overview of Alpha Vantage:

Alpha Vantage provides an API that allows developers to retrieve and analyze financial data programmatically. The API offers a range of functions and endpoints to access specific types of data, such as stock prices, technical indicators, and historical data. To use Alpha Vantage API, you need to obtain an API key by signing up on the Alpha Vantage website. The API key is used to authenticate and authorize your requests. Once you have the API key, you can make HTTP requests to the Alpha Vantage API endpoints, passing the necessary parameters such as the desired function, symbol, output size, and your API key. The API will respond with the requested financial data in JSON format. You can then process and utilize the data in your applications for various purposes, such as building trading algorithms, performing financial analysis, displaying stock charts, or generating reports.

Overall, Alpha Vantage simplifies the process of accessing and integrating financial market data into your applications, allowing you to leverage this information for financial analysis and decision-making.

B. The User Interface

Since Flutter is cross-platform, you can use the same code base for your iOS and Android app. This can save you both time and resources. Dart compiles into native code and there is no need to access OEM widgets as Flutter has its own. This means less mediated communication between the app and the platform.

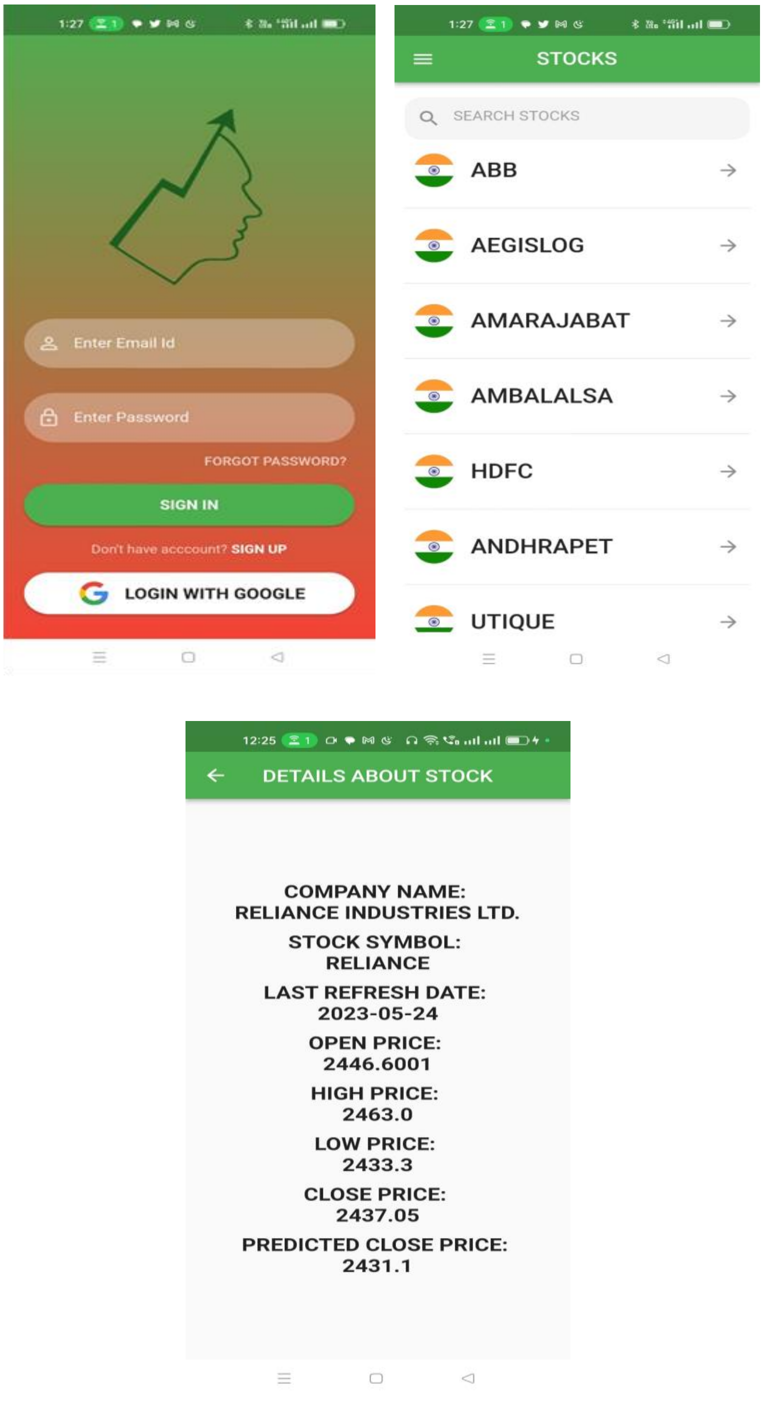


Fig: 2- User Interface

C. Machine Learning

In this section we use Machine Learning technique LSTM (Long Short-term Memory) for forecasting the time series data and to predict the stock price. LSTM is a special network structure with three "gate" structures. Three gates are placed in an LSTM unit, called input gate, forgetting gate and output gate. While information enters the LSTM's network, it can be selected by rules. Only the information conforms to the algorithm will be left, and the information that does not conform will be forgotten through the forgetting gate.

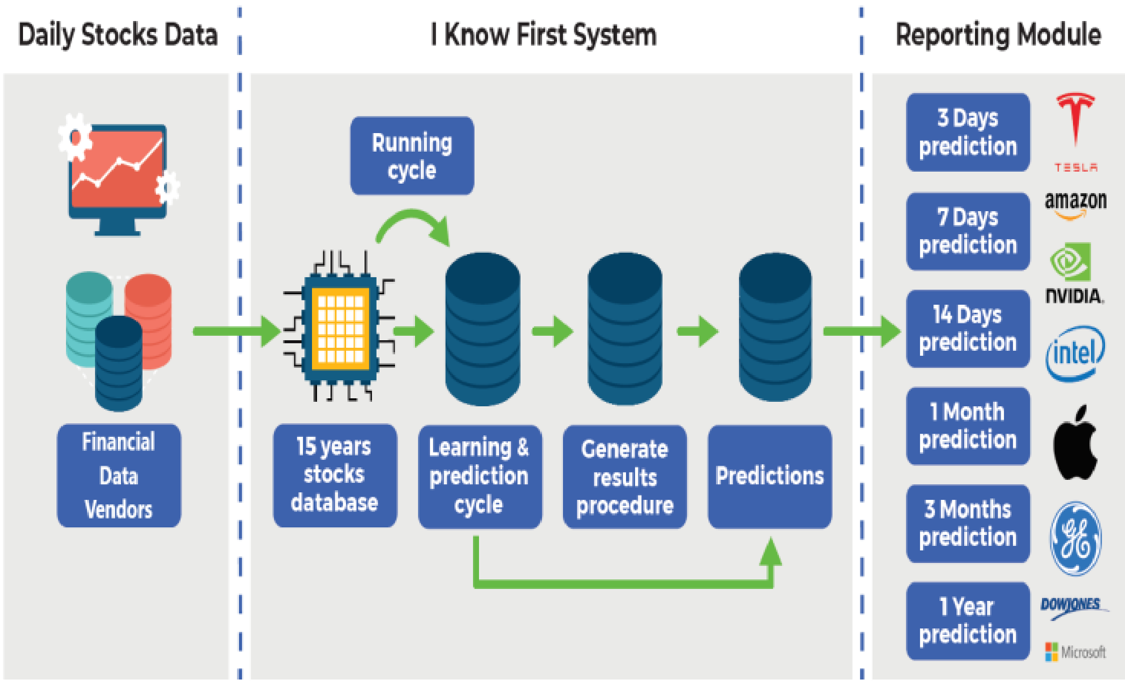


Fig:3- Flow Diagram

Stock market is regarded as aggressive, uncertain, and non-linear in nature. Anticipating stock prices is a tough task as stock prices are influenced by a broad no of factors, which includes but is not limited to current supply of that product or service, the competition faced, financial results of past few quarters and the consumption of products or services provided, and so on. So to widen the profits and narrowing the losses, techniques for forecasting share values ahead of time by analysing movements over the last few months could be extremely useful for predicting stock market movements.

Commonly, two methodologies are presented for anticipating a company's stock price: Technical analysis forecast ultimate stock prices by employing previous stock prices such as opening value, highest traded value, lowest traded value, closing value, volumes, and so on. The qualitative analysis is accomplished according to independent factors such as company reputation, revenue, operations cost, management decisions, profits and earning per share. Progressive, sophisticated approaches based on either fundamental or technical research are currently used to forecast share values. The figures for stock price prediction market is enormous and non-linear. To deal with this variety of figures, a competent algorithm that can identify unseen trends and complex associations in this enormous data set is necessary. Machine learning techniques in this area had shown a boost in efficacy by 61–87 percent when compared to earlier methods.

Most foregoing work in the vicinity has used scholastic algorithms like simple regression, random walk theory (RWT), relative strength index (RSI), and some linear models like autoregressive integrated moving average (ARIMA), seasonal autoregressive integrated moving average model (SARIMA) and autoregressive moving average (ARMA) to predict stock prices. Late research indicates that machine learning can improve stock market predictions. Some neural network based techniques, such as shift invariant or space invariant artificial neural networks (SIANN), simulated neural networks (SNN), Feedback neural networks (FNN), and deep neural networks (LSTM), had given promising results.

A prosperous stock prediction can generate significant profits for both the investor and the business. Predictions might be made by cautiously reviewing the background of the relevant stock market because it is often claimed that it is chaotic rather than random. Machine learning can be used to adequately describe such processes. Financial trend analysis and forecasting of anticipated stock value trends and returns have long been important areas of investigation.

1.5 TECHNOLOGY USED

The Technologies that we have used in this project are-

1. **Machine Learning**
2. **Long short-term memory network (LSTM)**
3. **Flutter**
4. **Dart**
5. **Android Studio**

1.5.1 Machine learning

Machine learning is a branch of artificial intelligence (AI) that enables computer systems to learn and improve from experience without being explicitly programmed. It is revolutionizing various industries by empowering intelligent systems to analyse and interpret vast amounts of data, make accurate predictions, and automate complex tasks.

1. **Principles of Machine Learning:**

   Machine learning operates on the following fundamental principles:

   - **Data-driven approach:** Algorithms learn patterns and relationships from data rather than relying on explicit instructions.
   - **Training and inference:** Models are trained on labelled data to make predictions or classify new, unseen data.
   - **Iterative improvement:** Algorithms continuously refine their performance by iteratively adjusting parameters based on feedback.

2. **Types of Machine Learning:**

   a) Supervised Learning: In supervised learning, algorithms learn from labelled examples to make predictions or classify new data. It involves input-output pairs, enabling the model to learn the underlying mapping.

   b) Unsupervised Learning: Unsupervised learning deals with unlabelled data, allowing algorithms to discover hidden patterns or structures without explicit guidance.

   c) Reinforcement Learning: Reinforcement learning involves training an agent to interact with an environment and learn optimal actions based on rewards or punishments.

3. Applications of Machine Learning:

Machine learning finds application across various domains, including:

- **Natural Language Processing:** Enabling machines to understand and generate human language.
- **Computer Vision:** Facilitating image and video analysis, object recognition, and autonomous navigation.
- **Healthcare:** Assisting in disease diagnosis, drug discovery, personalized medicine, and patient monitoring.
- **Finance:** Supporting fraud detection, risk assessment, algorithmic trading, and customer segmentation.

1.5.2 Long short-term memory network (LSTM):

LSTM (Long Short-Term Memory) is a type of recurrent neural network (RNN) architecture that addresses the vanishing gradient problem and is well-suited for processing and predicting sequential data. Unlike traditional RNNs, LSTM networks have memory cells with gating mechanisms that selectively retain and update information over long sequences.

LSTMs consist of three main components: the input gate, the forget gate, and the output gate. These gates control the flow of information within the network by either allowing or blocking the input, memory, and output of each LSTM cell. This gating mechanism enables LSTMs to learn long-term dependencies and capture context from the input sequence. The input gate determines which values from the input should be stored in the memory cell. The forget gate decides which information to discard from the memory cell. Finally, the output gate regulates the output values based on the current input and the memory content.

Due to their ability to model long-term dependencies, LSTMs have proven effective in various applications, such as speech recognition, natural language processing, machine translation, and time series prediction. They can capture intricate patterns and relationships in sequential data, making them a valuable tool in deep learning research and applications.

Dropout and Dense layers

Dropout and Dense layers can be used in conjunction with LSTM (Long Short-Term Memory) layers to improve the performance and generalization capabilities of the model.

Dropout is a regularization technique that can be applied to the LSTM layer. During training, dropout randomly sets a fraction of the LSTM units (cells) to zero at each time step. This helps prevent overfitting and encourages the LSTM layer to learn more robust and generalizable representations of the input sequence. By randomly dropping out units, dropout reduces the reliance on specific LSTM cells and encourages the network to learn from a diverse set of cells.

Dense layers, also known as fully connected layers, can be added after the LSTM layer in the network architecture. These layers allow for additional non-linear transformations and learning of complex patterns in the LSTM's output. Dense layers connect every LSTM unit to every neuron in the subsequent layer, enabling the model to capture intricate relationships and extract high-level features from the LSTM's output sequence.

The combination of Dropout and Dense layers with LSTM can enhance the performance of the model by reducing overfitting and enabling the learning of more expressive representations. Dropout helps regularize the LSTM layer, while Dense layers provide additional capacity for capturing complex patterns in the LSTM's output. This combination can improve the model's ability to generalize to unseen data and enhance its overall performance in tasks such as sequence classification, time series prediction, and natural language processing.

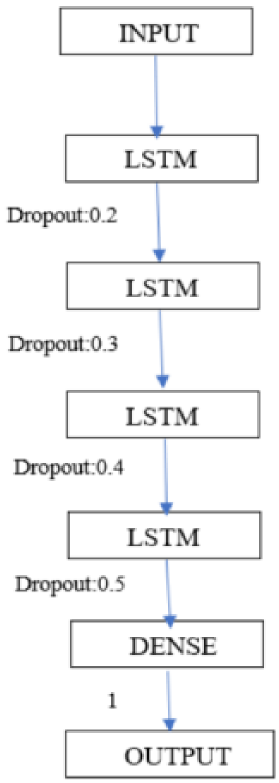
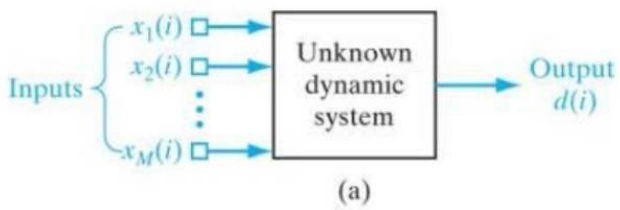


Fig. 4: LSTM Layers

LMS filter:

One type of adaptive filter used to address linear issues is the LMS filter. The purpose of the filter is to discover the filter coefficients by minimizing the least mean square of the error signal in order to minimize a system.



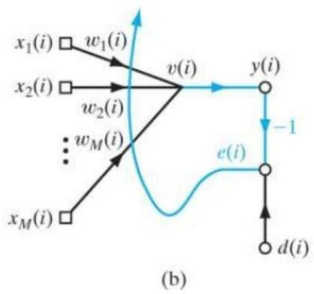


Fig. 5: LMS Inputs and Outputs

Fig 6: LMS updating weights

Algorithm 1: LMS

Input:
x : input vector
d: desired vector
μ: learning rate
N: filter order
Output:
y: filter response
e: filter error
begin
  $M = size(x)$;
  $x_n(0) = w_n(0) = [0\ 0\ \ldots\ 0]^T$;
  while $n < M$ **do**
    $x_{n+1} = [x(n);\ x_n(1:N)]$;
    $y(n) = w_n^H * x_n$;
    $e(n) = d(n) - y(n)$;
    $w_{n+1} = w_n + 2\mu e(n) x_n$;
  end
end

Typically, we test both a linear and a non-linear algorithm because we are unsure if the problem can be solved effectively with a linear approach. We will use LMS to demonstrate that stock market prediction can be done with linear algorithms with a good degree of precision since the internet always depicts non-linear approaches.

But this filter mimetizes a system, that is, if we apply this filter in our data, we will have the filter coefficients trained, and when we input a new vector, our filter coefficients will output a response that the original system would (in the best case).

So we just have to do a tricky modification for using this filter to predict data. .

LSTM Architecture

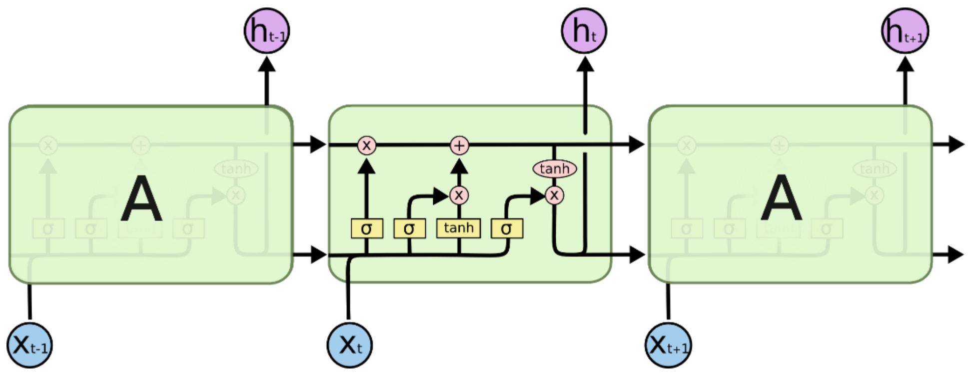


Fig. 7: LSTM Architecture

Input Gate:

- The input gate regulates the flow of information into the memory cell.
- It decides which parts of the input should be stored in the memory cell.
- Computed based on the current input and the previous hidden state.

Forget Gate:

- The forget gate determines which information should be discarded from the memory cell.
- It considers the previous hidden state and the current input to calculate the forget factor for each element in the memory cell.

Output Gate:

- The output gate controls the flow of information from the memory cell to the next hidden state and the output of the LSTM unit.
- It combines the current input and the previous hidden state to compute the output factor.

Hidden State:

- Each LSTM unit maintains a hidden state, which serves as the memory of the LSTM.
- It carries information about the previous inputs and their relevance.

Memory Cell State:

- The memory cell state stores long-term information over time.
- It is regulated by the input and forget gates, allowing selective storage and removal of information.

Working of LSTM:

Three "gate" structures make up the unique network structure known as LSTM. An LSTM unit has three gates: an input gate, a forgetting gate, and an output gate. Information can be chosen by rules as it enters the LSTM network. Only the information conforms to the algorithm will be left, and the information that does not conform will be forgotten through the forgetting gate.

The historical data that were downloaded from the Internet and used as experimental data in this study. The experiments made use of three data sets. It is necessary to find an optimization algorithm with a quicker convergence rate and fewer resource requirements.

- Used Long Short-term Memory (LSTM) with embedded layer and the LSTM neural network with automated encoder.
- To prevent gradients from bursting and disappearing, LSTM is employed in place of RNN.
- In this project, the model is trained in Python, and the input dimensions are reduced using MATLAB. MySQL is used as a dataset to store and retrieve data.
- The historical stock data table contains the information of opening price, the highest price, lowest price, closing price, transaction date, volume and so on.

This LSTM model's accuracy for this project is 67%.

1.5.3 Flutter

Flutter is an open-source UI software development kit (SDK) created by Google that enables developers to build visually appealing and high-performance mobile, web, and desktop applications using a single codebase. With its unique approach to UI development, Flutter simplifies the process of creating beautiful and consistent user interfaces across multiple platforms.

1. **Key Features of Flutter:**

   a) Hot Reload: Flutter's hot reload feature allows developers to instantly see the changes they make to the code, speeding up the development process and enhancing productivity.

   b) Widget-Based Architecture: Flutter utilizes a widget-based architecture, where everything is a widget. Widgets are reusable UI components that can be combined and nested to create complex and interactive interfaces.

   c) Cross-Platform Development: Flutter enables developers to write code once and deploy it across multiple platforms, including iOS, Android, web, and even desktop platforms like Windows, macOS, and Linux.

   d) Fast and Native Performance: Flutter's framework renders UI directly on the device's canvas, resulting in smooth animations, fast rendering, and a native-like performance experience.

   e) Rich UI Customization: Flutter provides a rich set of customizable widgets and allows developers to create stunning and pixel-perfect UI designs using its flexible styling and theming options.

2. **Benefits of Flutter:**

   a) Faster Development: With a single codebase and hot reload, Flutter significantly reduces development time, enabling faster iterations and prototyping.

   b) Native-Like Performance: Flutter's performance is comparable to native applications, as it compiles to machine code and directly interacts with device-specific features and APIs.

   c) Consistent UI and UX: Flutter offers a consistent user interface (UI) and user experience (UX) across platforms, ensuring a seamless and familiar app experience for users.

   e) Strong Community and Resources: Flutter has a thriving community and extensive documentation, providing developers with ample resources, libraries, and packages to accelerate development and troubleshoot issues.

3. **Use Cases of Flutter:**

   a) Mobile Apps: Flutter is ideal for developing mobile applications of any complexity, from simple utility apps to feature-rich social media platforms and e-commerce applications.

   b) Web Apps: Flutter's support for web development allows developers to create responsive and performant web applications that run seamlessly across different browsers.

c) Desktop Apps: Flutter's desktop support enables developers to build cross-platform desktop applications with native-like performance and a consistent user interface.

d) Embedded Systems and IoT: Flutter can be used to create UI interfaces for embedded systems and IoT devices, allowing for unified control and monitoring experiences.

1.5.4 Dart

Dart is a modern, object-oriented programming language developed by Google. It serves as the primary language for building applications using the Flutter framework and is designed to be fast, efficient, and flexible. Dart offers a wide range of features that make it suitable for various types of applications, including mobile, web, desktop, and server-side development.

1. **Simplicity and Readability:** Dart prioritizes simplicity and readability, making it easy for developers to understand and write clean code. Its syntax is similar to languages like JavaScript and Java, allowing developers with prior experience in these languages to quickly grasp Dart concepts.

2. **Strong and Static Typing:** Dart supports static typing, which enables catching potential errors during compile-time and improves code reliability. Strong typing ensures that variables have a specific type, reducing unexpected behaviour and making the code more predictable.

3. **Just-in-Time (JIT) and Ahead-of-Time (AOT) Compilation:** Dart employs a unique compilation approach, combining JIT and AOT compilation. During development and debugging, Dart uses JIT compilation to provide hot reload and faster development cycles. For production deployment, Dart uses AOT compilation to generate highly optimized machine code, resulting in fast and efficient app performance.

4. **Asynchronous Programming:** Dart includes built-in support for asynchronous programming, making it easier to handle time-consuming operations such as network requests and file I/O without blocking the execution of the program. This improves the responsiveness and performance of applications.

5. **Garbage Collection and Memory Management:** Dart features automatic garbage collection, which efficiently manages memory allocation and deallocation, reducing the burden on developers. Dart's garbage collector identifies and collects unused objects, freeing up memory and improving app performance.

6. **Libraries and Packages**: Dart offers a rich collection of libraries and packages that provide a wide range of functionalities, including HTTP requests, JSON parsing, unit testing, and cryptography. These libraries simplify development tasks and allow developers to leverage existing code and solutions.

7. **Cross-platform Development with Flutter:** One of the significant strengths of Dart is its tight integration with the Flutter framework. Dart serves as the primary language for Flutter app development, enabling developers to create high-performance, cross-platform applications for mobile, web, and desktop platforms using a single codebase.

1.5.5 Android Studio

Android Studio is the official integrated development environment (IDE) for Android app development. Created by Google, it provides a comprehensive suite of tools and features to streamline the entire app development process, from designing the user interface to coding, debugging, and testing. Android Studio offers a robust and efficient environment for developers to create high-quality Android applications.

1. **Features of Android Studio:**

   a) Layout Editor: Android Studio's Layout Editor enables developers to visually design the app's user interface (UI) by dragging and dropping widgets, arranging layouts, and previewing the UI in real-time.

   b) Code Editor: Android Studio includes a powerful code editor with intelligent code completion, syntax highlighting, and refactoring capabilities, making it easier to write clean and efficient code.

   c) Gradle Build System: Android Studio utilizes the Gradle build system, which automates the process of building, testing, and packaging Android apps, ensuring reliable and efficient build workflows.

   d) Android Emulator: Android Studio provides a built-in emulator that allows developers to test their apps on a variety of virtual devices with different screen sizes, resolutions, and Android versions.

   e) Debugger and Profiler: The IDE features a debugger and profiler that help developers identify and fix bugs, optimize app performance, and analyse CPU, memory, and network usage.

   f) Instant App Development: Android Studio supports the creation of instant apps, which allow users to experience parts of an app without having to install it fully.

   g) Integration with Google Services: Android Studio seamlessly integrates with various Google services and APIs, such as Firebase, Google Maps, and Google Play services, simplifying the integration of powerful features into Android apps.

2. **Benefits of Android Studio:**

   a) Official and Up-to-Date: Being the official IDE for Android development, Android Studio ensures compatibility with the latest Android SDKs, APIs, and features, keeping developers up-to-date with the latest advancements.

   b) Rich Plugin Ecosystem: Android Studio supports a wide range of plugins and extensions that enhance productivity, provide additional functionalities, and integrate with other tools and services.

   c) Robust Testing Capabilities: Android Studio offers comprehensive testing frameworks, including unit testing, integration testing, and UI testing, enabling developers to ensure the quality and stability of their apps.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

The majority of us have always considered "what other people think" to be a crucial piece of knowledge when making decisions. Nowadays, it is possible to learn about the perspectives and experiences of a huge group of individuals who are neither our close friends nor well-known professionals in the field of criticism, i.e., people we have never heard of. This is made possible by the Internet and the Web, among other things. Conversely, a growing number of people are using the Internet to share their ideas with complete strangers. The motivation behind this area of research is the individual users' interest in online reviews of goods and services as well as the potential influence these reviews may have. Additionally, there are a lot of obstacles to overcome along this procedure in order to get the right results. We looked at the fundamental technique used in this procedure on a regular basis as well as the steps that need to be performed to go beyond the difficulties.

2.2 LITERATURE SURVEY

2.2.1 Stock Market Prediction Using Machine Learning

The study was conducted by V Kranthi Sai Reddy, a student in the ECM department at the Sreenidhi Institute of Science and Technology in Hyderabad, India. One of the most crucial activities in the financial sector is stock trading. The act of making a stock market forecast involves attempting to anticipate the future value of a stock or other financial instrument traded on a stock exchange. This paper illustrates how machine learning is used to predict a stock. The majority of stock brokers base their stock predictions on technical, fundamental, or time series research. Python is the computer language used to make machine learning-based stock market predictions. In this research, we offer a Machine Learning (ML) approach that will be taught using the stock data currently accessible and gain intelligence before using the learned information to make an accurate prediction. In this situation, this study employs a machine learning method called Support Vector Machine (SVM) to forecast stock prices for both large and small capitalizations and in the three separate markets, using prices with both daily and up-to-the-minute frequencies.

2.2.2 Forecasting the Stock Market Index Using Artificial Intelligence Techniques

The study conducted by Lufuno Ronald Marwala a dissertation submitted to the Master of Science in Engineering programme at the University of the Witwatersrand at Johannesburg's Faculty of Engineering and the Built Environment. The weak version of the efficient market hypothesis (EMH) asserts that it is difficult to predict the price of an asset's future based on data from its history prices. Forecasting is therefore impossible because the market acts like it is going on a random walk. Due to the financial system's inherent complexity, financial forecasting is a challenging task. This project aimed to model and forecast the future price of a stock using artificial intelligence techniques. A stock market index's future price is predicted using previous price data using three artificial intelligence techniques: neural networks (NN), support vector machines, and neuro-fuzzy systems. Artificial intelligence methods are used to anticipate financial time series because they can account for the complexity of the financial system.

Autoregressive Moving Average (ARMA), a linear modelling methodology, and random walk (RW) are the two methods used to test AI methods. Data from the Johannesburg Stock Exchange were used for the experiment. The All Share Index's past closing prices were the source of the data. The outcomes demonstrated that the three strategies can forecast the price of the Index with a respectable degree of accuracy. Each of the three artificial intelligence methods fared better than the linear model. However, all other methods were outperformed by the random walk method. These methods demonstrate a capacity for price forecasting, but it is not possible to demonstrate that any of the three methods can refute the weak form of market efficiency due to the costs associated with trading on the open market. The findings demonstrate that the ranking of support vector machines, neuro-fuzzy systems, and multilayer perceptron neural networks depends on the accuracy metric employed.

2.2.3 Indian stock market prediction using artificial neural networks on tick data

The research was carried out by Dharmaraja Selvamuthu, Vineet Kumar, and Abhishek Mishra at the Indian Institute of Technology Delhi's mathematics department in Hauz Khas, New Delhi, India (110016). A stock market is a venue where shares and derivatives of a company can be traded at a predetermined price. The stock market is based on supply and demand for shares. The stock market is one of the fastest-growing industries in any nation. Many people today are involved in this industry either directly or indirectly. Therefore, being aware of industry trends becomes crucial. People are interested in stock price forecasting as a result of the growth of the stock market. Predicting the stock price, however, is a difficult assignment because of the dynamic character and potential for rapid fluctuations in stock price. Share m previous research has put forth excellent techniques for learning event representations that can gather syntactic and semantic data from text corpora, demonstrating their usefulness for subsequent tasks like script event prediction. On the other hand, events that are retrieved from raw texts are devoid of common information, such as the participants' intentions and feelings, which can be used to discriminate between event pairs when there are only slight variations in their surface realizations. In order to solve this problem, it is suggested in this paper to make use of outside commonsense information about the purpose and mood of the event.

Experiments on three event-related tasks, including event similarity, script event prediction, and stock market prediction, demonstrate that our model significantly improves event embeddings for the tasks, achieving 78% improvements on the hard similarity task, producing more precise inferences on subsequent events under given contexts, and improving accuracies in predicting the volatilities of the stock market1. (Ahangar et al. 2010) Markets are primarily a nonparametric, non-linear, noisy, and deterministic chaotic system. As technology advances, stock traders are switching from using basic research to Intelligent Trading Systems to forecast stock values, which enables them to make quick investment choices. Predicting stock prices allows a trader to sell a stock before its value declines or acquire a stock before its price increases. According to the efficient market hypothesis, stock prices cannot be predicted and behave like they are in a random walk. It seems to be very difficult to replace the professionalism of an experienced trader for predicting the stock price. But thanks to technological advancements and the availability of a remarkable amount of data, it is now possible to create a prediction algorithm that will increase profits for traders or investment firms. As a result, an algorithm's accuracy is directly correlated with the profits it produces.

2.2.4 The Stock Market and Investment

Manh Ha Duong Boriss Siliverstovs's investigation. Examining the relationship between stock prices and total investment in important European nations including France, Germany, Italy, the Netherlands, and the United Kingdom. A stronger correlation between equity prices in various European countries is likely to be the result of the growing integration of European financial markets. If stock market developments have an impact on actual economic factors like investment and consumption, this process may also result in convergence in economic development across European nations. Our vector autoregressive models do in fact imply that the generally significant positive correlation between changes in equity prices and investment. Therefore, monetary authorities should keep an eye on how share prices respond to changes in monetary policy and how these changes affect the business cycle.

2.2.5 Automated Stock Price Prediction Using Machine Learning

The study was conducted by Mariam Moukalled Wassim El-Hajj Mohamad Jaber of the American University of Beirut's Computer Science Department. Investors have historically examined stock prices, stock indicators, and news pertaining to these stocks in order to forecast market movement. Consequently, news has a significant impact on stock price movement. Most of the earlier work in this field concentrated on either classifying the issued market news as (positive, negative, neutral) and proving their influence on the stock price or focused on the historical price movement and projected their future movement.

In this study, we suggest an automated trading system that combines mathematical operations, machine learning, and additional external factors like news sentiments in order to improve stock prediction accuracy and execute profitable trades. We specifically want to ascertain the price or trend of a certain stock for the next end-of-day taking into account the first few trading hours of the day. To accomplish this, we created and trained numerous deep learning models while also training traditional machine learning algorithms, taking into account the significance of the pertinent news. Several experiments were carried out, with the SVM used for the Apple Inc. (AAPL) stock achieving the highest accuracy (82.91%).

2.2.6 Stock Price Correlation Coefficient Prediction with ARIMA-LSTM Hybrid Model

The study was conducted by Hyeong Kyu Choi, a B.A. student at the business administration department of Korea University in Seoul, Korea. For portfolio optimization, it's critical to predict the price correlation of two assets across upcoming time frames. In order to forecast the stock price correlation coefficient of two distinct equities, we use LSTM recurrent neural networks (RNN). RNN’s are competent in understanding temporal dependencies. Its long-term prediction abilities are further improved by the introduction of LSTM cells. We also use the ARIMA model to account for both linearity and nonlinearity in the model.

The LSTM model receives the residual value that the ARIMA model left over after filtering the data for linear trends. In comparison to other conventional predictive financial models, including the whole historical model, constant correlation model, single-index model, and multi-group model, the ARIMA-LSTM hybrid model performs better. In our empirical analysis, the prediction performance of the ARIMA-LSTM model proved out superior to all other financial models by a substantial scale. According to our research, it is worthwhile to take the ARIMALSTM model into account when forecasting correlation coefficient for portfolio optimization.

2.2.7 Event Representation Learning Enhanced with External Common-sense Knowledge

Xiao Ding, Kuo Liao, Ting Liu, Zhongyang Li, and Junwen Duan's research was conducted at the Harbin Institute of Technology's Research Centre for Social Computing and Information Retrieval in China. Previous research has put forth excellent techniques for learning event representations that can gather syntactic and semantic data from text corpora, proving their usefulness for subsequent tasks like script event prediction. On the other hand, events that are retrieved from raw texts are devoid of common information, such as the participants' intentions and feelings, which can be used to discriminate between event pairs when there are only slight variations in their surface realizations.

In order to solve this problem, it is suggested in this paper to make use of outside commonsense information about the purpose and mood of the event. Experiments on three event-related tasks—event similarity, script event prediction, and stock market prediction—show that our model significantly improves event embeddings for the tasks, achieving 78% improvements on the hard similarity task, producing more precise inferences on subsequent events under given contexts, and improving accuracy in predicting the volatilities of the stock market.

2.2.8 Forecasting directional movements of stock prices for intraday trading using LSTM and random forests

Ariel Neufeld, Jajati Keshari Sahoo, and Pushpendu Ghosh's researchDepartment of Mathematics, BITS Pilani K.K.Birla Goa campus, India; Division of Mathematical Sciences, Nanyang Technological University; Department of Computer Science & Information Systems, BITS Pilani K.K.Birla Goa campus, India.

In order to evaluate the performance of random forests and LSTM networks (more specifically, CuDNNLSTM) in predicting intraday directional movements of the stocks that make up the S&P 500 from January 1993 to December 2018 using out-of-sample data, we use both as training approaches. We introduce a multi-feature setting consisting not only of the returns with respect to the closing prices, but also with respect to the opening prices and intraday returns. We use Krauss et al. (2017) and Fischer & Krauss (2018) as our benchmarks for our trading strategy, and on each trading day, we buy the 10 stocks with the highest probability and sell short the 10 stocks with the lowest probability to outperform the market in terms of intraday returns - all with equal financial weight.

According to our empirical findings, the multi-feature setting offers a daily return using LSTM networks of 0.64% and 0.54% before transaction costs. Hence, we outperform the single feature setting in Fischer & Krauss (2018) and Krauss et al. (2017) consisting only of the daily returns with respect to the closing prices, having corresponding daily returns of 0 .41% and of 0 .39% with respect to LSTM and random forests, respectively. 1 Keywords: Random forest, LSTM, Forecasting, Statistical Arbitrage, Machine learning, Intraday trading.

2.2.9 A Deep Reinforcement Learning Library for Automated Stock Trading in Quantitative Finance

The research was conducted by Xiao-Yang Liu1, Hongyang Yang, Qian Chen4, Runjia Zhang, Liuqing Yang, Bowen Xiao, Christina Dan Wang, Electrical Engineering, Computer Science, Statistics, and Ion Media Networks at Columbia University, Imperial College, and New York University (Shanghai).

For beginners, getting practical experience is appealing because deep reinforcement learning (DRL) has been proven to be a successful strategy in the field of quantitative finance. To develop a practical DRL trading agent, though, that chooses where to trade, at what price, and in what quantity, requires laborious, error-prone development. In this paper, we introduce a DRL library called FinRL, which helps novices learn about quantitative finance and create their own stock trading strategies. Users can streamline their own developments and compare them with existing schemes with the help of the FinRL library's easily reproducible tutorials.

In FinRL, trading agents are trained using neural networks, virtual environments are set up with stock market datasets, and extensive back testing is examined using trading performance. Additionally, it incorporates crucial trading restrictions like transaction costs, market liquidity, and the level of risk aversion of the investor.

A feature of FinRL that benefits beginners is completeness, practical instruction, and reproducibility: FinRL provides fine-tuned state-of-the-art DRL algorithms (DQN, DDPG, PPO, SAC, A2C, TD3, etc.), commonly used reward functions, and standard evaluation baselines to reduce the debugging workloads and encourage reproducibility; (i) FinRL simulates trading environments across various stock markets, including NASDAQ-100, DJIA, S&P 500, HSI, SSE 50, and CSI 300; and (ii) Additionally, we added three examples of application, including portfolio allocation, multiple stock trading, and single stock trading.

2.2.10 An innovative neural network approach for stock market prediction

Xiongwen Pang, Yanqiang Zhou, Pan Wang, and Weiwei Lin's research. to create a cutting-edge neural network strategy for better stock market predictions. For real-time and offline stock analysis as well as the outcomes of visualisations and analytics, data were taken from the active stock market. This was done to demonstrate the use of the Internet of Multimedia Things for stock analysis. To study the influence of market characteristics on stock prices, traditional neural network algorithms may incorrectly predict the stock market, since the initial weight of the random selection problem can be easily prone to incorrect predictions.

We illustrate the idea of "stock vector" using the deep learning word vector as an example. The input is no longer a single index or single stock index, but multi-stock high-dimensional historical data.

We suggest the long short-term memory neural network with automatic encoder and the deep long short-term memory neural network (LSTM) with embedded layer for stock market prediction. In these two models, we vectorize the data using the embedded layer and automatic encoder, respectively, in an effort to forecast the stock using a long short-term memory neural network.

The experimental results show that the deep LSTM with embedded layer is better. For example, two models' accuracy for the Shanghai A-shares composite index is 57.2 and 56.9%, respectively. For individual stocks, they are additionally 52.4 and 52.5%, respectively. We present new IMMT research results for neural network-based financial analysis. 2.2.11 A Smart Method for Stock Market Prediction.

2.2.11 An Intelligent Technique for Stock Market Prediction

The study was carried out by M. Mekayel Anik and M. Shamsul Arefin (B), both of the Department of Computer Science and Engineering at Chittagong University of Engineering and Technology in Chittagong, Bangladesh.

A stock market is a loosely organized system of economic exchanges between buyers and sellers that are based on stocks, also referred to as shares. Stocks serve as ownership claims for companies in stock markets. Both publicly traded securities and those that are only traded privately may be included in this. A stock exchange is a place where brokers can buy and/or sell stocks, bonds, and other securities. Due to its volatility, the stock market is a very risky place for investments. Due to a sharp decline in the price of shares on global stock markets, we recently experienced severe financial difficulties. The international and domestic financial systems were both severely harmed by this phenomenon. The stock market caused many people to lose their last remaining savings. Bangladesh's stock market suffered a catastrophic collapse during the 2010–2011 fiscal year [1]. Strict oversight, for example, and stock market analysis can help control this phenomenon. If we can accurately and promptly analyse the stock market, it can develop into a source of significant profit and potentially become less vulnerable for investors.

Stock market is all about prediction and speedy decision making regarding investment, which cannot be done without extensive analysis of the market. We can prevent the negative effects of a significant market collapse and be able to take the required actions to make the market resistant to such circumstances if we can accurately anticipate the stock market by properly studying historical data.

2.2.12 Stock Price Prediction using Machine Learning and Sentiment Analysis

This paper discusses the use of Machine Learning and Sentiment Analysis to predict stock prices. It focuses on three different models: ARIMA, ARIMA, LSTM, Linear Regression, and Nave Bayes. ARIMA has the best accuracy for every stock, while ARIMA and LSTM have the best accuracy for every stock. The proposed system consists of three components: collection of stock data, classification of stock tickers, and performing analysis on labels obtained after classification. The dataset is made using tickers of different stocks from Yahoo Finance API and the tweets for sentiment analysis is taken from the Twitter API called Tweepy.

Data preprocessing was done by using Regular Expressions and a estimator that uses randomized decision tree to fit various subsamples of the data set. Results show that the ARIMA model is giving the best accuracy when forecasting short term results, while the LSTM model is better for long term prediction. References include Y. Wang and Y. Wang, X. Li, H. Xie, Y.Song, S.Zhu, Q.Li and F.L. Wang.

2.2.13 Stock Market Prediction Using LSTM Recurrent Neural Network

This article aims to build a model using Recurrent Neural Networks (RNN) and especially Long-Short Term Memory model (LSTM) to predict future stock market values. The main objective of this paper is to see in which precision a Machine learning algorithm can predict and how much the epochs can improve our model. c 2020 The Authors. In general machine learning is a term used for all algorithm's methods using computers to reveal patterns based only on data and not using any programming instructions. For quantitative finance and specially assets selections several models supply a large number of methods that can be used with machine learning to forecast future assets value.

Recently, the combination of statistics and learning models have polished several machine learning algorithms, such as acritical neural networks, gradient boosted regression trees, support vector machines and, random forecast. A large number of studies is currently active on the subject of machine learning methods used in finance, some studies used tree-based models to predict portfolio returns, others used deep learning in the production of future values of financial assets.

This paper aim to use ML algorithm based on LSTM RNN to forecast the adjusted closing prices for a portfolio of assets, the main objective here is to obtain the most accurate trained algorithm, to predict future values for our portfolio.

In general, an Artificial Neural Network (ANN) consists of three layers:

1) input layer, 2) Hidden layers, 3) output layer

The hidden layer nodes apply a sigmoid or tangent hyperbolic (tanh) function on the sum of weights coming from the input layer which is called the activation function, this transformation will generate values, with a minimized error rate between the train and test data using the SoftMax function. The classes of NN that predict future value base on passed sequence of observations is called Recurrent Neural Network (RNN) this type of NN make use of earlier stages to learn of data and forecast futures trends. The earlier stages of data should be remembered to predict and guess future values, in this case the hidden layer act like a stock for the past information from the sequential data.

CHAPTER 3

SOFTWARE REQUIREMENT SPECIFICATION

3.1 Introduction

We are building a Flutter based Mobile Application (APP) through which user can analyze and predict prices of stock and based upon that they can decide whether they should buy the stock or not and if they want to buy then for how many days, they should hold it in order earn maximum profit. Our goal is to build a user-friendly Mobile Application so that we can reach to maximum audiences and serve them with our product. We are using Machine Learning Techniques to do the prediction of prices of stock our prediction is basically based upon two factors the Conventional method and Modern Perspective.

Purpose

Software requirements for PRESTOCK release 1.0 and version 1.0. The purpose of our software is to predict future stock prices based on the current stock prices and after analyzing the past trend for the particular stock. It will also comparethe stock with its peers and give chances of stock performing well in future.

Document Conventions

In The document priorities for higher-level requirements are assumed to be inherited by detailed requirements

Intended Audience and Reading Suggestions

This SRS is made for the developers, project managers, users, testers, and documentation writers. Later SRS contains what software does and what is the scope of software, what are the requirements of system to run the software and other non-functional requirements. The document should be read in the order written.

Product Scope

It will analyze each stock individually with use of its past performance and that when the user should buy a particular stock in future so as to gain maximum profit from it. Also, it tells stocks in user portfolio that the user should sell to book profit or to reduce future losses.

3.2 Overall Description

Product Perspective

It is a new, self-contained product. It is a standalone software that works on its own by taking data from the respective websites.

Product Functions

- Predict stock prices for long term
- Predict stock prices for short time
- Best time to buy stock
- Best time to sell stock
- Estimated gain for specific time period

User Classes and Characteristics

- It will be used by users who want to just use predefined strategies to predict prices.
- It can be used by active traders to analyze price movement in day.
- It can be used by speculators to see the movement and their predictions according to data.
- It can be used by investors to just invest on the data provided by app.
- It can be used by anyone who want to see their strategies and see how efficient they in market are.

Operating Environment

It will operate on mobile devices with at least 2 GB RAM and 4 GB ROM.

Design and Implementation Constraints

It will have to fetch data on real time basics as trading have to be done on real time.

Calculations have to be fast enough to display data in real time.

User Documentation

- App will have a user manual
- It will have a video tutorial for the user
- It will be an app that is self-explanatory user interface

Assumptions and Dependencies

- BSE INDIA Website for data
- Data Released by Companies

3.3 External Interface Requirements

User Interfaces

- It will Have tutorial button on each page.
- It will have brief description of each ratio.
- I t will Have Value for each stock.
- It will have self-explanatory user interface

Hardware Interfaces

- It will work on android devices with android version 6 or above.
- Device must have 2 GB Of RAM
- Device must have 4 GB Of ROM
- Device Must Have Internet Connection of 5 Mb/s or above.

Software Interfaces

- It will have a database management system
- It will use machine learning algorithms
- It will use data analysis
- It Will use A.I to predict future stocks price

Communications Interfaces

- web browser
- Minimum 5 Mb/s data transfer
- FTP
- HTTPS

3.4 System Features

Stock Prediction for Retail Investor with Small Amount

Description and Priority

It will predict prices for future stocks and has 1st priority Within the Amount Specified by Retail Investor and Of Particular Category If He/She Wants to Choose a Particular Category.

Stimulus/Response Sequences

It will be used by the user when he wishes

Functional Requirements

Previous Data required To predict Future prices

Stock Prediction for Retail Investor with Large Amount

Description and Priority

It will predict prices for future stocks and has 1st priority With Different Categories and With the Amount Specified by The Investor.

Stimulus/Response Sequences

It will be used by the user when he wishes

Functional Requirements

Previous Data required to predict Future prices

Stock Prediction for Institutional Investor

Description and Priority

It will predict prices for future stocks and has 1st priority Within the Constraints That If It Wants in Particular Category E.g.: Only Technology Stock, Only Bank Stocks Etc.

Stimulus/Response Sequences

It will be used by the user when he wishes

Functional Requirements

Previous Data required to predict Future prices

CHAPTER 4

PROPOSED METHODOLOGY

In our Major Project we are building a Flutter based Mobile Application (APP) through which user can analyze and predict prices of stock and based upon that they can decide whether they should buy the stock or not and if they want to buy then for how many days, they should hold it in order earn maximum profit. Our goal is to build a user-friendly Mobile Application so that we can reach to maximum audiences and serve them with our product. We are using Machine Learning Techniques to do the prediction of prices of stock our prediction is basically based upon two factors the Conventional method and Modern Perspective.

We have compared different methods to predict the price of stocks so the more accurate method can be analyzed. The methods we used for comparison are 100 days simple moving average (100ma), 200 days simple moving average (200ma) and LSTM (Long Short-Term Memory). We have also analyzed the predicted results and compared it by plotting graph.

4.1 STRUCTURE OF PROJECT

4.1.1 User Interface

Since Flutter is cross-platform, you can use the same code base for your iOS and Android app. This can save you both time and resources. Dart compiles into native code and there is no need to access OEM widgets as Flutter has its own. This means less mediated communication between the app and the platform.We have used Firebase for login process, Firebase is a product of Google which helps developers to build, manage, and grow their apps easily. It helps developers to build their apps faster and in a more secure way.

The user interface (UI) of a Flutter app for stock price prediction would aim to provide a visually appealing and intuitive experience for users. The UI would typically consist of various components, such as charts, input fields, buttons, and textual information. The charts would display historical stock data and predicted trends, allowing users to visualize the price fluctuations over time. Interactive features like zooming and panning might be included to enable users to explore the data in detail. Input fields would allow users to enter specific parameters or select stocks of interest. Buttons could trigger actions such as fetching real-time data, generating predictions, or saving personalized watchlists. The UI would also incorporate clear and concise textual information, presenting predicted stock prices and relevant insights in an easy-to-understand format. Overall, the UI would prioritize simplicity, usability, and effective data visualization to provide users with a seamless experience in analyzing and predicting stock prices.

1- Splash Screen

A splash screen is a brief introductory screen that appears when launching an app. It serves as a visual transition from the app launch to the main user interface and provides users with a sense of the app's branding and identity. The splash screen typically displays a logo, app name, or an engaging graphic that represents the app's purpose or theme. It serves multiple purposes, including giving the app time to initialize and load necessary resources in the background, enhancing the user experience by providing a visual cue that the app is launching, and reinforcing the app's branding and aesthetics. The duration of a splash screen is usually short, typically a few seconds, to prevent user frustration. A well-designed and visually appealing splash screen can leave a positive first impression on users, setting the tone for their interaction with the app and conveying a sense of professionalism.

Fig:8- Splash Screen

2- LogIn Page

The login page in a Flutter app using Firebase provides users with a secure and streamlined way to access the app's features and services. It typically consists of input fields for email and password, along with a "Login" button. When users enter their credentials and click the login button, the app validates the information using Firebase Authentication. Firebase Authentication handles user authentication, including email/password authentication, and provides a secure way to manage user accounts. Upon successful authentication, the app can navigate to the main interface, granting users access to their personalized content and functionality. In case of any authentication errors, appropriate error messages can be displayed on the login page, allowing users to correct their credentials or recover their account if needed. The login page using Firebase in a Flutter app ensures a reliable and secure authentication process, enhancing the user experience and safeguarding user data.

Fig:9- Login Page

3- Search Stocks

Searching for stocks within a stock market app offers users a convenient way to find specific companies or securities of interest. The search functionality allows users to enter keywords, stock symbols, or company names to quickly locate the desired stock. As users type in the search bar, the app dynamically displays matching results, narrowing down the list in real-time. The search results typically include relevant stock symbols, company names, and other pertinent information, providing users with a snapshot of each stock's key metrics. Advanced search features may also be available, allowing users to filter stocks based on criteria such as sector, market cap, dividend yield, or price range. The ability to search for stocks within the app simplifies the process of discovering specific investments, saving time and effort for users as they navigate the vast universe of available securities.

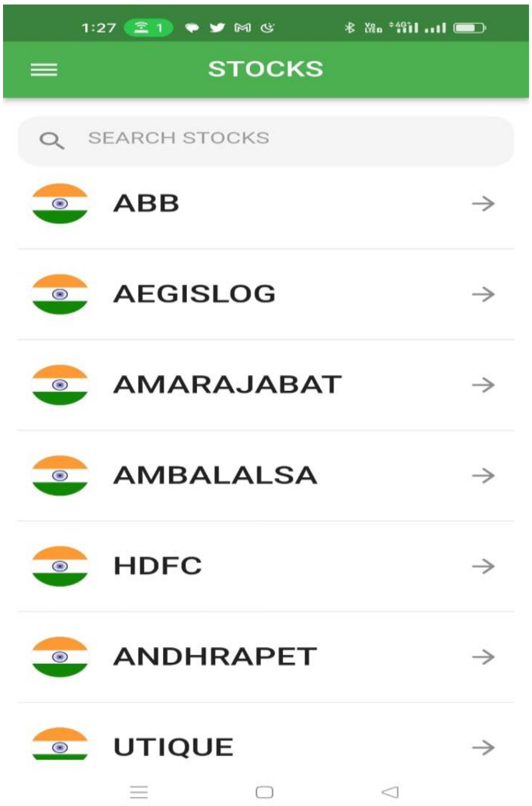


Fig:10- List Of Stocks

4- Details About Stock

Detailed descriptions of individual stocks, offering valuable insights and information about specific companies. When users select a stock from the list or search results, they can access a dedicated stock detail page that presents comprehensive information about the company and its securities. The detail description typically includes the company's name, stock symbol, industry sector, market capitalization, dividend yield, earnings per share (EPS), price-to-earnings (P/E) ratio, and other key financial metrics.

Fig:11- Details About Stock

5- Predicted Close Price

Here we display the predicted close price of selected stock. It's important to note that stock price predictions are estimates and subject to uncertainties. Factors such as market conditions, news events, and economic indicators can impact stock prices, making accurate predictions challenging. It is advisable to consider predicted close prices as a tool for decision support rather than relying solely on them for investment choices. Implementing risk management strategies and consulting with financial professionals can help mitigate potential risks associated with stock market investments.

Fig:12- Predicted Close Price

4.1.2 Machine Learning Code with Output

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import pandas_datareader as data

from alpha_vantage.timeseries import TimeSeries
```

```
API_key='EG7F71P0XMBDB6YM'

ts=TimeSeries(key=API_key,output_format='pandas')

data=ts.get_daily_adjusted('BRITANNIA.BSE',outputsize='full')df=data[0]

df=df.reset_index()
```

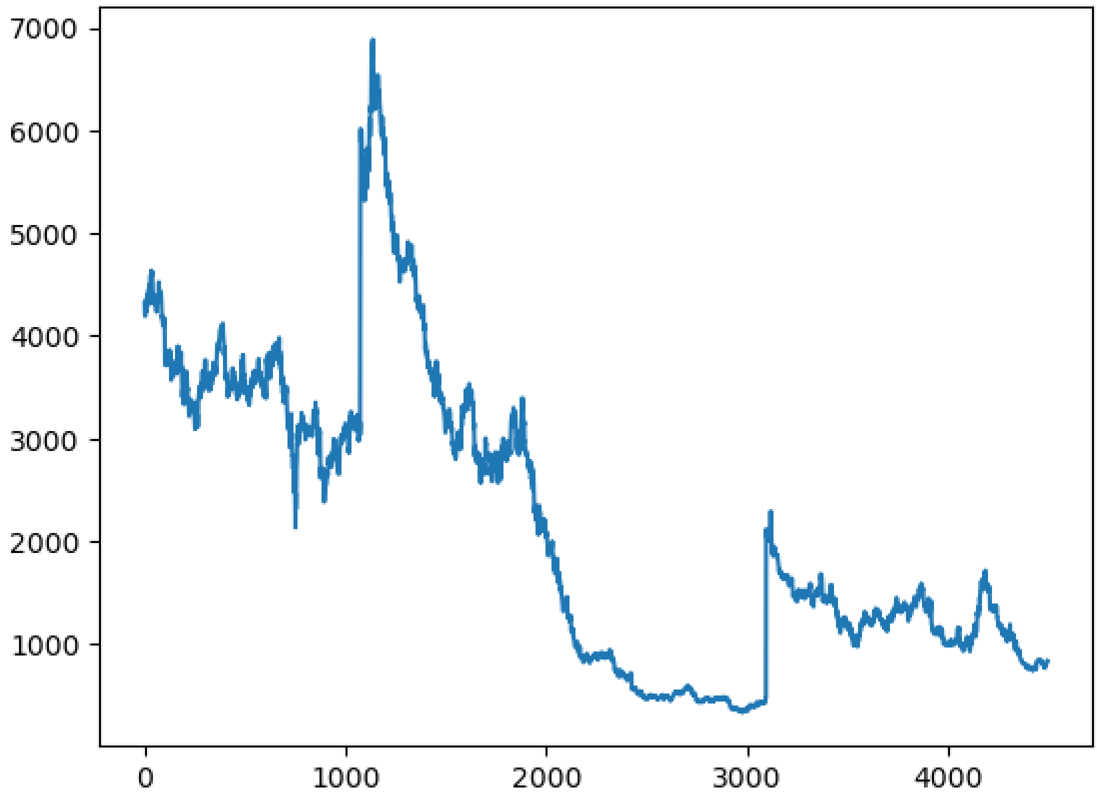
	date	1. open	2. high	3. low	4. close	5. adjusted close	6. volume	7. dividend amount	8. sp coefficie
4505	2005-01-07	834.1420	834.1420	807.5272	812.3168	61.3251	6260.0	0.0	1
4506	2005-01-06	813.3562	834.9102	780.9124	819.9534	61.9016	182350.0	0.0	1
4507	2005-01-05	849.5054	853.5722	817.8748	826.6862	62.4099	2090100.0	0.0	1
4508	2005-01-04	840.4680	849.5054	836.0398	845.3030	63.8154	88030.0	0.0	1
4509	2005-01-03	840.4680	849.5054	813.3562	842.3208	63.5902	16330.0	0.0	1

Table. 1: Britannia Stock Data

```
df.set_axis(['open', 'high', 'low','close','volume'], axis='columns', inplace=True)

df.head()
```

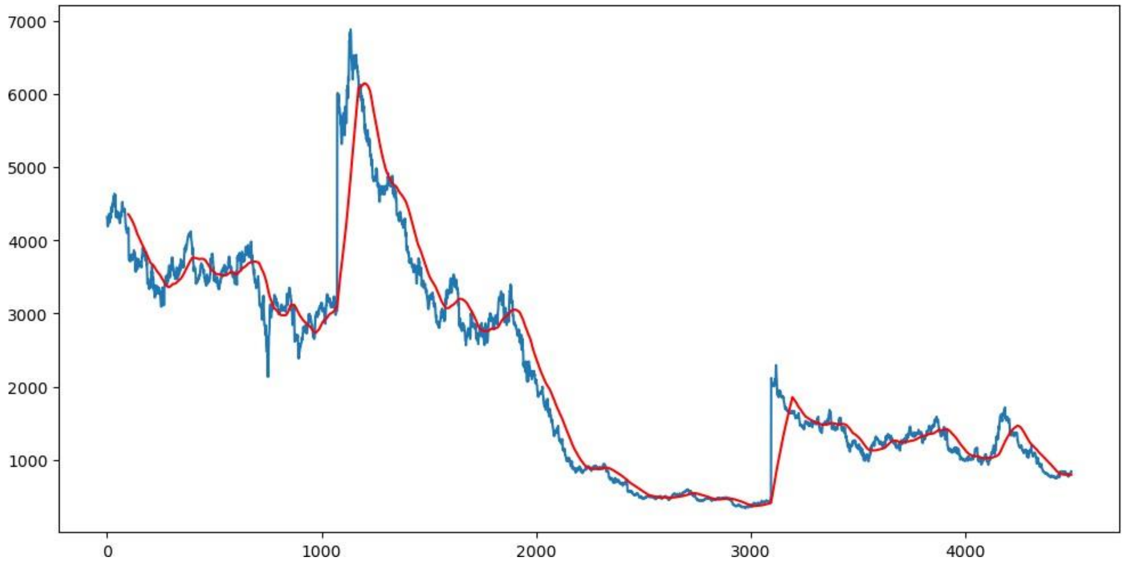
	open	high	low	close	volume
0	4240.0498	4332.8501	4240.0498	4322.0000	6234.0
1	4209.9502	4293.7998	4199.7998	4275.8999	6715.0
2	4214.7500	4225.6001	4154.0000	4199.3501	2863.0
3	4205.0498	4242.0000	4199.3501	4211.5498	3355.0
4	4242.7998	4242.7998	4191.0000	4195.6499	6298.0

```
plt.plot(df.close)
```



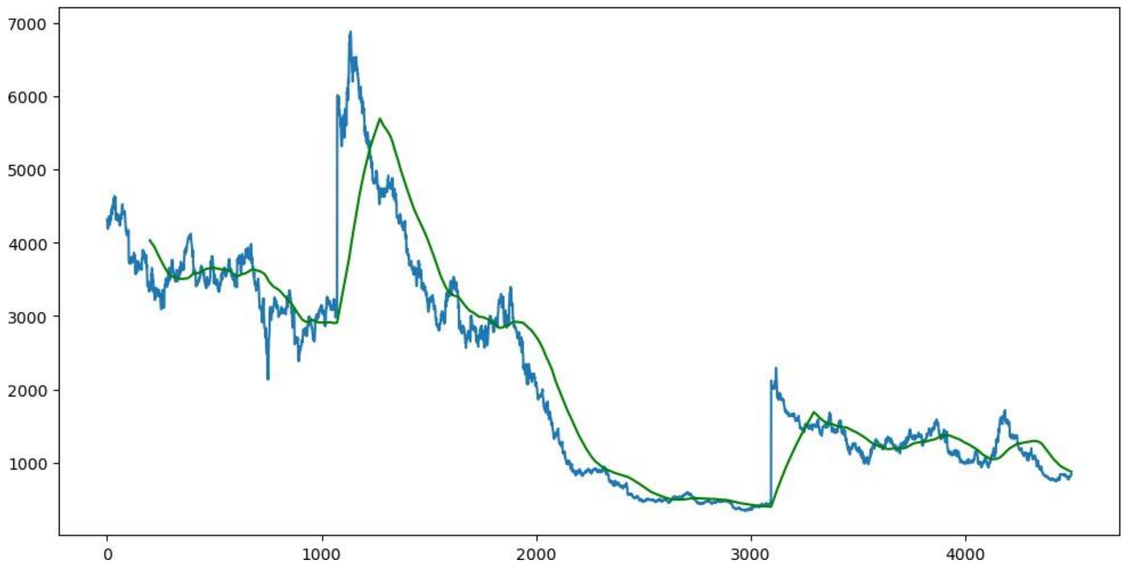
```
ma100=df.close.rolling(100).mean()
```

```
plt.figure(figsize=(12,6))
plt.plot(df.close)

plt.plot(ma100,'r')
```




```
ma200=df.close.rolling(200).mean()
```

```
plt.figure(figsize=(12,6))
plt.plot(df.close)

plt.plot(ma200,'g')
```



```
#splitting data into training and testing

train=pd.DataFrame(df['close'][0:int(len(df)*0.70)])

test=pd.DataFrame(df['close'][int(len(df)*0.70):int(len(df))])

print(train.shape)

print(test.shape)
```

On[13]:

(3147, 1)

(1349, 1)

```
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler(feature_range=(0,1))
```

```
train_array=scaler.fit_transform(train)

train_array
```

Out[15]:

```
array([[0.60867207],
       [0.60162991],
       [0.58993632],
       ...,
      [0.2325283 ],
      [0.2322457 ]])
```

```
x_train=[]
y_train=[]

for i in range(100,train_array.shape[0]):
x_train.append(train_array[i-100:i])

    y_train.append(train_array[i,0])

x_train,y_train=np.array(x_train),np.array(y_train)
```

```
from   keras.layers import Dense, Dropout, LSTM

from keras.models import Sequential
```

```
model=Sequential()

model.add(LSTM(units=50,activation='relu',return_sequences=True,
                              input_shape=(x_train.shape[1],1)))

model.add(Dropout(0.4))

model.add(LSTM(units=60,activation='relu',return_sequences=True))
model.add(Dropout(0.4))

model.add(LSTM(units=80,activation='relu',return_sequences=True))


model.add(Dropout(0.4))


model.add(LSTM(units=120,activation='relu'))


model.add(Dropout(0.4))


model.add(Dense(units=1))
```

```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 100, 50)	10400
dropout (Dropout)	(None, 100, 50)	0
lstm_1 (LSTM)	(None, 100, 60)	26640
dropout_1 (Dropout)	(None, 100, 60)	0
lstm_2 (LSTM)	(None, 100, 80)	45120
dropout_2 (Dropout)	(None, 100, 80)	0
lstm_3 (LSTM)	(None, 120)	96480
dropout_3 (Dropout)	(None, 120)	0
dense (Dense)	(None, 1)	121

Total params: 178,761

Trainable params: 178,761

Non-trainable params: 0

Table. 2: Model Summary

```
model.compile(optimizer='adam',loss='mean_squared_error')
model.fit(x_train,y_train,epochs=25)
```

```
Epoch 1/25
96/96 [==============================] - 23s 202ms/step - loss: 0.0214
Epoch 2/25
96/96 [==============================] - 23s 244ms/step - loss: 0.0051
Epoch 3/25
96/96 [==============================] - 23s 237ms/step - loss: 0.0045
Epoch 4/25
96/96 [==============================] - 22s 230ms/step - loss: 0.0042
Epoch 5/25
96/96 [==============================] - 20s 208ms/step - loss: 0.0037
Epoch 6/25
96/96 [==============================] - 19s 196ms/step - loss: 0.0037
Epoch 7/25
96/96 [==============================] - 20s 206ms/step - loss: 0.0038
Epoch 8/25
96/96 [==============================] - 25s 265ms/step - loss: 0.0034
Epoch 9/25
96/96 [==============================] - 23s 239ms/step - loss: 0.0030
Epoch 10/25
96/96 [==============================] - 20s 208ms/step - loss: 0.0029
Epoch 11/25
96/96 [==============================] - 21s 218ms/step - loss: 0.0030
Epoch 12/25
96/96 [==============================] - 21s 216ms/step - loss: 0.0030
Epoch 13/25
96/96 [==============================] - 21s 216ms/step - loss: 0.0030
Epoch 14/25
96/96 [==============================] - 22s 224ms/step - loss: 0.0026
Epoch 15/25
96/96 [==============================] - 22s 225ms/step - loss: 0.0024
Epoch 16/25
96/96 [==============================] - 19s 201ms/step - loss: 0.0025
Epoch 17/25
96/96 [==============================] - 20s 205ms/step - loss: 0.0024
Epoch 18/25
96/96 [==============================] - 19s 203ms/step - loss: 0.0024
Epoch 19/25
96/96 [==============================] - 21s 216ms/step - loss: 0.0024
Epoch 20/25
96/96 [==============================] - 24s 251ms/step - loss: 0.0021
Epoch 21/25
96/96 [==============================] - 22s 230ms/step - loss: 0.0024
Epoch 22/25
96/96 [==============================] - 19s 202ms/step - loss: 0.0028
Epoch 23/25
96/96 [==============================] - 20s 204ms/step - loss: 0.0021
Epoch 24/25
96/96 [==============================] - 22s 229ms/step - loss: 0.0022
Epoch 25/25
96/96 [==============================] - 19s 203ms/step - loss: 0.0020
```

```
past_100_days=train.tail(100)

final_df=past_100_days.append(test,ignore_index=True)
```

```
final_df.head()
```

	close
0	407.35
1	409.80
2	414.10
3	423.90
4	431.25

In [25]:

```
input_data=scaler.fit_transform(final_df)

input_data
```

Out[25]:

```
array([[0.        ],
       [0.00129874],
       [0.00357815],
       ...,
       [0.22228853],
       [0.23215723],
       [0.23057637]])
```

```
x_test=[]
y_test=[]

for i in range(100,input_data.shape[0]):
    x_test.append(input_data[i-100:i])

    y_test.append(input_data[i,0])
```

```
x_test,y_test=np.array(x_test),np.array(y_test)
print(x_test.shape)

print(y_test.shape)
```

In [28]:

(1349, 100, 1)

(1349,)

```
#Making Prediction

y_predict=model.predict(x_test)
```

43/43 [==============================] - 4s 69ms/step

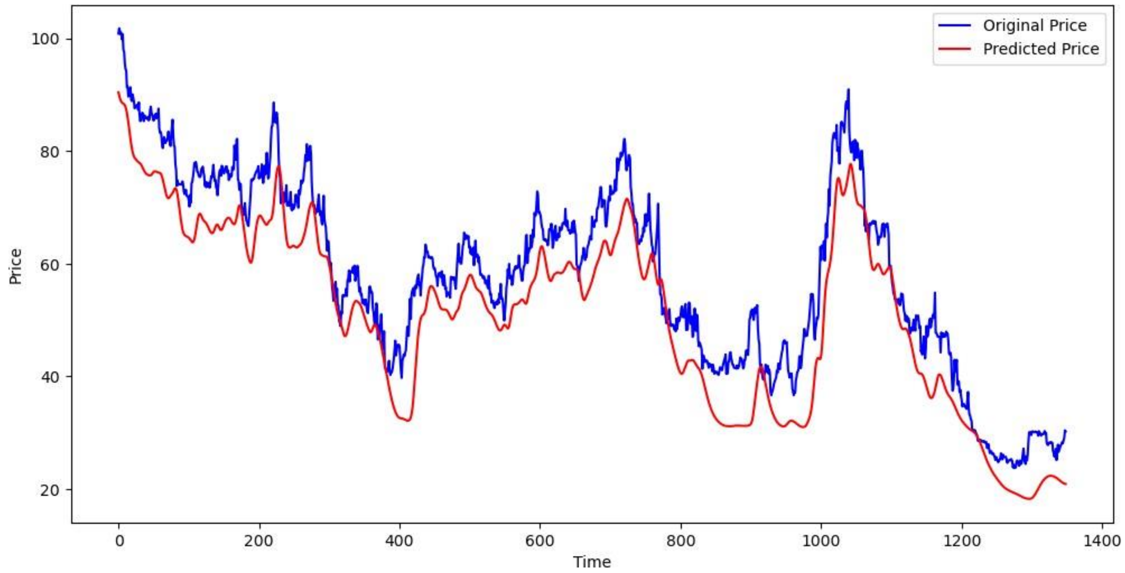
```
scaler.scale_
```

Out[33]:

array([0.0005301])

```
scale_factor=1/0.00762951

y_predict=y_predict*scale_factor
y_test=y_test*scale_factor
```

```
plt.figure(figsize=(12,6))

plt.plot(y_test,'b',label='Original Price')

plt.plot(y_predict,'r',label='Predicted Price')plt.xlabel('Time')

plt.ylabel('Price')
plt.legend()
```



CHAPTER 5

DESIGN

5.1 Structure Chart

In software engineering and organisational theory, a structure chart (SC) is a diagram that depicts the breakdown of a system to its most manageable levels. In structured programming, they are employed to organise programme modules into a tree. Each module is symbolised by a box that contains its name.

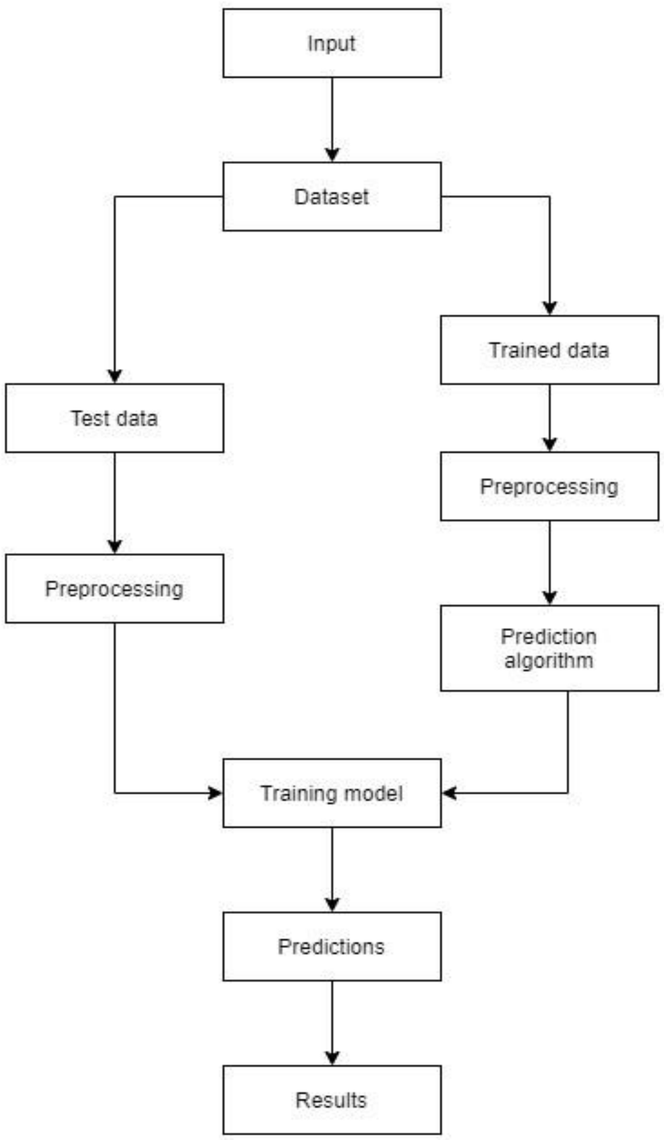


Fig. 13: Training and prediction

5.2 UML Diagrams

A partial graphical representation (view) of a model of a system that is being designed, being implemented, or that is currently in use is called a UML diagram. A UML diagram contains graphical elements (symbols) that represent the components of the designed system's UML model. These graphical elements are UML nodes connected with edges (also known as paths or flows). Additional documentation, such as use cases that are created as templated texts, may also be included in the system's UML model.

The key graphical symbols displayed on the diagram serve to describe its kind. A class diagram, for instance, is a diagram where the classes are the main symbols in the contents area. Use case diagram is a visual representation of actors and use cases. The order in which messages are sent between lifelines is shown in a sequence diagram.

The UML definition does not exclude combining multiple types of diagrams, for as when showing a state machine nested inside a use case by combining structural and behavioural components. As a result, the distinctions between the different categories of diagrams are not properly observed. While working on a certain sort of diagram, some UML Tools do limit the set of graphical components that may be utilised.

Structure diagrams and behaviour diagrams are the two main categories of UML diagrams defined by the UML standard.

Structure diagrams display the static structure of the system, its components, and their interrelationships at various abstraction and implementation levels. A structure diagram's components, which might comprise abstract, actual-world, and implementation ideas, describe the significant concepts of a system.

Behaviour diagrams display an object's dynamic behaviour, which may be characterised as a series of system changes through time.

5.2.1 Use Case Diagram

A use case diagram in the Unified Modelling Language (UML) can condense the specifics of your system's users (sometimes referred to as actors) and their interactions with the system. You'll need a certain set of connections and symbols to construct one. Your team may discuss and visualise the following using a good use case diagram:

- Scenarios in which your system or application interacts with individuals, groups, or external systems.
- Objectives that those entities (sometimes referred to as actors) are helped by your system or application to accomplish.
- Your system's scope.

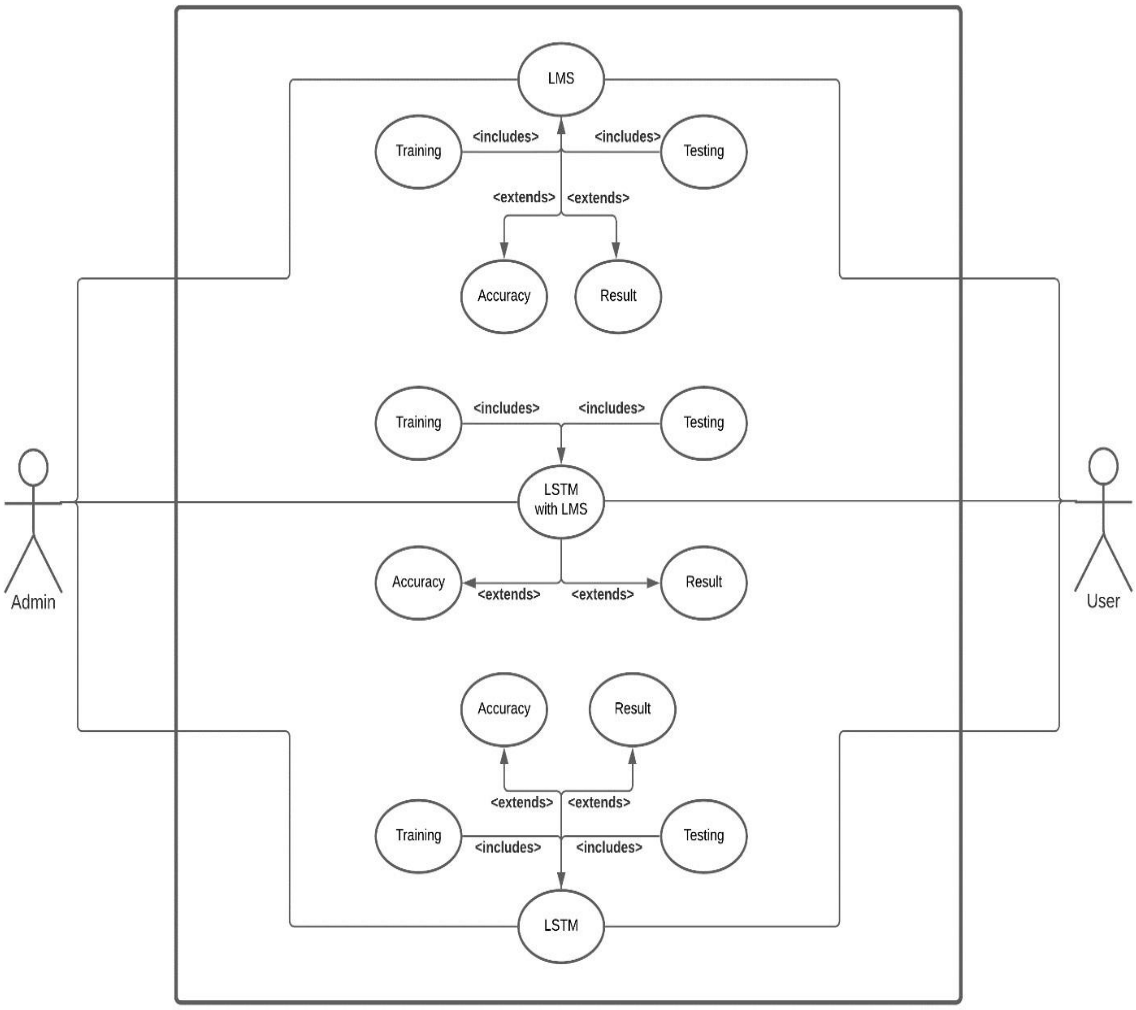


Fig. 14: Using LMS, LSTM and LSTM with LMS in the system

5.2.2 Sequence Diagram

Because it illustrates the interactions between a collection of items and the order in which they take place, a sequence diagram is a sort of interaction diagram. Software engineers and business experts use these diagrams to comprehend the specifications for a new system or to describe an existing procedure. Event diagrams and event scenarios are other names for sequence diagrams.

For corporations and other organisations, sequence diagrams may be a helpful resource. Consider creating a flowchart to:

- Display the specifics of a UML use case.
- Recreate the logic of a complex process, feature, or activity.
- Observe how elements and things work together to complete a process.
- Create a thorough functional plan for a current or potential circumstance.

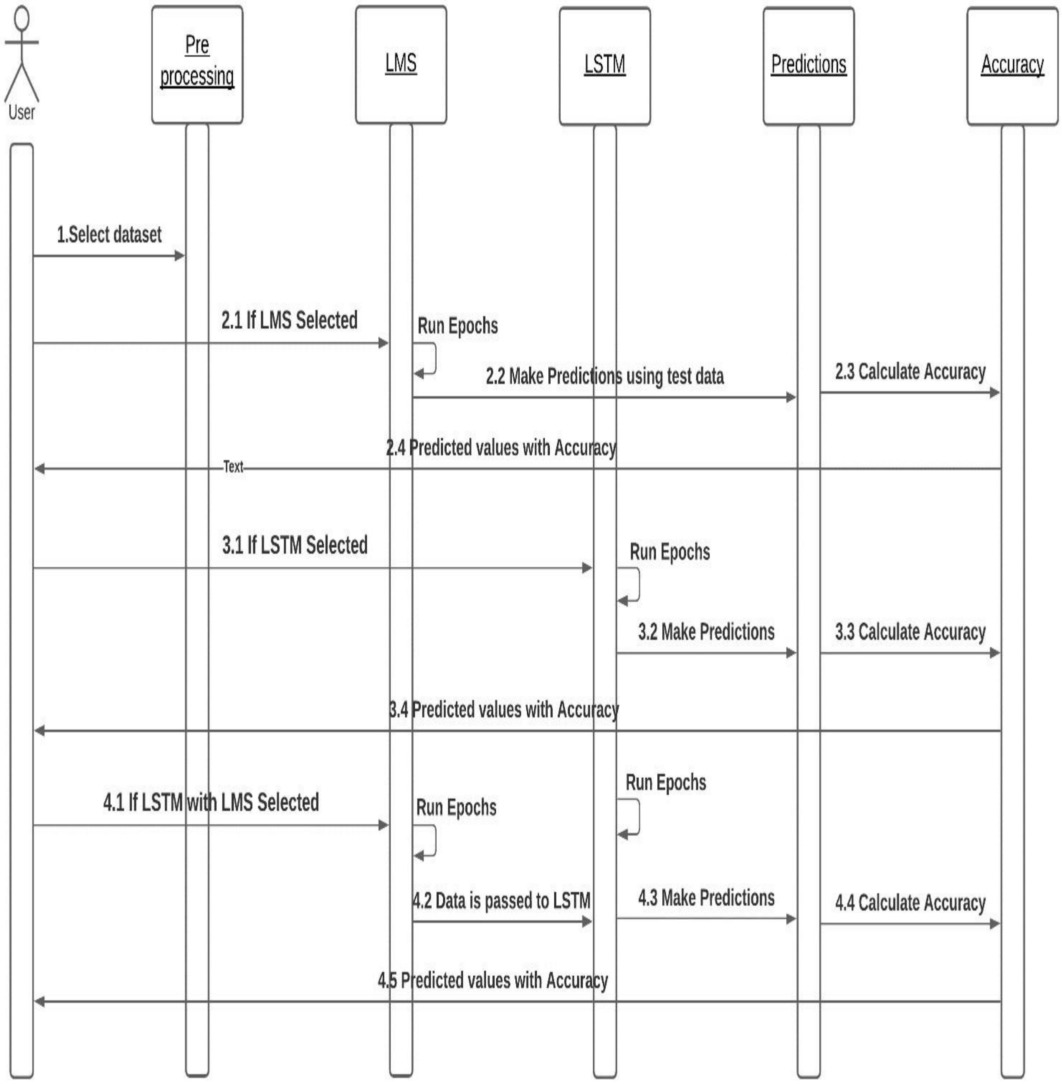


Fig. 15: Execution based on model selection

5.2.3 Activity Diagram

An activity diagram is a behavioral diagram i.e. it depicts the behavior of a system. An activity diagram portrays the control flow from a start point to a finish point showing the various decision paths that exist while the activity is being executed.

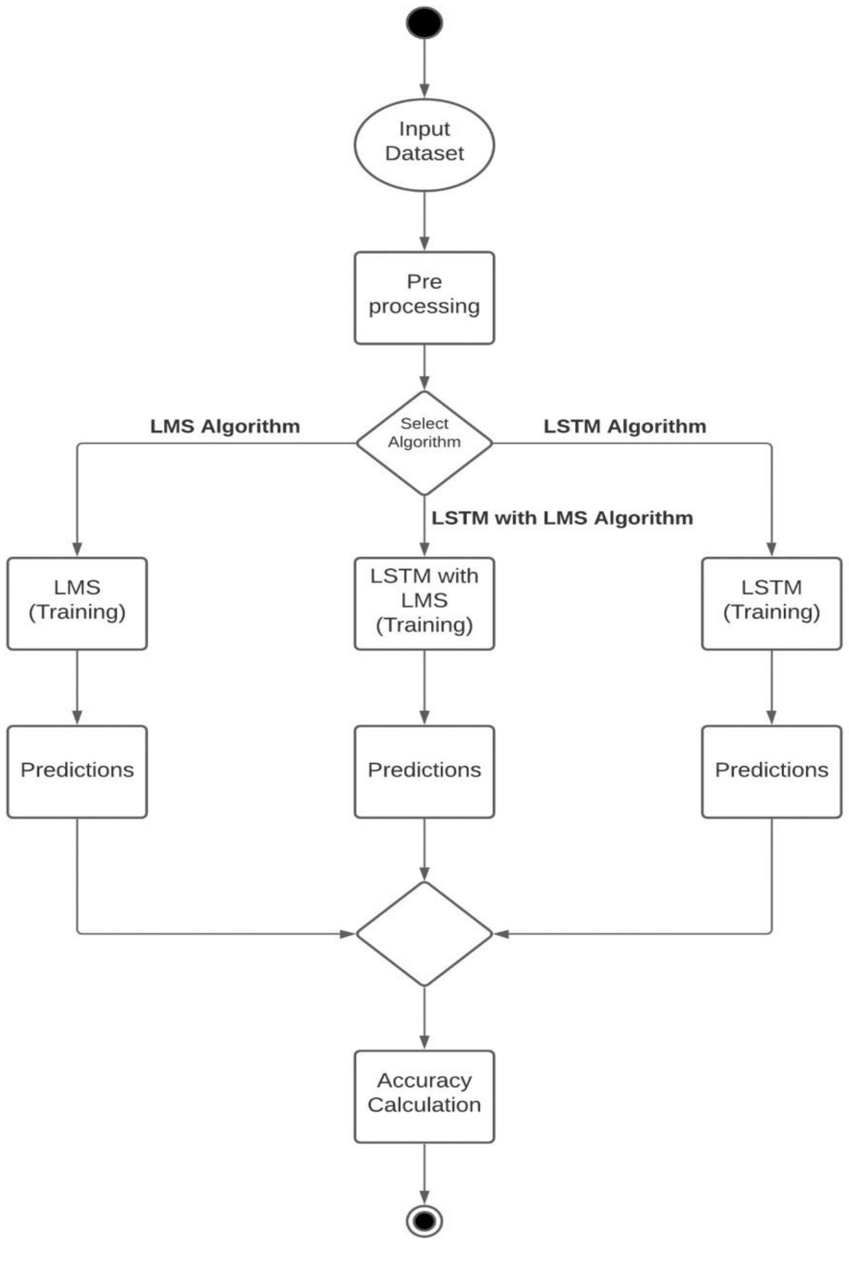


Fig. 16: Execution based on algorithm selection

5.2.4 Collaboration Diagram

Collaboration diagrams are used to demonstrate how objects work together to carry out a certain use case's behaviour or a section of it. Designers utilise collaboration in addition to sequence diagrams to specify and elucidate the responsibilities of the objects that carry out a certain flow of events in a use case. They serve as the main information source for establishing the roles and relationships between classes.

When it is crucial to show the interaction between the objects, collaborations are employed. The information is the same in both the sequence and cooperation diagrams, but they depict it quite differently. The analysis of use cases is best accomplished with the collaboration diagrams.

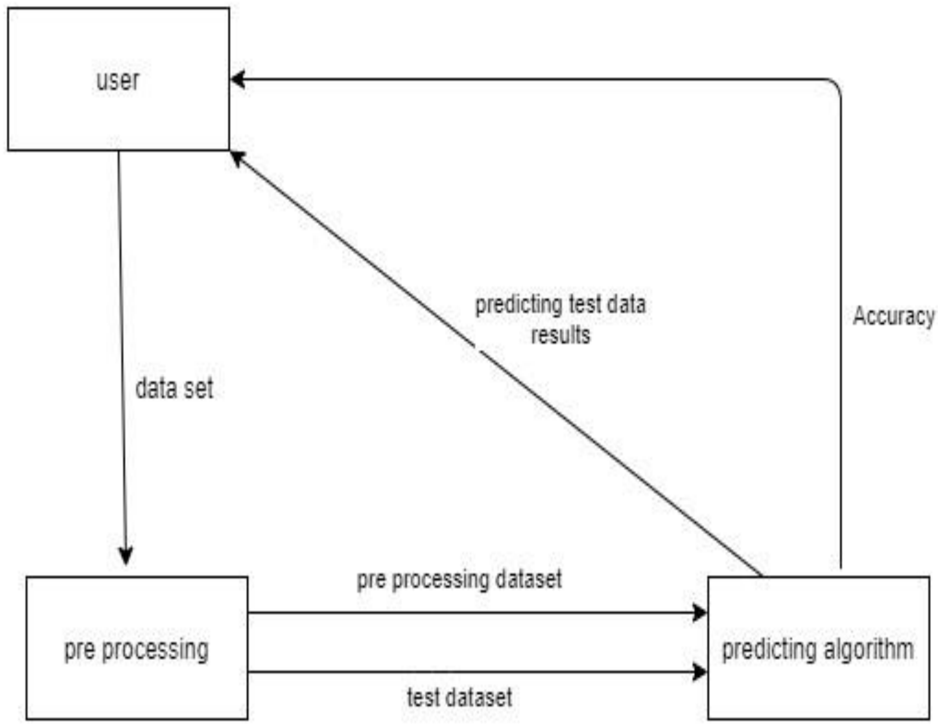


Fig. 17: Data transfer between modules

5.2.5 Flow Chart

A diagram that depicts a workflow or process is called a flowchart. Another definition of a flowchart is a diagrammatic description of an algorithm or a step-by-step process for addressing a problem. The flowchart displays the stages as a series of boxes of varying sizes, with arrows joining the boxes in the correct order.

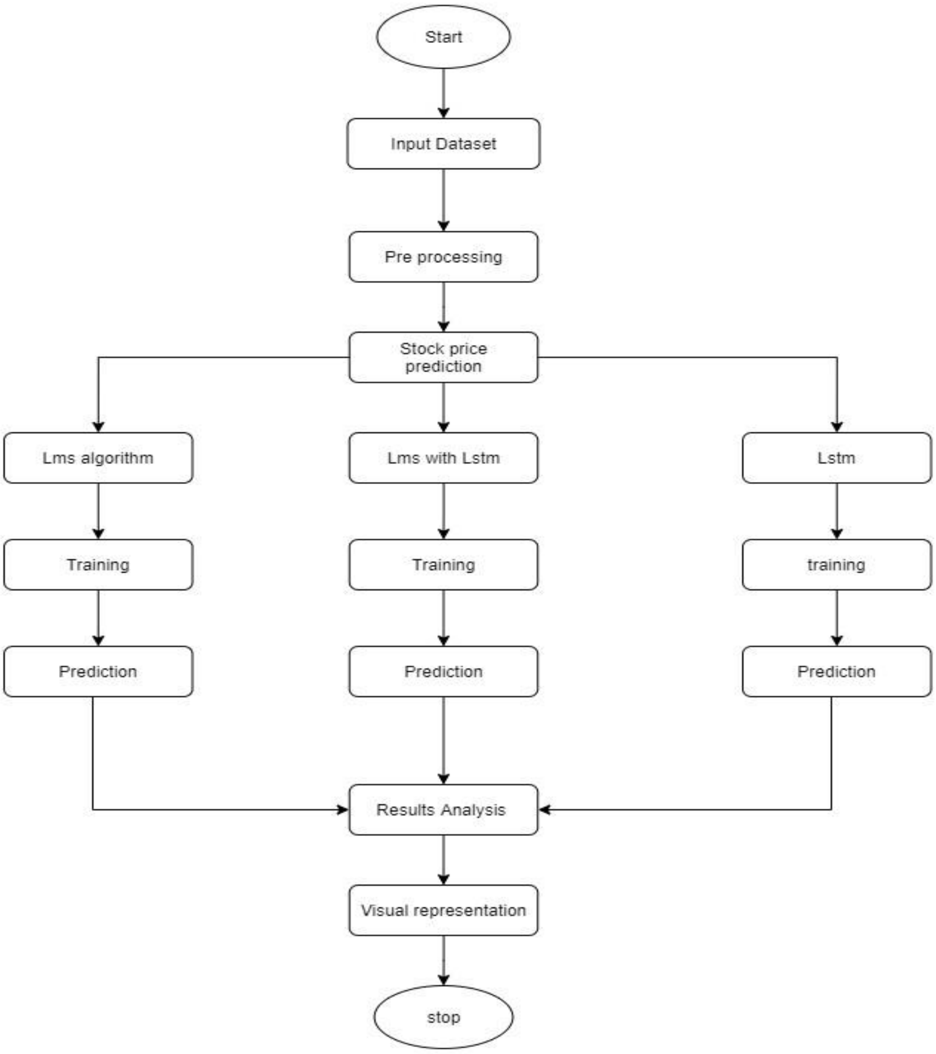


Fig. 18: Flow of execution

5.2.6 Component Diagram

A specific type of UML diagram is a component diagram. In addition, the goal is distinct from the previous diagrams mentioned. Although it does not define the system's functionality, it does describe the parts that go into creating that functionality.

In order to visualize, describe, and document component-based systems as well as to build executable systems through forward and reverse engineering, component diagrams are used to depict the physical features of object-oriented systems. Component diagrams, which are basically class diagrams that concentrate on a system's components and are frequently used to depict the static implementation perspective of a system, are a subset of class diagrams.

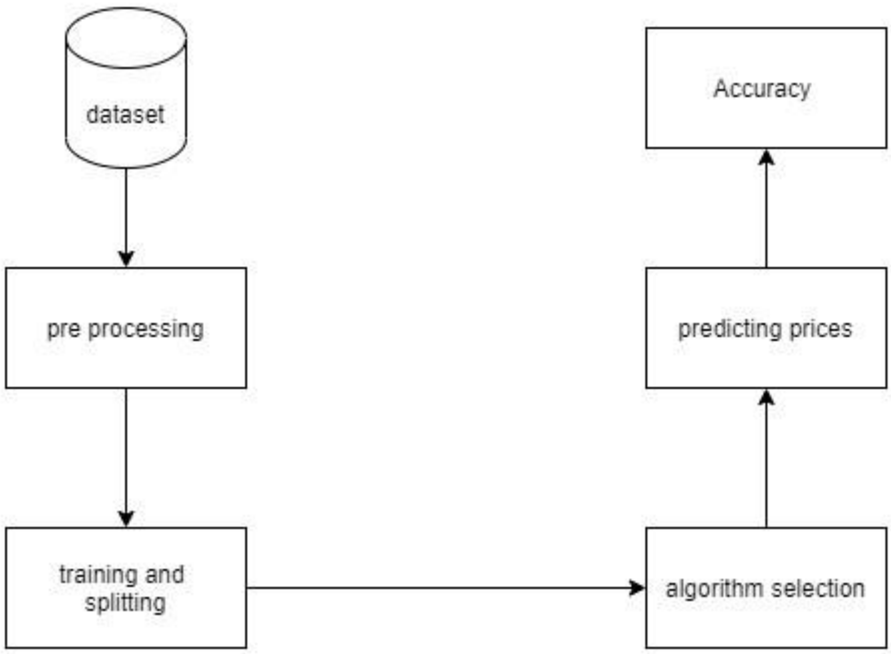


Fig. 19: Components present in the system

CHAPTER 6

RESULTS

6.1 RESULTS

Performance metrics and forecasts made using various forecasting techniques are demonstrated and compared. The result of the comparison led us to conclude that machine learning technique LSTM gives superior results compared to the moving average techniques.

6.1.1 100-Day Moving Average

In this we can depict from the graph that the 100 day moving average (100ma) figure out the mid-term price trends over the past 20 weeks and determines whether the price trend is up or down and based on that they can analyze the stock.

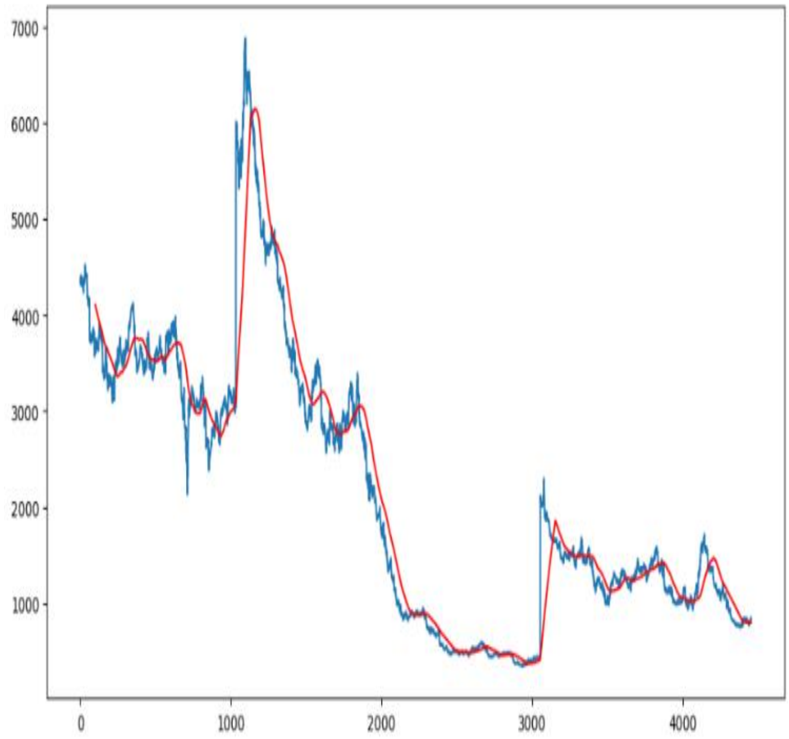


Fig. 20: 100-Day Moving Average

6.1.2 200-Day Moving Average

It is a moving average of a security's or index's closing prices over the previous 200 trading days. Traders and investors frequently utilise the 200 day simple moving average to evaluate overall trend of market or of a specific security. If a security's current price is higher than its 200 day simple moving average, than it is regarded as an upwards trend; if it is lower than its 200 day simple moving average, it is considered an downwards trend. This information may be used by traders and investors to make trading choices, such as purchasing or selling a security.

A security's 200 days simple moving average may also be employed as a resistance level or support level. If the price of a security goes below its 200 day simple moving average, it may operate as support level, restraining additional price declines. If, on the other hand, the price of a security rises above its 200-day moving average, than it may operate as barrier, preventing the price from increasing higher.

Although the 200 day simple moving average is a well known technical indicator, it should not be employed in isolation. Before making any trading choices, traders and investors should evaluate additional technical indications as well as fundamental research.

In this we can depict from the graph that the 200 day simple moving average (200ma) figure out the mid-term price trends over the past 20 weeks and determine whether the price trend is up or down and based on that they can analyse the stock.

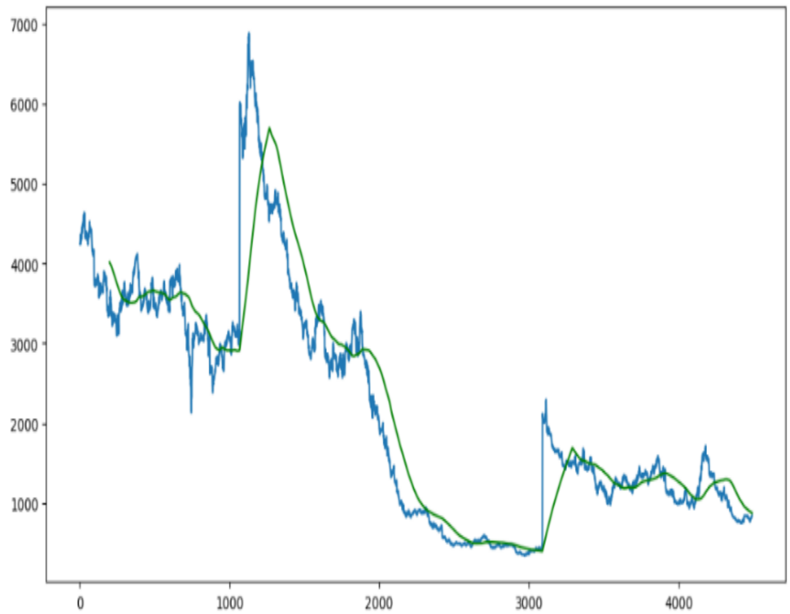


Fig. 21: 200-Day Moving Average

6.1.3 Original Price Vs Predicted Price

We have created LSTM models by training it on the ‘Close’ values of different stocks so that it can give us the best predicted result. We have use four LSTM layers with different Dropouts and a Dense layer with unit one.

We have fitted the model by training it to 100 epochs and based on the constructed model we get the predicted price corresponding to the original closing price.

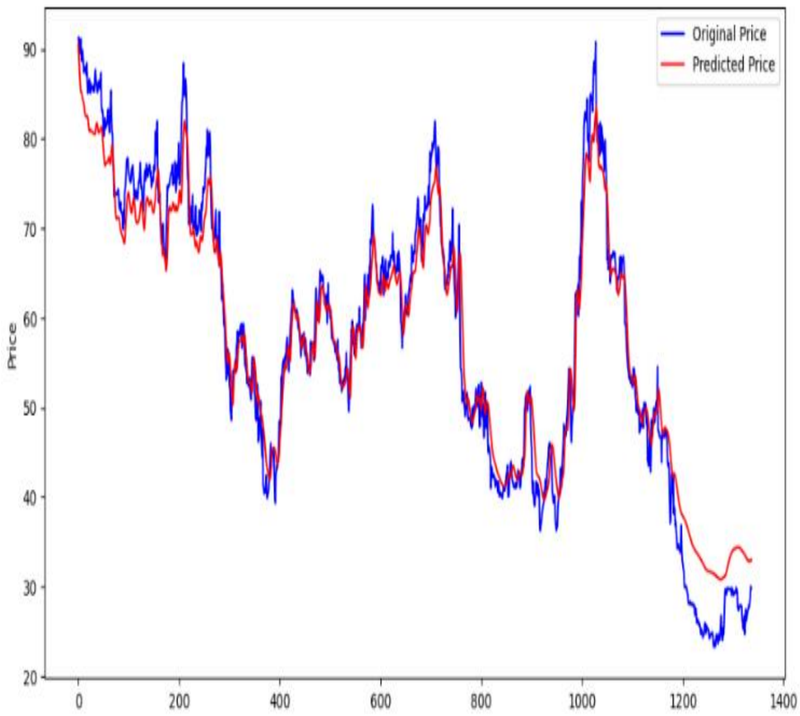


Fig. 22: Original Price Vs Predicted Price

6.1.4 Result Table

Stock Name	Last Closing Price	Predicted Closing Price	Actual Closing Price	Difference
POWERGRID	228.3	222.27	226	-1.63%
SBIN	425.2	417.86	422	-0.97%
HINDUNILVR	2,326.40	2317.77	2,328.30	-0.45%
INFY	1,402.25	1405.86	1,407.70	-0.13%
NESTLEIND	17,746.70	17474.28	17,545.00	-0.40%
BAJAJ-AUTO	4,246.10	4186.67	4,203.00	-0.38%
HDFCBANK	1,482.65	1462.66	1,507.75	-3.04%
INFY	1,402.25	1405.86	1,407.70	-0.13%
BRITANNIA	3,414.65	3433.87	3,428.70	0.15%
TITAN	1,594.25	1594.81	1,578.20	1.04%
ITC	211.15	213.27	212.9	0.18%
ADANIPORTS	751.4	779.89	777	0.38%
QUESS	680.85	671.57	689	-2.56%
HINDZINC	328.75	329.13	326.65	0.75%
RELIANCE	1,976.10	2111.16	2,094.45	0.85%
TATASTEEL	1096.65	1113.61	1,104.00	0.88%
GRANULES	315.9	322.81	316.7	1.93%
SUNPHARMA	699.5	678.95	672.65	0.90%
ASIANPAINT	2,949.35	2964.87	2,935.70	0.99%
SHREECEM	28,066.05	27993.64	27,599.00	1.41%

Table. 3: Result Table

CHAPTER 7

CONCLUSION AND FUTURE SCOPE

7.1. Conclusion

As the stock market is bound tightly to a country's economic growth and brings in huge investments by the investors and issues equities in the public interest, forecasting the movement of the stock prices and the market becomes essential in order to prevent huge losses and make relevant decisions. In this paper, we proposed a comparative study of various algorithms for forecasting the prices of different stocks.

The study was extended from the traditional ML algorithms such as RF, KNN, SVM, Naive Bayes, etc. to Deep Learning and Neural Network models such as Convolutional Neural Networks, Artificial Neural Networks, Long Short-Term Memory, etc. The study also includes various other approaches such as Sentiment analysis, Time series analysis and Graph-Based algorithms and compares results of these algorithms to predict the stock prices of various companies.

The development of a stock price prediction app using machine learning has the potential to revolutionize the way investors make informed decisions in the stock market. By harnessing the power of advanced algorithms and historical data, such an app can provide valuable insights and predictions about future stock prices.The integration of machine learning algorithms allows the app to analyze vast amounts of data, including historical price patterns, financial indicators, market news, and even social media sentiment. This comprehensive analysis enables the app to identify relevant patterns, correlations, and trends that human analysts might overlook, leading to more accurate predictions.

Investors can benefit from the app's ability to generate real-time predictions, allowing them to make timely investment decisions based on the most up-to-date information. By considering multiple factors and incorporating machine learning techniques, the app can provide a holistic view of the market dynamics and help investors identify potential opportunities and risks.

Additionally, the app can serve as a valuable educational tool for novice investors, providing them with insights into the complexities of the stock market and helping them navigate the investment landscape with greater confidence. It can empower users by presenting them with data-driven predictions and fostering a deeper understanding of the factors influencing stock prices. However, it is essential to acknowledge the inherent limitations of stock price prediction models, including the unpredictable nature of the market and the influence of external factors beyond the scope of historical data. Investors should exercise caution and not solely rely on the app's predictions, but rather use them as one of several inputs in their investment decision-making process.

In summary, the development of a stock price prediction app using machine learning offers significant potential to enhance investment strategies and decision-making in the stock market. By leveraging advanced algorithms and comprehensive data analysis, such an app can provide valuable insights, facilitate informed decision-making, and contribute to a more efficient and knowledgeable investor community.

7.2. Future Scope

The future scope of a stock price prediction app using machine learning is promising, with several potential avenues for growth and enhancement. Here are some key areas that hold great potential:

1. **Improved Accuracy and Performance:** As machine learning algorithms continue to evolve, there is room for further improvement in the accuracy and performance of stock price predictions. Ongoing research and development can lead to the refinement of existing models and the exploration of new techniques, resulting in more reliable predictions and reduced margin of error.

2. **Integration of Alternative Data Sources:** Currently, stock price prediction models primarily rely on historical financial and market data. However, the inclusion of alternative data sources, such as satellite imagery, social media sentiment analysis, and news sentiment analysis, can provide a more comprehensive view of market dynamics. Integrating these alternative data sources can lead to better predictions and insights into market behavior.

3. **Real-time Predictions and Adaptive Models:** Real-time predictions are crucial for investors who need to make quick decisions in a rapidly changing market. Future iterations of stock price prediction apps can focus on developing adaptive models that can continuously learn and adapt to changing market conditions. By incorporating real-time data feeds and utilizing advanced machine learning techniques like online learning, the app can provide up-to-the-minute predictions and adapt to market fluctuations effectively.

4. **Personalized Recommendations and Risk Assessment:** Customization and personalization are key areas for future development. By considering an investor's risk appetite, investment goals, and preferences, the app can generate personalized stock recommendations and risk assessments. This personalized approach can provide users with tailored insights that align with their individual investment strategies and preferences.

5. **Enhanced Visualization and Interpretability:** Presenting complex data and predictions in a visually appealing and easily interpretable manner is crucial for user engagement. Future versions of the app can focus on developing intuitive and interactive visualizations that enable users to understand the rationale behind predictions and explore different scenarios. This can enhance user trust and confidence in the app's recommendations.

6. **Integration with Trading Platforms:** Seamless integration with online trading platforms can streamline the investment process. The app can provide direct links to trading platforms, allowing users to execute trades based on the generated predictions without leaving the app. This integration can offer a seamless user experience and enhance the efficiency of investment decision-making.

In conclusion, the future scope of a stock price prediction app using machine learning is bright. Advancements in machine learning algorithms, integration of alternative data sources, real-time predictions, personalization, enhanced visualization, and integration with trading platforms can propel the app's capabilities to new heights. By continuously improving accuracy, customization, and user experience, such an app has the potential to become an indispensable tool for investors in navigating the complex and dynamic world of the stock market.

REFERENCES

[1] Stock Price Prediction Using LSTM on Indian Share Market by Achyut Ghosh, Soumik Bose1, Giridhar Maji, Narayan C. Debnath, Soumya Sen.

[2] S. Selvin, R. Vinayakumar, E. A. Gopalkrishnan, V. K. Menon and K. P. Soman, "Stock price prediction using LSTM, RNN and CNN-sliding window model," in International Conference on Advances in Computing, Communications and Informatics, 2017.

[3] Murtaza Roondiwala, Harshal Patel, Shraddha Varma, “Predicting Stock Prices Using LSTM” in Undergraduate Engineering Students, Department of Information Technology, Mumbai University, 2015.

[4] Xiongwen Pang, Yanqiang Zhou, Pan Wang, Weiwei Lin, “An innovative neural network approach for stock market prediction”, 2018

[5] Ishita Parmar, Navanshu Agarwal, Sheirsh Saxena, Ridam Arora, Shikhin Gupta, Himanshu Dhiman, Lokesh Chouhan Department of Computer Science and Engineering National Institute of Technology, Hamirpur – 177005, INDIA - Stock Market Prediction Using Machine Learning.

[6] Pranav Bhat Electronics and Telecommunication Department, Maharashtra Institute of Technology, Pune. Savitribai Phule Pune University - A Machine Learning Model for Stock Market Prediction.

[7] Anurag Sinha Department of computer science, Student, Amity University Jharkhand Ranchi, Jharkhand (India), 834001 - Stock Market Prediction Using Machine Learning.

[8] V Kranthi Sai Reddy Student, ECM, Sreenidhi Institute of Science and Technology, Hyderabad, India - Stock Market Prediction Using Machine Learning.

[9] Asset Durmagambetov currently works at the mathematics, CNTFI. Asset does research in Theory of Computation and Computing in Mathematics, Natural Science, Engineering and Medicine. Their current project is 'The Riemann Hypothesis-Millennium Prize Problems' - stock market predictions.

[10] Mariam Moukalled Wassim El-Hajj Mohamad Jaber Computer Science Department American University of Beirut - Automated Stock Price Prediction Using Machine Learning.

[11] Manh Ha Duong Boriss Siliverstovs June 2006 - The Stock Market and Investment.

[12] Dharmaraja Selvamuthu , Vineet Kumar and Abhishek Mishra Department of Mathematics, Indian Institute of Technology Delhi, Hauz Khas, New Delhi 110016, India - Indian stock market prediction using artificial neural networks on tick data.

[13] Lufuno Ronald Marwala A dissertation submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand, Johannesburg, in fulfilment of the requirements for the degree of Master of Science in Engineering - Forecasting the Stock Market Index Using Artificial Intelligence Techniques.

[14] Xiao-Yang Liu1 Hongyang Yang,Qian Chen4,Runjia ZhangLiuqing Yang Bowen Xiao Christina Dan Wang Electrical Engineering, 2Department of Statistics, 3Computer Science, Columbia University, 3AI4Finance LLC., USA, Ion Media Networks, USA, Department of Computing, Imperial College, 6New York University (Shanghai) - A Deep Reinforcement Learning Library for Automated Stock Trading in Quantitative Finance.

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[18] Hyeong Kyu Choi, B.A Student Dept. of Business Administration Korea University Seoul, Korea = Stock Price Correlation Coefficient Prediction with ARIMA-LSTM Hybrid Model.

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APPENDIX 1

1.1 Research Paper

LSTM and Moving Averages Comparison Research for Stock Price Forcasting

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***Abstract* — This research paper compares the utilization of machine learning techniques like Long Short-Term Memory (LSTM) and traditional methods including 100ma and 200ma for price prediction on different stocks. This study involves analyzing historical stock data with the Bombay Stock Exchange, furthermore, training an LSTM model to guess future stock prices, and based on that, comparing the predicted results with other methods. Overall, this research demonstrates the efficiency of using LSTM models for stock price prediction as well as the potential for incorporating additional data sources to further improve the accuracy of these predictions.**

Keywords—Alpha Vantage, 100-day moving average, 200-day moving average, open, high, low, close, volume, Long Short Term Memory.

INTRODUCTION

The history of stock exchanges begin when the Dutch East India Company in 1611 was listed on an official Stock Exchange. Since then, investors have been seeking new ways to learn about the companies listed on the stock exchanges and increase their investment returns. Investors used to rely only on historical knowledge to identify patterns and estimate share values. However, with over 30 million trading accounts in India and the industry increasing so quickly, conventional strategies are becoming obsolete [1].

Essentially, quantitative traders that carry a large amount of money in the stock market buy equities, derivatives, ETFs, futures, options and stock at a low price and then sell them at a high one. The eagerness for trend prediction in stock market prediction is classical phenomenon, but several organizations continue to debate on it. There are mainly two types of analysis of stock that investors do ahead of investing in any stock. The first is analysis of the fundamentals of the company or asset they are investing, in which they calculate the intrinsic value of stock as well as performance of the industry, reputation of the company, economy, sector growth and demand and so on to determine whether to put their money in the stock or not. Secondly they do Technical analysis to determine the correct time to entry in the stock which includes the study of market data such as past prices, trends and trading-volumes to predict the movement of stock.

Stock market is regarded as aggressive, uncertain, and non-linear in nature. Anticipating stock prices is a tough task as stock prices are influenced by a broad no of factors, which includes but is not limited to current supply of that product or service, the competition faced, financial results of past few quarters and the consumption of products or services provided, and so on. So to widen the profits and narrowing the losses, techniques for forecasting share values ahead of time by analysing movements over the last few months could be extremely useful for predicting stock market movements [2] [3]. Commonly, two methodologies are presented for anticipating a company's stock price: Technical analysis forecast ultimate stock prices by employing previous stock prices such as opening value, highest traded value, lowest traded value, closing value, volumes, and so on. The qualitative analysis is accomplished according to independent factors such as company reputation, revenue, operations cost, management decisions, profits and earning per share [4]. Progressive, sophisticated approaches based on either fundamental or technical research are currently used to forecast share values. The figures for stock price prediction market is enormous and non-linear. To deal with this variety of figures, an competent algorithm that can identify unseen trends and complex associations in this enormous data set is necessary. Machine learning techniques in this area had shown an boost in efficacy by 61–87 percent when compared to earlier methods [5].

Most foregoing work in the vicinity has used scholastic algorithms like simple regression, random walk theory (RWT) [7], relative strength index (RSI), and some linear models like autoregressive integrated moving average (ARIMA) [9], seasonal autoregressive integrated moving average model (SARIMA) and autoregressive moving average (ARMA) to predict stock prices. Late research indicates that machine learning can improve stock market predictions. Some neural network based techniques, such as shift invariant or space invariant artificial neural networks (SIANN), simulated neural networks (SNN), Feedback neural networks (FNN), and deep neural networks (LSTM) [5] [12], had given promising results.

A prosperous stock prediction can generate significant profits for both the investor and the business. Predictions might be made by cautiously reviewing the background of the relevant stock market because it is often claimed that it is chaotic rather than random. Machine learning can be used to adequately describe such processes. Financial trend analysis and forecasting of anticipated stock value trends and returns have long been important areas of investigation [13].

In this study, data from Alpha Vantage is used to apply supervised machine learning. Close, Open, Low, High, and Volume are the five variables—make up this dataset. Close, open, high, and low comprise several of the stock's bid prices at various moments with essentially plain labels. It is the volume of the total block of shares that were transferred from one proprietor to the next within the deadline. Next, the prototype is evaluated using the test results.

We have compared different methods to predict the price of stocks so the more accurate method can be analyzed. The methods we used for comparison are 100 days simple moving average (100ma), 200 days simple moving average (200ma) and LSTM (Long Short-Term Memory). We have also analyzed the predicted results and compared it by plotting graph.

BACKGROUND STUDY

Beside the introduction of new products such as stocks, bonds, options, and futures, the financial market has grown increasingly complicated. The stock market is the most common financial tool into which people put their money. Stock market is a market with large up and downs, with values fluctuating often because of a variety of variables such as economic and political developments as well as company-specific news.

Predicting the future price of a company is an important field of research for investors since it allows them to make informed investment decisions. Traditional financial models, such as the Black-Scholes model, have been employed in the past to forecast stock values. However, these models have not been particularly efficient in properly predicting stock values, and they do not take into consideration the complicated interactions between the various factors that impact stock prices.

Stock price prediction using machine learning:
Because of its capacity to understand complicated correlations between diverse elements that impact stock prices, machine learning has emerged as an advantageous tool for stock price forecasting. Machine learning techniques may produce accurate forecasts about future stock values by taking into consideration a wide range of elements, such as previous share values, financial measures, and news items.
Machine learning models are widely divided into two types: supervised learning and unsupervised learning. A model learns on the set of labelled data with the outcome variable known in supervised learning. Unsupervised learning involves training a model on a collection of unlabeled data and teaching the model to recognize trends in data.

Stock price prediction by supervised learning models:
Regression, support vector machines (SVM), and neural networks are supervised learning models that may be used to predict stock values.

For stock price prediction, regression models such as linear regression and logistic regression are often used. To create accurate forecasts regarding future stock values, regression models can take into consideration a wide range of elements, including past stock prices, economic indicators, and news items.

SVM models are another popular choice for stock price prediction. SVM models can consider a wide range of factors, including historical share values, financial measures, and news articles, to form accurate forecasting about ultimate share values. SVM models are particularly effective at identifying patterns in data that are not easily visible.

Another effective approach for stock price prediction is neural networks. To produce accurate forecasts regarding future share values, neural networks may use a wide range of data, including past stock prices, economic indicators, and news items. Neural networks are very good at detecting complicated patterns in data that are not readily obvious.
Models of Unsupervised Learning for Stock Price Prediction
Clustering and association rules are two unsupervised learning algorithms that may be used to forecast stock prices.
Clustering techniques may be used to detect patterns in the data and classify it into comparable groups. To produce reliable forecasts regarding future stock values, clustering models can take into consideration a wide range of elements, including past stock prices, economic indicators, and news items.

Association rule models may be used to detect patterns in data and predict outcomes based on those patterns. To produce reliable forecasts regarding future stock values, association rule models can take into consideration a wide range of data, including past stock prices, economic indicators, and news items.

METHODOLOGY

Using the stock API offered by Alpha Vantage, we will first retrieve the most recent updates and data for a certain stock. This stage will be very beneficial because the function we're making will automatically and continuously update itself with the most recent information. Users can access a wide range of data, including real-time updates and historical information on stocks, currencies, and cryptocurrencies, thanks to Alpha Vantage's free stock APIs.

	open	high	low	close	volume
0	4354.9500	4444.0000	4329.1000	4369.3000	13095.0
1	4391.0500	4417.1500	4264.2000	4318.1000	8130.0
2	4370.0000	4420.0000	4321.0500	4408.5500	3176.0
3	4356.6000	4437.3500	4355.6000	4380.3000	7776.0
4	4350.8501	4436.0000	4350.8501	4397.2002	1884.0
...	...	...	...	...	...
4451	834.1420	834.1420	807.5272	812.3168	6260.0
4452	813.3562	834.9102	780.9124	819.9534	182350.0
4453	849.5054	853.5722	817.8748	826.6862	2090100.0
4454	840.4680	849.5054	836.0398	845.3030	88030.0
4455	840.4680	849.5054	813.3562	842.3208	16330.0

Figure 1. Stock Data Fetched from Alpha Vantage

A. 100-Days Moving Average

The closing price average over the past 20 weeks or 100 days is known as a 100-day Moving Average (MA). The mid-term price trends are represented by it. Investors can observe how the stock has performed over the past 20 weeks and determine whether the price trend is up or down by using a moving average over 100 days. This also provides them a sense of the mood of the market.

A moving average is quite easy to calculate. The closing prices for each day (day 1, day 2, day 3, etc.), added together, are then divided by the total number of days. As a result, for 100 days, n's MA value will be 100.

B. 200-Days Moving Average

The mean of the closing prices over the past 20 weeks or 200 days is known as a 200-day Moving Average (MA). The mid-term price trends are represented by it. Investors can observe how the stock has performed over the past 20 weeks and determine whether the price trend is up or down by using a moving average over 200 days. This also provides them a sense of the mood of the market.

A moving average is quite easy to calculate. The closing prices for each day (day 1, day 2, day 3, etc.), added together, are then divided by the total number of days. As a result, for 200 days, n's MA value will be 200.

C. LSTM (Long short term memory)

Fundamentally, the fully connected network LSTM design belongs toward the recurrent neural network family (RNNs). The presence of feedback loops distinguishes RNNs from other deep neural networks. The disappearing and inflating gradient problem that plagues RNNs, prevents the system from ever converging to the point of the least error by either causing it to halt learning or maintain learning at a very high rate. The LSTM network topologies are found to be particularly well adapted for modelling intricate sequential data, including texts and time series, as vanishing or inflating gradient difficulties are never a problem.

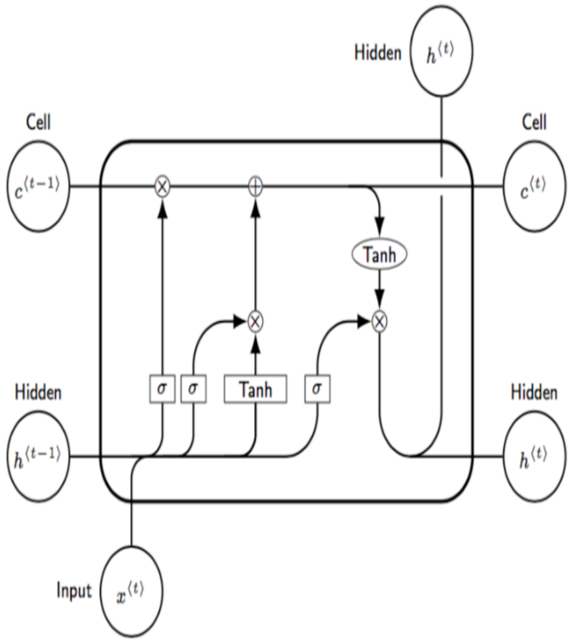

Figure 2. Long Short-Term Memory

These networks are made up of gates that control and regulate the information flow across these cells and cells that store the network's prior state data. Input gate, Output gate, and forget gate are the three different gates that are employed in LSTM networks. Retaining only the details that are important as long as this present window exists and deleting past information that is no longer relevant are both made possible by forget gates. The fresh data that is used to determine the network's current state is regulated by the input gates. The network's memory cells cleverly blend that past data on the state from the already stated forget gates with the network's current source input that is obtained from the input gate. The results of the network are finally produced by the output gates at the designated time slot. The model's predicted value for the current slot can be thought of as the output.

This research builds a sequential model by piling four LSTM layers with different dropouts on top of one another. The first layer is Input layer which provide data to the LSTM layers, and further there exist four LSTM layers with different Dropouts so that it can give us unique predicted value.

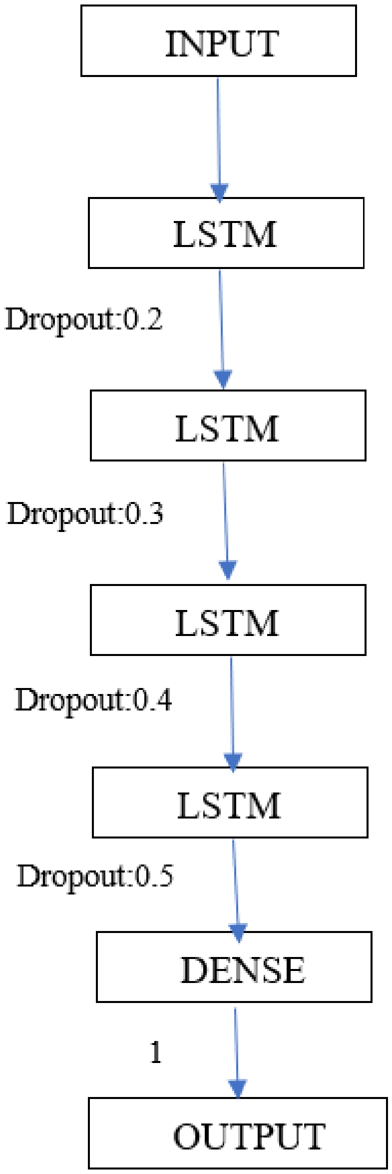

Figure 3. LSTM Layers

RESULTS

Performance metrics and forecasts made using various forecasting techniques are demonstrated and compared. The result of the comparison led us to conclude that machine learning technique LSTM gives superior results compared to the moving average techniques.

A. 100-Day Moving Average

In this we can depict from the graph that the 100 day moving average (100ma) figure out the mid-term price trends over the past 20 weeks and determines whether the price trend is up or down and based on that they can analyze the stock.

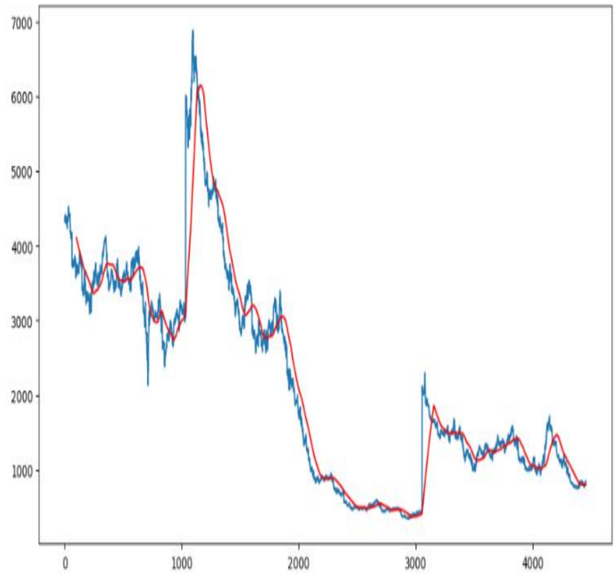

Figure 4. (a) 100ma

B. 200-Day Moving Average

It is a moving average of a security's or index's closing prices over the previous 200 trading days. Traders and investors frequently utilise the 200 day simple moving average to evaluate overall trend of market or of a specific security.

If a security's current price is higher than its 200 day simple moving average, than it is regarded as an upwards trend; if it is lower than its 200 day simple moving average, it is considered an downwards trend. This information may be used by traders and investors to make trading choices, such as purchasing or selling a security.

A security's 200 days simple moving average may also be employed as a resistance level or support level. If the price of a security goes below its 200 day simple moving average, it may operate as support level, restraining additional price declines. If, on the other hand, the price of a security rises above its 200-day moving average, than it may operate as barrier, preventing the price from increasing higher.

Although the 200 day simple moving average is a well known technical indicator, it should not be employed in isolation. Before making any trading choices, traders and investors should evaluate additional technical indications as well as fundamental research.

In this we can depict from the graph that the 200 day simple moving average (200ma) figure out the mid-term price trends over the past 20 weeks and determine whether the price trend is up or down and based on that they can analyse the stock.

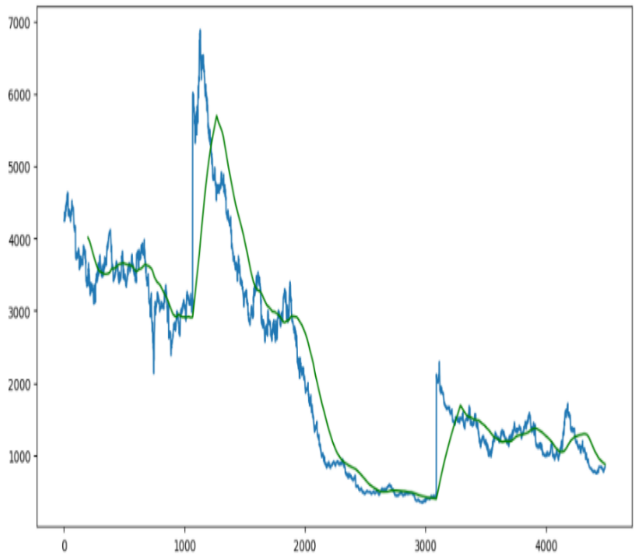

Figure 4. (b) 200ma

C. LSTM (Long short-term memory)

We have created LSTM models by training it on the 'Close' values of different stocks so that it can give us the best predicted result. We have use four LSTM layers with different Dropouts and a Dense layer with unit one.

We have fitted the model by training it to 100 epochs and based on the constructed model we get the predicted price corresponding to the original closing price.

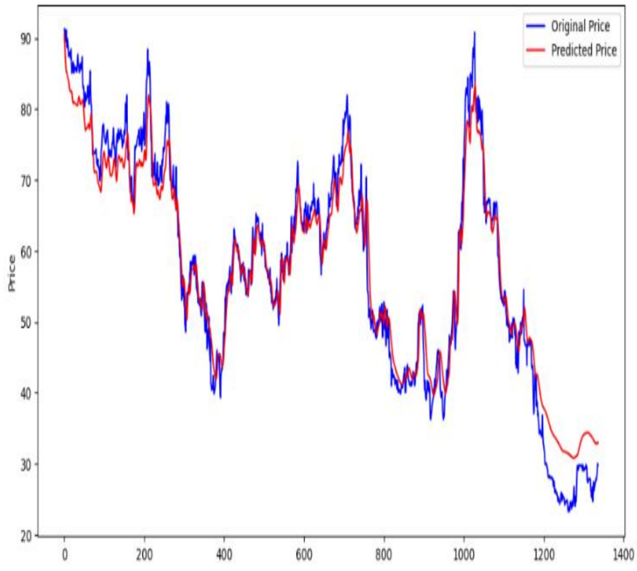

Figure 4. (c) Original Price Vs Predicted Price

CONCLUSION

Stock market prediction is a relatively new phenomenon, and there are mainly two types of analysis of stock that investors do ahead of investing in any stock. The first is analysis of the fundamentals of the company or asset they are investing, in which they calculate the intrinsic value of stock as well as performance of the industry, reputation of the company, economy, sector growth and demand and so on to determine whether to put their money in the stock or not. Secondly they do Technical analysis to determine the correct time to entry in the stock which includes the study of market data such as past prices, trends and trading-volumes to predict the movement of stock. Machine learning can be used to adequately describe such processes, and this study uses data from Alpha Vantage to apply supervised machine learning to analyze the stock market. Five variables are included in the dataset: close, open, high, and low, which comprise several of the stock's bid prices at various moments with essentially plain labels.

The prototype is evaluated using the test results, and comparisons are made using different methods. Stock market is regarded as aggressive, uncertain, and non-linear in nature. So to widen the profits and narrowing the losses, techniques for forecasting share values ahead of time by analysing movements over the last few months could be extremely useful for predicting stock market movements. Commonly, two methodologies are presented for anticipating a company's stock price: Fundamental Analysis and Technical analysis. Progressive, sophisticated approaches based on either fundamental or technical research are currently used to forecast share values.

Machine learning techniques in this area had shown an boost in efficacy by 61–87 percent when compared to earlier methods. Recent analysis announce that machine learning can enhance stock market predictions, with some simulated neural network based techniques, such as FNN, SIANN, RNN, and LSTM, providing encouraging results.

A relative evaluation among statistical methodologies, both in terms of prediction performances and accuracy, and machine learning approaches, following the analysis of each approach separately, reveals machine learning approaches to be the most accurate for predicting stock values.

Due to an improvement in forecast accuracy, both tactics have produced favorable results. Inspiring findings from recently created machine learning algorithms for stock prediction point to their use in lucrative trading strategies. As a result researchers have been led to the findings that stock market estimations can be produced more successfully and more precisely by utilizing machine learning techniques.

By using a dataset that is substantially bigger than the current one, it will now be possible to use it. In the future, the stock market's methods and approach could be greatly improved. The accuracy of our estimation techniques would consequently improve. Moreover, additional machine learning techniques could remain investigated to look at the accuracy rate resulting from them.

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We are pleased to express our gratitude to all of the team members and businesses who participated in this research on machine learning-based stock price prediction. In the First place, we prefer to state our recognition to our supervisor, Dr. Dilkeshwar Pandey, for his crucial advice and assistance during the project. We would also like to convey our appreciation to Alpha Vantage for helping us gather the required financial information.

References

Y. Wang and Y. Wang, "Using social media mining technology to assist in price prediction of stock market," 2016 IEEE International Conference on Big Data Analysis (ICBDA), Hangzhou, China, 2016, pp. 1-4, doi: 10.1109/ICBDA.2016.7509794.

Masoud, Najeb MH. (2017) "The impact of stock market performance upon economic growth." International Journal of Economics and Financial Issues 3 (4) : 788–798.

Murkute, Amod, and Tanuja Sarode. (2015) "Forecasting market price of stock using artificial neural network." International Journal of Computer Applications 124 (12) : 11-15.

Hur, Jung, Manoj Raj, and Yohanes E. Riyanto. (2006) "Finance and trade: A cross-country empirical analysis on the impact of financial development and asset tangibility on international trade." World Development 34 (10) : 1728-1741.

Li, Lei, Yabin Wu, Yihang Ou, Qi Li, Yanquan Zhou, and Daoxin Chen. (2017) "Research on machine learning algorithms and feature extraction for time series." IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC): 1-5.

Seber, George AF and Lee, Alan J. (2012) "Linear regression analysis." John Wiley & Sons 329.

Reichek, Nathaniel, and Richard B. Devereux. (1982) "Reliable estimation of peak left ventricular systolic pressure by M-mode echographicdetermined end-diastolic relative wall thickness: identification of severe valvular aortic stenosis in adult patients." American heart journal 103 (2) : 202-209.

Chong, Terence Tai-Leung, and Wing-Kam Ng. (2008) "Technical analysis and the London stock exchange: testing the MACD and RSI rules using the FT30." Applied Economics Letters 15 (14) : 1111-1114.

Zhang, G. Peter. (2003) "Time series forecasting using a hybrid ARIMA and neural network mode." Neurocomputing 50 : 159-175.

Suykens, Johan AK, and Joos Vandewalle. (1999) "Least squares support vector machine classifiers." Neural processing letters 9 (3) : 293-300.

Liaw, Andy, and Matthew Wiener. (2002) "Classification and regression by Random Forest." R news 2 (3) : 18-22.

Oyeyemi, Elijah O., Lee-Anne McKinnell, and Allon WV Poole. (2007) "Neural network-based prediction techniques for global modeling of M (3000) F2 ionospheric parameter." Advances in Space Research 39 (5) : 643-650.

M. Usmani, S. H. Adil, K. Raza and S. S. A. Ali, "Stock market prediction using machine learning techniques," 2016 3rd International Conference on Computer and Information Sciences (ICCOINS), Kuala Lumpur, 2016, pp. 322-327.

K. Raza, "Prediction of Stock Market performance by using machine learning techniques," 2017 International Conference on Innovations in Electrical Engineering and Computational Technologies (ICIEECT), Karachi, 2017, pp. 1-1.

H. Gunduz, Z. Cataltepe and Y. Yaslan, "Stock market direction prediction using deep neural networks," 2017 25th Signal Processing and Communications Applications Conference (SIU), Antalya, 2017, pp. 1-4.

M. Billah, S. Waheed and A. Hanifa, "Stock market prediction using an improved training algorithm of neural network," 2016 2nd International Conference on Electrical, Computer & Telecommunication Engineering (ICECTE), Rajshahi, 2016, pp. 1-4.

J. Sen, "Stock price prediction using machine learning and deep learning frameworks," In Proceedings of the 6th International Conference on Business Analytics and Intelligence, Bangalore, India, 2018.

M. Z. Asghar, F. Rahman, F. M. Kundi, and S. Ahmed, "Development of stock market trend prediction system using multiple regression", Computational and Mathematical Organization Theory, vol. 25, pp. 271-301, 2019.

Al-Mahasneh, A. J., Anavatti, S. G., and Garratt, M. A. (2018). Review of Applications of Generalized Regression Neural Networks in Identification and Control of Dynamic Systems. arXiv preprint arXiv:1805.11236.

Yetis, Yunus, Halid Kaplan, and Mo Jamshidi. (2014) "Stock market prediction by using artificial neural network." in2014 World Automation Congress (WAC): 718-722.

Mizuno, Hirotaka, Michitaka Kosaka, Hiroshi Yajima, and Norihisa Komoda. (1998) "Application of neural network to technical analysis of stock market prediction." Studies in Informatic and control 7 (3) : 111-120.

Kumar, Manish, and M. Thenmozhi. (2006) "Forecasting stock index movement: A comparison of support vector machines and random forest" In Indian institute of capital markets 9th capital markets conference paper.

D. Saxena, A. K. Singh and R. Buyya, " An Online VM Prediction based Multi-objective Load Balancing Framework for Resource Management at Cloud Datacenter," IEEE Transactions on Cloud Computing , 2021.

T. S. Kumar , "Data Mining Based Marketing Decision Support System Using, Hybrid Machine Learning Algorithm" Journal of Artificial Intelligence 2, vol. 3, pp. 185-193, 2020.

Sandhu, O. (2021). Stock market trend prediction using regression errors. https://doi.org/10.32920/ryerson.14645169.

1.2 Plagiarism Report Of Research Paper

stockprediction

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II. BACKGROUND STUDY

Beside the introduction of new products such as stocks, bonds, options, and futures, the financial market has grown increasingly complicated. The stock market is the most common financial tool into which people put their money. Stock market is a market with large up and downs, with values fluctuating often because of a variety of variables such as economic and political developments as well as company-specific news.

Predicting the future price of a company is an important field of research for investors since it allows them to make informed investment decisions. Traditional financial models, such as the Black-Scholes model, have been employed in the past to forecast stock values. However, these models have not been particularly efficient in properly predicting stock values, and they do not take into consideration the complicated interactions between the various factors that impact stock prices.

Stock price prediction using machine learning:
Because of its capacity to understand complicated correlations between diverse elements that impact stock prices, machine learning has emerged as an advantageous tool for stock price forecasting. Machine learning techniques may produce accurate forecasts about future stock values by taking into consideration a wide range of elements, such as previous share values, financial measures, and news items.
Machine learning models are widely divided into two types: supervised learning and unsupervised learning. A model learns on the set of labelled data with the outcome variable known in supervised learning. Unsupervised learning involves training a model on a collection of unlabeled data and teaching the model to recognize trends in data.

Stock price prediction by supervised learning models:
Regression, support vector machines (SVM), and neural networks are supervised learning models that may be used to predict stock values.

For stock price prediction, regression models such as linear regression and logistic regression are often used. To create accurate forecasts regarding future stock values, regression models can take into consideration a wide range of elements, including past stock prices, economic indicators, and news items.

SVM models are another popular choice for stock price prediction. SVM models can consider a wide range of factors, including historical share values, financial measures, and news articles, to form accurate forecasting about ultimate share values. SVM models are particularly effective at identifying patterns in data that are not easily visible.

Another effective approach for stock price prediction is neural networks. To produce accurate forecasts regarding future share values, neural networks may use a wide range of data, including past stock prices, economic indicators, and news items. Neural networks are very good at detecting complicated patterns in data that are not readily obvious.
Models of Unsupervised Learning for Stock Price Prediction
Clustering and association rules are two unsupervised learning algorithms that may be used to forecast stock prices. Clustering techniques may be used to detect patterns in the data and classify it into comparable groups. To produce reliable forecasts regarding future stock values, clustering models can take into consideration a wide range of elements, including past stock prices, economic indicators, and news items.

Association rule models may be used to detect patterns in data and predict outcomes based on those patterns. To produce reliable forecasts regarding future stock values, association rule models can take into consideration a wide range of data, including past stock prices, economic indicators, and news items.

III. METHODOLOGY

Using the stock API offered by Alpha Vantage, we will first retrieve the most recent updates and data for a certain stock. This stage will be very beneficial because the function we're making will automatically and continuously update itself with the most recent information. Users can access a wide range of data, including real-time updates and historical information on stocks, currencies, and cryptocurrencies, thanks to Alpha Vantage's free stock APIs.

	open	high	low	close	volume
0	4354.9500	4444.0000	4329.1000	4369.3000	13095.0
1	4391.0500	4417.1500	4264.2000	4318.1000	8130.0
2	4370.0000	4420.0000	4321.0500	4408.5500	3176.0
3	4356.6000	4437.3500	4355.6000	4380.3000	7776.0
4	4350.8501	4436.0000	4350.8501	4397.2002	1884.0
...	...	...	...	...	...
4451	834.1420	834.1420	807.5272	812.3168	6260.0
4452	813.3562	834.9102	780.9124	819.9534	182350.0
4453	849.5054	853.5722	817.8748	826.6862	2090100.0
4454	840.4680	849.5054	836.0398	845.3030	88030.0
4455	840.4680	849.5054	813.3562	842.3208	16330.0

Figure 1. Stock Data Fetched from Alpha Vantage

A. 100-Days Moving Average

The closing price average over the past 20 weeks or 100 days is known as a 100-day Moving Average (MA). The mid-term price trends are represented by it. Investors can observe how the stock has performed over the past 20 weeks and determine whether the price trend is up or down by using a moving average over 100 days. This also provides them a sense of the mood of the market.

A moving average is quite easy to calculate. The closing prices for each day (day 1, day 2, day 3, etc.), added together, are then divided by the total number of days. As a result, for 100 days, n's MA value will be 100.

B. 200-Days Moving Average

The mean of the closing prices over the past 20 weeks or 200 days is known as a 200-day Moving Average (MA). The mid-term price trends are represented by it. Investors can observe how the stock has performed over the past 20 weeks and determine whether the price trend is up or down by using a moving average over 200 days. This also provides them a sense of the mood of the market.

A moving average is quite easy to calculate. The closing prices for each day (day 1, day 2, day 3, etc.), added together, are then divided by the total number of days. As a result, for 200 days, n's MA value will be 200.

C. LSTM (Long short term memory)

Fundamentally, the fully connected network LSTM design belongs toward the recurrent neural network family (RNNs). The presence of feedback loops distinguishes RNNs from other deep neural networks. The disappearing and inflating gradient problem that plagues RNNs, prevents the system from ever converging to the point of the least error by either causing it to halt learning or maintain learning at a very high rate. The LSTM network topologies are found to be particularly well adapted for modelling intricate sequential data, including texts and time series, as vanishing or inflating gradient difficulties are never a problem.

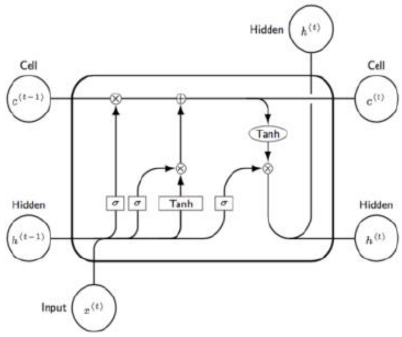

Figure 2. Long Short-Term Memory

These networks are made up of gates that control and regulate the information flow across these cells and cells that store the network's prior state data. Input gate, Output gate, and forget gate are the three different gates that are employed in LSTM networks. Retaining only the details that are important as long as this present window exists and deleting past information that is no longer relevant are both made possible by forget gates. The fresh data that is used to determine the network's current state is regulated by the input gates. The network's memory cells cleverly blend that past data on the state from the already stated forget gates with the network's current source input that is obtained from the input gate. The results of the network are finally produced by the output gates at the designated time slot. The model's predicted value for the current slot can be thought of as the output.

This research builds a sequential model by piling four LSTM layers with different dropouts on top of one another. The first layer is Input layer which provide data to the LSTM layers, and further there exist four LSTM layers with different Dropouts so that it can give us unique predicted value.

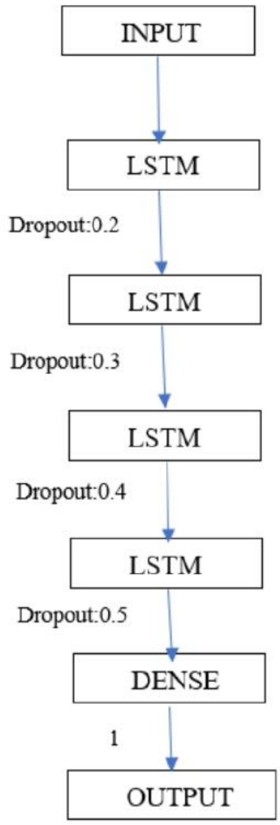

Figure 3. LSTM Layers

IV. RESULTS

Performance metrics and forecasts made using various forecasting techniques are demonstrated and compared. The result of the comparison led us to conclude that machine learning technique LSTM gives superior results compared to the moving average techniques.

A. 100-Day Moving Average

In this we can depict from the graph that the 100 day moving average (100ma) figure out the mid-term price trends over the past 20 weeks and determines whether the price trend is up or down and based on that they can analyze the stock.

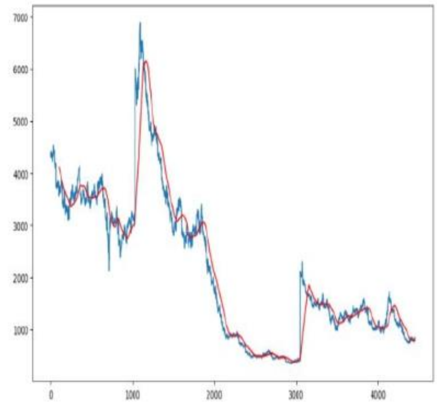

Figure 4. (a) 100ma

B. 200-Day Moving Average

It is a moving average of a security's or index's closing prices over the previous 200 trading days. Traders and investors frequently utilise the 200 day simple moving average to evaluate overall trend of market or of a specific security.

If a security's current price is higher than its 200 day simple moving average, than it is regarded as an upwards trend; if it is lower than its 200 day simple moving average, it is considered an downwards trend. This information may be used by traders and investors to make trading choices, such as purchasing or selling a security.

A security's 200 days simple moving average may also be employed as a resistance level or support level. If the price of a security goes below its 200 day simple moving average, it may operate as support level, restraining additional price declines. If, on the other hand, the price of a security rises above its 200-day moving average, than it may operate as barrier, preventing the price from increasing higher.

Although the 200 day simple moving average is a well known technical indicator, it should not be employed in isolation. Before making any trading choices, traders and investors should evaluate additional technical indications as well as fundamental research.

In this we can depict from the graph that the 200 day simple moving average (200ma) figure out the mid-term price trends over the past 20 weeks and determine whether the price trend is up or down and based on that they can analyse the stock.

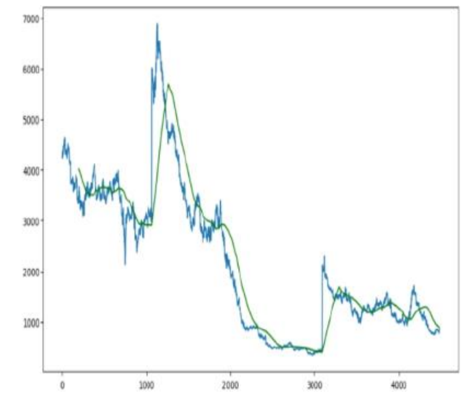

Figure 4. (b) 200ma

C. LSTM (Long short-term memory)

We have created LSTM models by training it on the 'Close' values of different stocks so that it can give us the best predicted result. We have use four LSTM layers with different Dropouts and a Dense layer with unit one.

We have fitted the model by training it to 100 epochs and based on the constructed model we get the predicted price corresponding to the original closing price.

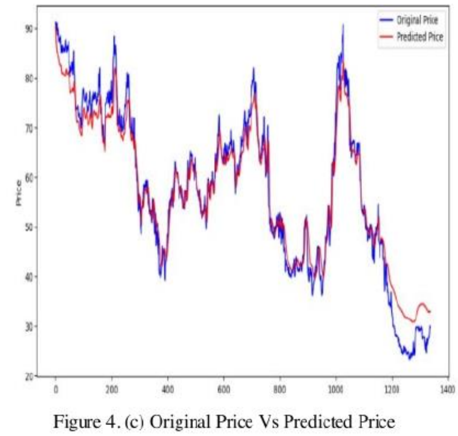

Figure 4. (c) Original Price Vs Predicted Price

V. CONCLUSION

Stock market prediction is a relatively new phenomenon, and there are mainly two types of analysis of stock that investors do ahead of investing in any stock. The first is analysis of the fundamentals of the company or asset they are investing, in which they calculate the intrinsic value of stock as well as performance of the industry, reputation of the company, economy, sector growth and demand and so on to determine whether to put their money in the stock or not. Secondly they do Technical analysis to determine the correct time to entry in the stock which includes the study of market data such as past prices, trends and trading-volumes to predict the movement of stock. Machine learning can be used to adequately describe such processes, and this study uses data from Alpha Vantage to apply supervised machine learning to analyze the stock market. Five variables are included in the dataset: close, open, high, and low, which comprise several of the stock's bid prices at various moments with essentially plain labels.

The prototype is evaluated using the test results, and comparisons are made using different methods. Stock market is regarded as aggressive, uncertain, and non-linear in nature. So to widen the profits and narrowing the losses, techniques for forecasting share values ahead of time by analysing movements over the last few months could be extremely useful for predicting stock market movements. Commonly, two methodologies are presented for anticipating a company's stock price: Fundamental Analysis and Technical analysis. Progressive, sophisticated approaches based on either fundamental or technical research are currently used to forecast share values.

Machine learning techniques in this area had shown an boost in efficacy by 61–87 percent when compared to earlier methods. Recent analysis announce that machine learning can enhance stock market predictions, with some simulated neural network based techniques, such as FNN, SIANN, RNN, and LSTM, providing encouraging results.

A relative evaluation among statistical methodologies, both in terms of prediction performances and accuracy, and machine learning approaches, following the analysis of each approach separately, reveals machine learning approaches to be the most accurate for predicting stock values.

Due to an improvement in forecast accuracy, both tactics have produced favorable results. Inspiring findings from recently created machine learning algorithms for stock prediction point to their use in lucrative trading strategies. As a result researchers have been led to the findings that stock market estimations can be produced more successfully and more precisely by utilizing machine learning techniques.

By using a dataset that is substantially bigger than the current one, it will now be possible to use it. In the future, the stock market's methods and approach could be greatly improved. The accuracy of our estimation techniques would consequently improve. Moreover, additional machine learning techniques could remain investigated to look at the accuracy rate resulting from them.

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REFERENCES

[1] K. Raza, "Prediction of Stock Market performance by utilising machine learning approaches," International Conference on Innovations in Electrical Engineering and Computational Technologies (ICIEECT), Karachi, 2017, pp. 1–1.

[2] "Stock market prediction utilising an enhanced training technique of neural network," 2nd International Conference on Electrical, Computer & Telecommunication Engineering (ICECTE), Rajshahi, Bangladesh, 2016, pp.

[3] R. S. Dhankar, Capital Markets and Investment Decision Making, 1st ed. Springer India, 2019, ch. Stock Market Operations and Long-Run Reversal Effect.

[4] Siami-Namini, S., & Namin, A. S. (2018). Forecasting economics and financial time series: Arima vs. lstm. arXiv preprint arXiv:1803.06386.

[5] Emerson, S., Kennedy, R., O'Shea, L., & O'Brien, J. (2019, May). Trends and Applications of Machine Learning in Quantitative Finance. In 8th International Conference on Economics and Finance Research (ICEFR 2019).

[6] Heaton, J. B., Polson, N. G., & Witte, J. H. (2017). Deep learning for finance: deep portfolios. Applied Stochastic Models in Business and Industry, 33(1), 3-12.

[7] Paiva, F. D., Cardoso, R. T. N., Hanaoka, G. P., & Duarte, W. M. (2018). Decision-Making for Financial Trading: A Fusion Approach of Machine Learning and Portfolio Selection. Expert Systems with Applications.

[8] Patterson J., 2017. Deep Learning: A Practitioner's Approach, O'Reilly Media.

[9] Yadav, A., Vishwakarma, D.K. Sentiment analysis using deep learning architectures: a review. Artif Intell Rev 53,4335–4385 (2020).

[10] A. Sarkar, A. K. Sahoo, S. Sah and C. Pradhan,"LSTMSA: A Novel Approach for Stock Market Prediction Using LSTM and Sentiment Analysis," 2020 International Conference on Computer Science, Engineering and Applications (ICCSEA), Gunupur, India, 2020, pp. 1-6, doi: 10.1109/ICCSEA49143.2020.9132928.

[11] R. Gupta and M. Chen, "Sentiment Analysis for Stock Price Prediction," 2020 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR), Shenzhen, China, 2020, pp. 213-218, doi: 10.1109/MIPR49039.2020.00051.

[12] Mizuno, Hirotaka, Michitaka Kosaka, Hiroshi Yajima, and Norihisa Komoda. (1998) "Application of neural network to technical analysis of stock market prediction." Studies in Informatic and control 7 (3) : 111-120.

[13] Lipo W., Shekhar G.: "Neural Networks and Wavelet DeNoising for Stock Trading and Prediction", Springer, Time Series Analysis, Modeling and Applications Intelligent Systems Reference Library Volume 47, pp 229-247, 2013.

[14] Honghai Y., Haifei L.: "Improved Stock Market Prediction by Combining Support Vector Machine and Empirical Mode Decomposition", Fifth International Symposium on Computational Intelligence and Design (ISCID), pp. 531 - 534 , 2012.

[15] S. S. A. Ali, M. Moinuddin, K. Raza, & S. H. Adil, "An adaptive learning rate for RBFNN using time-domain feedback analysis," The Scientific World Journal, 2014.

[16] Wei Huang, Yoshiteru Nakamori, Shou-Yang Wang, "Forecasting stock market movement direction with support vector machine", Computers & Operations Research, Volume 32, Issue 10, October 2005, Pages 2513–2522.

[17] J. Sen, "Stock price prediction using machine learning and deep learning frameworks," In Proceedings of the 6th International

Conference on Business Analytics and Intelligence, Bangalore, India, 2018.

[18] M. Z. Asghar, F. Rahman, F. M. Kundi, and S. Ahmed, "Development of stock market trend prediction system using multiple regression", Computational and Mathematical Organization Theory, vol. 25, pp. 271-301, 2019.

[19] Al-Mahasneh, A. J., Anavatti, S. G., and Garratt, M. A. (2018). Review of Applications of Generalized Regression Neural Networks in Identification and Control of Dynamic Systems. arXiv preprint arXiv:1805.11236.

[20] Yetis, Yunus, Halid Kaplan, and Mo Jamshidi. (2014) "Stock market prediction by using artificial neural network." in2014 World Automation Congress (WAC): 718-722.

[21] Mizuno, Hirotaka, Michitaka Kosaka, Hiroshi Yajima, and Norihisa Komoda. (1998) "Application of neural network to technical analysis of stock market prediction." Studies in Informatic and control 7 (3) : 111-120.

[22] Kumar, Manish, and M. Thenmozhi. (2006) "Forecasting stock index movement: A comparison of support vector machines and random forest" In Indian institute of capital markets 9th capital markets conference paper.

[23] D. Saxena, A. K. Singh and R. Buyya, " An Online VM Prediction based Multi-objective Load Balancing Framework for Resource Management at Cloud Datacenter," IEEE Transactions on Cloud Computing , 2021.

[24] T.S. Kumar , "Data Mining Based Marketing Decision Support System Using, Hybrid Machine Learning Algorithm" Journal of Artificial Intelligence 2, vol. 3, pp. 185-193, 2020.

[25] Sandhu, O. (2021). Stock market trend prediction using regression errors. https://doi.org/10.32920/ryerson.14645169.

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