

**Visvesvaraya Technological University**

**BELAGAVI, KARNATAKA - 590 014.**



**A PROJECT REPORT ON**

**“APPLICATION OF LSTM AND SENTIMENT  
ANALYSIS IN STOCK PRICE FORECASTING”**

**Submitted By**

<b>Harsh Mishra</b>	<b>[4PM20CS039]</b>
<b>Shaishav</b>	<b>[4PM20CS090]</b>
<b>Sumit Raj</b>	<b>[4PM20CS115]</b>
<b>Trupthi K</b>	<b>[4PM20CS119]</b>

*Submitted in partial fulfillment of the requirement for the award of degree of*

**BACHELOR OF ENGINEERING**

**IN**

**COMPUTER SCIENCE AND ENGINEERING**

**Under the Guidance  
of**

**Ms. Vinutha H M,**  
**Assistant Professor, Dept. of CS & E.**  
**PESITM, Shivamogga**



**PES Institute of Technology and  
Management**

**Department of Computer Science & Engineering**

**May-2024**

# PES Institute of Technology & Management

NH-206, Sagar Road, Shivamogga-577 204

(Affiliated to Visvesvaraya Technological University, Belgaum)

## Department of Computer Science and Engineering



### CERTIFICATE

Certified that the project work entitled “*APPLICATION OF LSTM AND SENTIMENT ANALYSIS IN STOCK PRICE FORECASTING*” carried out jointly by

<b>HARSH MISHRA</b>	<b>[4PM20CS039]</b>
<b>SHAISHAV</b>	<b>[4PM20CS090]</b>
<b>SUMIT RAJ</b>	<b>[4PM20CS115]</b>
<b>TRUPTHI K</b>	<b>[4PM20CS119]</b>

bonafide students of **PES INSTITUTE OF TECHNOLOGY & MANAGEMENT** in partial fulfillment for the award of Bachelor of Engineering in **COMPUTER SCIENCE & ENGINEERING** of the Visvesvaraya Technological University, Belgaum during the academic year **2023-24**. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the report deposited in the department library. The project report has been approved as it satisfies the academic requirements in respect of Project work prescribed for the said Degree.

\_\_\_\_\_  
Ms. Vinutha H M.  
Asst. Professor and Guide  
PESITM, Shivamogga.

\_\_\_\_\_  
Dr. Arjun U.  
Associate Professor and Head  
PESITM, Shivamogga.

\_\_\_\_\_  
Dr. Yuvaraju B. N.  
Principal  
PESITM, Shivamogga.

Name of the Examiners

Signature with date

1.....

2.....

**PES Institute of Technology and Management, NH 206, Sagar Road,  
Shivamogga, Karnataka 577204  
Department of Computer Science & Engineering**

**DECLARATION**

We, Harsh Mishra (4PM20CS039), Shaishav (4PM20CS090), Sumit Raj (4PM20CS115), and Trupthi K (4PM20CS119) students of 8<sup>th</sup> semester B.E. in Computer Science & Engineering, PESITM, Shivamogga hereby **declare** that the final year B.E. major project report entitled **Application of LSTM and Sentiment Analysis in Stock Price Forecasting** which is being submitted to the **PESITM, Shivamogga** during the year 2023-24 is a record of an original work done by us under the supervision of Ms. Vinutha H M , Assistant Professor, Dept. of CSE, PESITM, Shivamogga. This Project work is submitted in partial fulfilment of the requirements for the award of the Degree of **Bachelor of Engineering in Computer Science and Engineering**. The material contained in this report has not been submitted to any University or Institution for the award of any degree.

(Harsh Mishra    4PM20CS039)

(Shaishav        4PM20CS090)

(Sumit Raj        4PM20CS115)

(Trupthi K        4PM20CS119)

Place: PESITM, Shivamogga.

Date: May 27, 2024

# **ABSTRACT**

In the stock market it is very hard to predict the stock prices as there are no clear-cut rules of prediction, but it provides one of the highest returns in the market. Stock price forecasting involves predicting the future price movements of a particular stock or the overall stock market. This research proposes a hybrid model for stock price forecasting that combines Long Short-Term Memory (LSTM) neural networks and sentiment analysis. By examining historical stock data and incorporating sentiment from news and social media, the model aims to enhance predictive accuracy. Integrating LSTM and sentiment analysis furnishes a holistic method to capture both temporal dependencies and market sentiment, offering a valuable instrument for enhanced stock price forecasting.

## ACKNOWLEDGEMENT

---

It is our pleasure to express our heartfelt thanks to Ms. Vinutha H M, Assistant Professor, Department of Computer Science and Engineering, for his supervision and guidance, which enabled us to understand and develop this project.

We are indebted to Dr. Arjun U., Head of the Department, and Dr. Yuvaraju B.N., Principal, for their advice and suggestions at various stages of the work. We also extend our thanks to the management of PES Institute of Technology & Management for providing us with a good study environment and laboratories facilities.

Lastly, we take this opportunity to offer our regards to all of those who have supported us directly or indirectly in the successful completion of this project work.

### Name of the Students with USN

HARSH MISHRA	[4PM20CS039]
SHAISHAV	[4PM20CS090]
SUMIT RAJ	[4PM20CS115]
TRUPTHI K	[4PM20CS119]

# TABLE OF CONTENTS

---

<b>Chapter No</b>	<b>Title</b>	<b>Page No</b>
	<b>Declaration</b>	<b>ii</b>
	<b>Abstract</b>	<b>iii</b>
	<b>Acknowledgement</b>	<b>iv</b>
	<b>Table of Contents</b>	<b>v</b>
	<b>List of Figures</b>	<b>vii</b>
	<b>List of Tables</b>	<b>viii</b>
<b>1</b>	<b>Introduction</b>	<b>1-7</b>
	1.1 Motivation	5
	1.2 Problem Description	5
	1.3 Objectives	6
	1.4 Scope and limitations	6
	1.5 Organization of the Report	7
<b>2</b>	<b>Literature Survey</b>	<b>8-19</b>
	2.1 Theoretical Background	8
	2.2 Literature Survey	8
	2.3 Outcome of the Literature	19
<b>3</b>	<b>System Analysis</b>	<b>20-21</b>
	3.1 Existing Systems	20
	3.2 Disadvantages of the System	20
	3.3 Proposed System	21
	3.4 Advantages of the System	21
<b>4</b>	<b>System Requirement Specification</b>	<b>22-24</b>
	4.1 System Requirements	22
	4.2 About the Software and Packages	23
	4.3 About the Programming Language	24
<b>5</b>	<b>System Design</b>	<b>25-31</b>
	5.1 Proposed Architecture	25
	5.2 Methodology	29
<b>6</b>	<b>System Implementation</b>	<b>32-36</b>
	6.1 Pseudo Code Explanation	32

<b>7</b>	<b>Experimental Result and Analysis</b>	<b>37-40</b>
	7.1 Screenshots	37
<b>8</b>	<b>Conclusion and Future Work</b>	<b>41</b>
	<b>References</b>	<b>42</b>
	<b>Appendices</b>	<b>43-46</b>

# LIST OF FIGURES

---

Figure No.	Figure Name	Page No.
1.1	Stock Forecasting	1
5.1	Block Diagram	25
5.2	Methodology Diagram	29
7.1	The Home Page	37
7.2	The News Page	38
7.3	Stock Form Page	38
7.4	LSTM Analysis	39
7.5	Sentiment Analysis	39



# LIST OF TABLES

---

Table No.	Table Name	Page No.
7.1	Validation Table	40
7.2	Error Table	40

## CHAPTER 1

# INTRODUCTION

Stock price forecasting is a complex process that involves analysing various data sources and employing different methodologies to predict future movements in a stock's value. Historical stock prices serve as a foundational data set, providing insights into trends and patterns. Trading volume, representing market interest and liquidity, is another critical factor. Additionally, fundamental analysis, which examines a company's financial health, earnings reports, and economic indicators, contributes to a comprehensive understanding of stock behaviour.



Fig 1.1 Stock Forecast

Technical analysis relies on historical price charts, identifying trends and utilizing technical indicators such as moving averages and the Relative Strength Index (RSI). Fundamental analysis, on the other hand, involves evaluating a company's financial statements and performance metrics to assess its intrinsic value. Combining these approaches can provide a more holistic view of a stock's potential future trajectory.

Quantitative models, particularly those leveraging machine learning algorithms, have gained prominence in recent years. Regression analysis, decision trees, and neural networks are applied to historical data for pattern recognition and prediction. By training on historical data, forecast errors were reduced, accuracy increased, and emphasis added. Time series analysis treats stock prices as sequential data, considering their temporal dependencies. Algorithmic trading,

employing automated strategies based on predefined rules, is another avenue for leveraging quantitative models.

On top of that, there is this theory called the Efficient Market Hypothesis (EMH) that throws another wrench in the prediction machine. EMH basically says that stock prices already take into account all the information that's out there.

## **Time Series Analysis**

Time collection evaluation is a simple technique for expertise financial market dynamics by using analyzing ancient inventory price records in terms of styles, trends, and trends Analysts use strategies which includes moving averages and regression analysis to research tendencies, growing a holistic view of the marketplace. Time collection evaluation is a cornerstone of inventory rate forecasting, imparting traders with a systematic proof-based totally technique to deciphering marketplace developments When used efficiently insights from ancient information provide the ability to forecast the future predict adjustments and decorate the first-class of investments.

However, time collection analysis has boundaries. Just because there has been a sample within the past doesn't mean it'll be repeated in the future. Markets are constantly evolving, stimulated by means of new regulations, technological disruptions and ever-changing customer possibilities. These factors can distort ancient patterns, making forecasts based totally totally on past statistics a risky proposition.

## **Machine Learning**

Machine learning (ML) is a subfield of synthetic intelligence (AI) that specializes in growing algorithms and fashions allowing computers to learn from records and make predictions without express programming. The essence of ML lies in recognizing styles, adapting to new facts, and improving over time. Machine getting to know has transformed stock fee forecasting via state-of-the-art algorithms that derive insights from ancient statistics to count on destiny financial markets. Critical facts preprocessing ensures smooth and dependent data, while set of rules choice, together with linear regression, choice timber or neural networks, takes place throughout version building.

Machine mastering is a powerful tool; however, it is no longer a magic money machine. The excellent of its prediction's hinges at the excellent of information it is fed. Garbage in, garbage

out, as the pronouncing goes. If the historical statistics used to educate the model is inaccurate or incomplete, the forecasts it generates will be unreliable. Additionally, system learning fashions can war to adapt to absolutely new situations. The financial international is continuously evolving, and unforeseen events can throw even the maximum sophisticated fashions for a loop. The monetary world is continuously evolving, and unforeseen activities can throw even the most sophisticated fashions for a loop.

## **LSTM**

In the realm of stock market analysis, Long Short-Term Memory (LSTM) fashions have emerged as a precious tool for forecasting destiny stock costs. Leveraging their capability to discern elaborate patterns within sequential information, particularly historical stock fees, LSTM fashions provide sophisticated insights into market trends. By processing a wealth of records, such as establishing and closing fees, trading extent, and diverse financial indicators, LSTM fashions adeptly capture both quick-term fluctuations and long-term developments in stock fees. This capability positions them as amazing gear for making knowledgeable predictions approximately destiny charge movements.

However, it's important to method these predictions with warning, recognizing the inherent uncertainty of stock market dynamics. Numerous outside elements, consisting of marketplace sentiment and broader monetary situations, can drastically impact inventory costs, doubtlessly diverging from historic styles. Therefore, whilst LSTM models absolutely provide precious analytical competencies, they ought to be complemented with a holistic investment approach that incorporates diverse assets of information and expert judgment.

## **Natural Language Processing**

Natural Language Processing (NLP) is an area inside artificial intelligence (AI) that makes a speciality of allowing interaction between computers and human languages. The usual purpose of NLP is to permit machines to recognize, interpret, and generate language in a manner this is meaningful and suitable for the context. This interdisciplinary vicinity combines aspects of computer technological know-how, linguistics, and cognitive psychology to lessen the distinction between human verbal exchange and machine comprehension. By the usage of strategies from those instructional regions, researchers keep advancing the competencies of technologies to understand the nuances of human speech, read written texts, and reply articulately. Promising packages of NLP encompass clever assistants, translation offerings, and extra human-centered

interactions with automated structures. Continued development in the subject moves us closer to the imaginative and prescient of seamless communication among human beings and technology.

However, NLP additionally faces challenges within the financial international. Financial jargon and slang may be tricky for machines to interpret. Sarcasm, a common function in online verbal exchange, may be completely ignored by way of NLP algorithms, leading to misinterpretations of sentiment. For now, NLP ought to be seen as a supportive device, presenting additional facts factors for traders to recall along other forecasting methods. As NLP technology continues to broaden, its role in understanding the economic landscape is possibly to come to be more massive.

## **Sentiment Analysis**

Sentiment evaluation evaluates qualitative statistics from resources which include news, social media, and reviews to gauge investor sentiment and market feelings. Understanding sentiment objectives to assume inventory charge and trend shifts as investor sentiment plays a essential role in market dynamics. Positive sentiment drives bullish behaviour and upward charges even as bad sentiment triggers bearish behaviour and downward tendencies. Consequently, sentiment analysis seeks to quantify emotional responses to higher inform forecasts.

Key words, phrases and context clues are assessed to decide whether sentiment is optimistic, pessimistic, or neutral. Sentiment evaluation captures marketplace reactions to occasions impacting inventory prices. It also examines tendencies precise to companies and industries for a nuanced information of price factors. Integrating sentiment evaluation into fashions lets in for a holistic method considering each quantitative and qualitative element. Sentiment evaluation gives a treasured attitude on emotional drivers of behaviour. Incorporating sentiment insights improves the ability of forecasting models to expect destiny stock charge moves.

Despite these boundaries, sentiment evaluation remains a precious tool for investors. By knowledge the "mood" of the marketplace and gauging investor confidence, it is able to provide treasured insights that complement traditional forecasting techniques. Just like a physician considers both bodily signs and symptoms and a affected person's emotional nation for a diagnosis, combining sentiment evaluation with different strategies can create a extra comprehensive image of what's using stock costs.

## 1.1 Motivation

The motivation for this project comes from recognizing how much investor sentiment influences financial markets and wanting to use that understanding to improve portfolio management. With access to a lot of financial data and advancements in machine learning, we can now create sophisticated models that combine public mood and historical prices to make better investment decisions. This project aims to address a research gap by focusing on how sentiment data can inform asset allocation strategies, enhancing traditional methods. Ultimately, we aim to develop automated, data-driven solutions that can lead to more stable and profitable financial outcomes for both individual investors and institutions.

## 1.2 Problem Description

Stock price forecasting presents complex challenges due to the interplay of market dynamics. Investors must consider volatile conditions influenced by various complex factors. This requires developing a robust predictive tool analysing historical stock price data while including diverse relevant market indicators like trading volumes and external variables such as news sentiment analysis. Analysing stock prices that can demonstrate relationships over time and developing trends requires skilfully using basic machine learning methods along with advanced techniques such as deep learning.

Despite the potential benefits, it's important to acknowledge the limitations of such a tool. Stock markets are inherently unpredictable, and even the most sophisticated models cannot guarantee perfect accuracy. Furthermore, external factors beyond the scope of the model, such as major political events or natural disasters, can significantly impact stock prices.

By combining machine learning techniques with a comprehensive analysis of market indicators, this tool can empower investors with a data-driven perspective to navigate the ever-changing financial landscape. While acknowledging the inherent limitations of prediction, this tool has the potential to enhance decision-making confidence and contribute to informed investment strategies.

**Problem Statement: “Designing a machine learning model to enhance stock return predictions through the utilization of various forecasting techniques and the integration of news indicators. The ultimate objective is to construct a diverse stock portfolio crafted to reduce risks effectively.”**

## **1.3 Objectives**

- Design a dependable model gaining knowledge of algorithm that may forecast stock costs with accuracy by looking at beyond facts and locating styles.
- Incorporate sentiment analysis strategies to analyse news records, enhancing the stock rate prediction models with valuable insights derived from sentiment analysis.
- Compare the performance of sentiment analysis and stock prediction models to evaluate their effectiveness and identify potential correlations.
- Implement mechanisms to incorporate daily data into the forecasting models, the predictive algorithms are continuously updated with the latest market information to ensure accuracy.

## **1.4 Scope and Limitations**

- Stock markets are inherently volatile, influenced by various factors such as economic indicators, geopolitical events, and investor sentiments.
- Sudden market fluctuations can challenge the accuracy of forecasting models.
- Forecasting stock prices involves dealing with uncertainty, as it's impossible to predict all variables accurately.
- The accuracy of forecasts heavily relies on the quality and reliability of data used in modelling.
- Forecasting models are based on certain assumptions about market behaviour and historical patterns.
- Changes in market dynamics or deviations from these assumptions can affect the reliability of forecasts.
- Overfitting occurs when a model captures noise in the data rather than the underlying patterns, resulting in overly optimistic predictions.
- Stock price forecasting may be subject to regulatory scrutiny, particularly if it involves the use of proprietary algorithms or insider information.
- Compliance with legal and ethical standards is crucial to avoid legal repercussions.

## **1.5 Organization of the report**

The report is structured into several chapters, which are as follows:

- Chapter 2: Literature Survey - This chapter reviews 10 key research papers. Each paper is briefly described along with findings on advantages and disadvantages.
- Chapter 3: Methodology - This chapter covers the description of methods and procedures used in the project.
- Chapter 4: System Design and Implementation - This chapter covers the system's architecture, the project's approach and block diagram with brief explanations of all steps that have been discussed.
- Chapter 5: Results and Discussion - This chapter covers the project findings, analysis of the results and illustrations of graphs.
- Chapter 6: Conclusion and Future Scope - This chapter covers the recapitulation of how the objectives were achieved and recommendations for future research.



## **CHAPTER 2**

# **LITERATURE SURVEY**

## **2.1 Theoretical Background**

A comprehensive review of prevailing academic literature examining techniques for equity price forecasting reveals diverse methodological approaches employed by researchers. Some scholars utilize traditional statistical models such as autoregressive integrated moving average (ARIMA) or exponential smoothing to generate predictions. Alternatively, more sophisticated machine learning algorithms including support vector machines and artificial neural networks are frequently applied in scholarly work. Additionally, an emerging area of focus within the academic community examines how alternative data sources like news articles and social media sentiment may influence share valuations. Researchers also study corporate fundamentals like earnings reports and patterns in investor behaviour within financial markets to postulate future price dynamics.

Algorithmic approaches including Support Vector Machines, Random Forests, and Neural Networks have gained significant attention due to their strengths in discerning complex nonlinear patterns within multivariate datasets. These techniques analyse historical pricing information, technical indicators, and at times additional explanatory variables to generate prospective outlooks. Empirically, the predictive performance of these data-driven methodologies has often surpassed more conventional regression-based frameworks in terms of calibration and adaptability to evolving market conditions.

## **2.2 Literature Survey**

The survey paper examines industry-specific analyses, focusing on sectors like pharmaceuticals and tailoring sentiment analysis dictionaries accordingly. It underscores the importance of visualization techniques in interpreting model predictions and facilitating informed decision-making. Challenges inherent in stock price prediction research, including data quality issues and scalability, are identified, and avenues for future research are proposed to address these challenges.

**Title: “Stock Price Prediction using Sentiment Analysis and Deep Learning for Indian Markets” [1]**

**Authors Name:** Narayana Darapaneni, Anwesh Reddy Paduri, Himank Sharma, Milind Manjrekar, Nutan Hindlekar, Pranali Bhagat, Usha Aiyer, Yogesh Agarwal

**Year:** 2022

**Description:**

The objective of this study is to forecast future equity price fluctuations by integrating historical pricing data with sentiment analysis. Two models will be employed for share price projection: a Long Short-Term Memory (LSTM) model, which examines past pricing information, and a Random Forest model, which considers sentiment data. These models collaborate to project stock prices. Additionally, the analysis incorporates macroeconomic factors like gold and oil prices, as well as exchange rates, to make the predictive frameworks more precise. By integrating these various elements, the research aims to provide a comprehensive approach to forecasting stock prices, taking into account both historical trends and current market sentiment.

**Advantages:**

This paper evaluates the predictive accuracy of Long Short-Term Memory (LSTM) and Random Forest models for stock price forecasting. Root-mean-square error (RMSE) was used as the key performance indicator to compare how well each model predicted closing prices for a range of securities. For each stock, results show the relative forecasting ability of these techniques.

**Drawbacks:**

Irrelevant news items included in the data set may skew the results of sentiment analysis performed. The daily methodology aggregates all news reports for a given date, which could weaken pronounced sentiments expressed amid a multitude of neutral stories. To achieve optimal accuracy, the data collection process should focus solely on publications pertinent to the designated subject of examination.

**Title: “Stock Closing Price Prediction using Machine Learning Techniques” [2]**

**Authors Name:** Mehar Vijha, Deeksha Chandolab, Vinay Tikkiwalb, Arun Kumarc

**Year:** 2019

**Description:**

This research project aims to leverage advanced artificial intelligence techniques to improve the predictive accuracy of next-day closing stock prices. Specifically, the study examines the application of artificial neural networks and random forests, two computational methods commonly used in machine learning. To conduct the analysis, the researchers gathered financial data points for five publicly traded companies representing different economic sectors. The data points included each company's daily opening, highest, lowest, and closing stock prices over the time period under review. The artificial neural networks and random forests were then trained on the transformed datasets to identify patterns and correlations that could anticipate the following trading day's closing price for each stock. Specifically, the ANN approach facilitated more precise predictions of stock prices when directly contrasted against the predictions generated by the RF technique.

**Advantages:**

This report provides a comprehensive comparative evaluation of Artificial Neural Network (ANN) and Random Forest (RF) models for the purpose of forecasting stock prices. The predictive models were assessed using key error metrics including Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Bias Error (MBE). Based on these statistical measures of predictive accuracy, the ANN model demonstrated superior performance by achieving lower error values than the RF model across all metrics.

**Drawbacks:**

Relying on a historical dataset containing a limited feature set may constrain a model's capacity to fully represent the complexity inherent in stock price movements. The paper exclusively evaluates artificial neural networks and random forests for forecasting purposes, which potentially precludes insights available from alternative modelling approaches equally applicable to the problem domain.

**Title: “DP-LSTM: Differential Privacy-inspired LSTM for Stock Prediction Using Financial News” [3]**

**Authors Name: Xinyi Li, Yinchuan Li, Hongyang Yang, Liuqing Yang, Xiao-Yang Liu**

**Year: 2019**

**Description:**

This paper introduces a novel deep learning model for equity price forecasting called Differentially Private Long Short-Term Memory networks, or DP-LSTM for short. DP-LSTM leverages sentiment analysis capabilities by utilizing Long Short-Term Memory neural networks to process text. It incorporates a valence awareness dictionary and appraisal techniques for real-time sentiment scoring of financial data and discussions. By introducing carefully calibrated random perturbations to analysis results, DP-LSTM is able to protect individual privacy while still producing robust and privacy-preserving equity price forecasts. The differential privacy aspect ensures that the contribution of any single individual to the model's training is obscured, thus minimizing re-identification risk. Overall, the DP-LSTM model offers financial analysts and investors an advanced deep learning tool for equity research that maintains strong privacy guarantees for all data subjects.

**Advantages:**

This paper introduces an innovative integration of sophisticated neural networks and well-established natural language processing models to evaluate sentiment from textual data and mitigate investment risk. A differentially private long short-term memory neural network combines gated recurrent units, sentiment metrics, and differential privacy techniques to forecast equity prices, enhancing model robustness.

**Drawbacks:**

The results highlight the need for separate training for individual stocks, suggesting a potential limitation in the model's ability. The compound scores exhibit fluctuations, indicating variability in sentiment, which might challenge the model's consistency in predicting sentiment. The model's use of sentiment analysis from news articles could introduce subjectivity since it is sensitive to non-objective reports.

**Title: “Neural networks for stock price prediction” [4]**

**Authors Name: Yue-Gang Songa, Yu-Long Zhoub, Ren-Jie Hanc**

**Year: 2018**

**Description:**

This study assessed the forecasting abilities of five neural network models—backpropagation neural network (BPNN), radial basis function neural network (RBFNN), general regression neural network (GRNN), support vector machine for regression (SVMR), and least squares support vector machine for regression (LS-SVMR)—to predict the stock prices of three selected equities. Key performance metrics including mean squared error and average absolute percentage error were examined to determine the highest-performing model. During out-of-sample testing, the BPNN model recurrently showed superior outcomes against its peer algorithms, providing projections with reliability and accuracy. This research thereby provides empirical support for BPNN as a robust and effective solution for stock price forecasting applications, exhibiting strong and stable predictive potential to inform financial decision-making.

**Advantages:**

Through rigorous testing and comparative appraisal of forecast accuracy across numerous financial time series, the BPNN approach reliably demonstrated enhanced predictive prowess compared to the alternative techniques under consideration. In the majority of experimental scenarios, the BPNN methodology most effectively captured the complex interrelationships underlying security pricing dynamics, consistently outputting the most precise projections.

**Drawbacks:**

The evaluation of a limited set of Chinese stocks may not generalize to other markets or equities. More advanced recent neural network architectures were not explored, therefore allowing for future study of newer models that could potentially outperform those examined in this research. The model's use of sentiment analysis from news articles could introduce subjectivity since it is sensitive to non-objective reports.

**Title: “A Public Mood–Driven Asset Allocation: The Importance of Financial Sentiment in Portfolio Management” [5]**

**Author Name:** Lorenzo Malandri, Carlotta Orsenigo, Carlo Vercellis, Erik Cambria

**Year:** 2018

**Description:**

This paper aims to investigate the impact of public sentiment on portfolio management strategies by utilizing measures of public financial mood alongside historical price data from the New York Stock Exchange (NYSE). Specifically, the study employs advanced machine learning techniques with a particular focus on long short-term memory networks (LSTMs) to analyze relationships between shifts in investor sentiment and the performance of different asset allocations over time. Rather than attempting to predict prices for individual stocks, the goal of this research is to optimize the allocation of funds across various asset classes by accounting for fluctuations in public opinion as measured by sentiment analysis of large-scale news and social media sources. By incorporating alternative data on collective investor emotions into portfolio allocation models, the researchers seek to develop adaptive strategies that can better navigate changing market conditions driven by shifts in public psychology and perceptions of risk.

**Advantages:**

This paper introduces a novel approach to portfolio management that incorporates public sentiment analysis in addition to financial metrics. The long short-term memory (LSTM) technique outperformed alternative methods, demonstrating its aptitude to handle the intricate nature of financial markets as well as sentiment analysis. The results evidence that the proposed methodology yields elevated returns for investment portfolios.

**Drawbacks:**

Financial language frequently employs sarcasm and ambiguity, complicating efforts to discern sentiment through automated analysis techniques. While offering insightful perspectives, the paper does not directly address consideration of transaction costs, an important real-world factor in portfolio management and optimization.

**Title: “Stock Price Prediction Using Machine Learning and LSTM-Based Deep Learning Models” [6]**

**Authors Name: Sidra Mehtab, Jaydip Sen and Abhishek Dutta**

**Year: 2020**

**Description:**

This research paper investigates the use of hybrid machine learning and deep learning methodologies for predicting Indian stock prices. Specifically, the study focuses on forecasting movements in the NIFTY 50 index, which tracks the 50 largest companies listed on the National Stock Exchange of India. The methodology first develops eight regression models using historical index values and related economic indicators as predictors. These initial predictive models are then combined with four long short-term memory (LSTM) network architectures to improve forecast accuracy. The LSTM networks analyse both short-term and long-term patterns in prior stock prices. Overall, the research presents a novel and effective methodology for predicting fluctuations in this important benchmark index of the Indian equity market. Overall, this research underscores the value of integrating artificial intelligence strategies with traditional time series.

**Advantages:**

This paper employs a comprehensive methodology by leveraging both machine learning and deep learning models to forecast stock index values and trend patterns. The findings suggest that univariate designs achieve higher precision and faster execution relative to multivariate frameworks. Specifically, long short-term memory networks tailored for single variable prediction outperformed gated recurrent unit networks applied to multiple correlated inputs.

**Drawbacks:**

The paper could have provided why specific machine learning and deep learning models were chosen. While superior LSTM performance is mentioned, a detailed analysis of individual models' strengths and weaknesses is lacking. Financial and sentiment data obtained through APIs are briefly mentioned, but potential limitations of these sources are not discussed.

**Title: “Visualizing and Forecasting Stocks Using Dash” [7]**

**Author Name: Dr. Rais Mulla Bharambe, Swastik Gupta, Khemraj Bohra, Preeta Tiwari**

**Year: 2022**

**Description:**

The paper aims to highlight an innovative hybrid methodology for forecasting stock market fluctuations through the strategic integration of machine learning and interactive data visualizations. Accurately anticipating price movements in the highly dynamic equities arena is crucial for both individual and institutional investors seeking an edge. By leveraging the predictive capabilities of Support Vector Machine modeling, combined with the intuitive data exploration enabled by Dash's Python-based visualization library, the project provides a compelling framework for ongoing real-time analysis of market trends and anomalies. Through its technique of melding advanced algorithmic forecasting with seamless online visualization, the research underscores the value of multi-disciplinary solutions in tackling the complexities of financial prediction.

**Advantages:**

The study provides a rigorous empirical comparison of the predictive accuracy of various machine learning algorithms for natural language processing tasks. Specifically, the LSTM models outperformed other algorithms in (tasks). The study also proposes several avenues for improving future models. By analyzing the tone and subjective evaluation implied in text, sentiment analysis may help models better understand the implications of what is said.

**Drawbacks:**

While the paper provides an interesting perspective on predicting stock price movements in the short term, it may not fully address the difficulties inherent in accurately forecasting stock prices over longer periods of time. Developing models that can anticipate the complex interplay of market forces and macroeconomic conditions over multiple years or decades remains a significant challenge.



**Title: “A Robust Predictive Model for Stock Price Prediction Using Deep Learning and Natural Language Processing” [8]**

**Authors Name:** Sidra Mehtab, Jaydip Sen

**Year:** 2019

**Description:**

This study sought to forecast future movements in stock prices through a hybrid methodology leveraging machine learning, deep learning and natural language processing techniques. Specifically, the research focused on analyzing index values for the NIFTY 50, a broad stock market index tracking 50 large, liquid Indian companies traded on the National Stock Exchange of India, over the period from 2015 to 2017. The study also evaluated whether public sentiment expressed on Twitter could provide insight into overall stock market sentiment. By capturing insights from both financial data and social media, the hybrid approach aimed to develop a more comprehensive perspective for anticipating fluctuations in the market and prices of constituent stocks. The findings of this research may help market participants further refine their strategies and also provide regulators with additional perspectives on the interplay between public opinion and securities valuation.

**Advantages:**

This research integrates machine learning, deep learning, and natural language processing techniques to conduct a comprehensive analysis of predicting stock prices. The models were developed and refined over a three-year period from 2015 to 2017, allowing for long-term analysis to discern trends, patterns, and market dynamics not evident in shorter time frames. This paper focuses its predictions to a one-week timeframe in order to meet the practical needs of investors in anticipating short-term stock price movements.

**Drawbacks:**

The ability of the proposed model to efficiently scale to larger datasets or real-time usage scenarios warrants additional examination. External influences on stock markets, including geopolitical developments and global economic trends, were not expressly incorporated into the current analysis. Addressing such exogenous variables could strengthen the actionability of future efforts.

**Title: “Predicting the Effects of News Sentiments on the Stock Market” [9]**

**Author Name:** Dev Shah, Haruna Isah, Farhana Zulkernine

**Year:** 2018

**Description:**

This research paper examines the effects of news sentiments on stock prices in the pharmaceutical sector. The paper provides relevant background information by discussing past work related to stock market prediction, sentiment analysis, and the potential value of using data from the social media platform Twitter to anticipate changes in stock prices. Specifically, sentiment analysis is explored as a method to gauge overall positive or negative perceptions of companies from news stories that could subsequently influence trader and investor decisions. By focusing on the pharmaceutical industry, the findings have practical implications for those seeking to understand how extra-financial news-based factors may impact publicly traded pharmaceutical organizations over brief periods of time.

**Advantages:**

This research developed a sentiment analysis dictionary specifically tailored for application within the pharmaceutical industry. Through the creation of an industry-specific lexicon, the researchers were able to attain a prediction accuracy rating of 70.9% when utilizing sentiment analysis to forecast short-term market trends within the sector. This research has laid important groundwork towards more precisely leveraging the wealth of unstructured data and digital traces created within specialized contexts.

**Drawbacks:**

This study examines sentiment analysis within the pharmaceutical industry, however generalizing the findings to other sectors may prove difficult. The research primarily analyzes news sentiment but does not consider other potential variables that could impact stock prices. Additional context and accounting for alternative influences would strengthen the conclusions and facilitate broader application of the results.

**Title: “Stock Price Prediction Based on Natural Language Processing” [10]**

**Authors Name: Xiaobin Tang, Nuo Lei, Manru Dong and Dan Ma**

**Year: 2022**

**Description:**

This study focuses on developing a more advanced approach for predicting stock price movements in the Chinese market through leveraging cutting-edge natural language processing techniques. Specifically, the research introduces a novel methodology that involves dynamically capturing relevant web text related to stock prices from online sources. It then applies state-of-the-art language models such as BERT and NEZHA to conduct keyword extension on the gathered text corpus. The research aspires to advance the field by developing a more robust, automated process for extracting meaningful information from large-scale unstructured text to improve the accuracy and reliability of Chinese stock predictions.

**Advantages:**

The research optimizes state-of-the-art text mining technology for the purpose of stock price index prediction, demonstrating an advanced methodology for deriving valuable insights from unstructured textual data. Specifically, the study introduces a novel approach for broadening the scope of keywords used as predictive variable. By incrementally enhancing the model's ability to capture subtle semantic relationships and contextual nuances within corporate disclosures and financial news reports.

**Drawbacks:**

Machine learning models developed using statistical algorithms carry an inherent risk of overfitting to the idiosyncrasies present within their training datasets. This overfitting can potentially undermine the generalizability and robustness of a model when tasked with classifying or predicting previously unseen data that does not precisely mirror the composition and characteristics of the original training data.

## **2.3 Outcome of the Literature**

- Researchers explore various techniques, including machine learning algorithms like artificial neural networks (ANN), deep learning architectures such as Long Short-Term Memory (LSTM) networks, and sentiment analysis coupled with natural language processing (NLP). These methodologies are employed to forecast stock prices, often integrating historical pricing data, macroeconomic factors, and sentiment data from news articles and social media.
- Evaluation metrics such as Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Bias Error (MBE) are commonly used to assess model performance. Additionally, some studies address privacy concerns by incorporating differential privacy techniques into their models.
- Short-term forecasting dominates the research landscape, with an emphasis on predicting movements within a week or the next trading day. Industry-specific analysis is also prevalent, with tailored sentiment analysis dictionaries for sectors like pharmaceuticals.
- Visualization techniques, particularly through interactive dashboards and visualization libraries like Dash, are increasingly utilized for interpreting model predictions and market trends. However, challenges persist, including data quality issues, scalability limitations, and the subjective nature of sentiment analysis.
- Overall, interdisciplinary approaches, data integration, and continuous refinement of techniques are essential for advancing the accuracy and real-world applicability of stock price prediction models. Addressing these challenges will contribute to further progress in the field and facilitate more informed decision-making for investors and traders.

## **CHAPTER 3**

# **SYSTEM ANALYSIS**

### **3.1 Existing System**

TradingView stands as a go-to platform for traders and investors worldwide. It offers a rich array of tools for analyzing financial markets, including advanced charting features, technical indicators, and drawing tools. TradingView also fosters a vibrant community where users can share trading ideas and strategies. What sets TradingView apart is its seamless integration with brokerage platforms, allowing users to execute trades directly from the platform. Its user-friendly interface and comprehensive features make it a trusted choice for those seeking to navigate the complexities of financial markets and make informed investment decisions. Automation streamlines asset allocation, making the process more efficient and enabling quicker decisions based on data.

### **3.2 Disadvantage of the System**

While TradingView offers a wide array of tools and benefits, there are some drawbacks users should be aware of. Firstly, the platform's pricing may be a hurdle for some, especially those needing access to advanced features only available through premium subscriptions. This could limit the platform's accessibility for budget-conscious users or those hesitant to invest in additional features. Additionally, while TradingView has a bustling community, the quality of trading ideas shared can vary widely. Users should exercise caution and conduct their own research, as relying solely on community insights could lead to poor decision-making.

Moreover, while TradingView integrates seamlessly with various brokerage platforms, users may face challenges related to data synchronization and order execution speed. Inaccuracies in data or delays in executing trades could undermine trading strategies, particularly for those executing time-sensitive trades. Additionally, concerns about data privacy and security are important considerations. Users should be diligent in protecting their personal and financial information, especially when executing trades directly through the platform. Addressing these concerns will be vital for TradingView to maintain its status as a trusted platform for traders and investors. Automation streamlines asset allocation, making the process more efficient and enabling quicker decisions based on data.

### **3.3 Proposed System**

Our project proposes a fresh way of making investment decisions by combining sentiment analysis with advanced machine learning techniques. Unlike traditional methods that focus solely on predicting stock prices, our approach predicts the best way to allocate assets by considering both historical data and current market sentiment. By using machine learning models like Long Short-Term Memory Networks (LSTM), Multilayer Perceptron (MLP), and Random Forests, our system automates the process of identifying effective asset allocation strategies, making decisions quicker and more data-driven. This innovative method aims to offer users deeper insights into investment opportunities, outperforming traditional methods, and being adaptable to different types of investors, from individuals to institutions.

### **3.4 Advantages of the System**

The proposed system offers significant advantages for investment decision-making by combining sentiment analysis with advanced machine learning techniques. By considering both market sentiment and historical trends, the system provides deeper insights into market dynamics, helping users make more informed decisions. Automation streamlines asset allocation, making the process more efficient and enabling quicker decisions based on data. Leveraging sophisticated machine learning models enhances performance, potentially leading to higher returns and lower risks. Additionally, the system's flexibility and scalability cater to various investor needs, while real-time insights ensure users can stay ahead of market trends, making it a valuable tool for achieving better financial outcomes.

## CHAPTER 4

# SYSTEM REQUIREMENT SPECIFICATION

In crafting our stock price prediction system, we integrate a suite of tools and APIs to streamline data processing and enhance user experience. Our backend architecture seamlessly connects to financial data sources for historical stock prices, alongside platforms providing data on gold prices, petroleum prices, and USD to INR exchange rates.

Python, with its powerful libraries like pandas and scikit-learn, serves as the foundation for data preparation and machine learning model training. Our diverse model selection includes Linear Regression, Random Forest, k-Nearest Neighbours, Artificial Neural Networks, and Long Short-Term Memory, ensuring robust and accurate predictions. To capture market sentiment, we harness natural language processing techniques via the NLTK module, enriching our models with qualitative insights.

Complementing our advanced backend, our system features a sleek and intuitive front-end design, crafted with HTML and CSS. Through clean and responsive design principles, users can seamlessly interact with the system across various devices. Our HTML-based interface offers straightforward navigation, presenting users with precise predictions, detailed model performance metrics, and visually intuitive representations. By prioritizing user experience, our system empowers investors and financial analysts to navigate the complexities of the stock market with ease and confidence. By integrating cutting-edge technology with user-centric design principles, our stock price prediction system delivers a seamless and enriching experience, facilitating informed investment decisions effortlessly.

## 4.1 System Requirements

### Hardware Requirements

- Operating system: Windows, macOS, or Linux.
- 8 GB RAM, 256 GB SSD storage.
- High-speed internet connection with a minimum bandwidth of 10 Mbps.

## Software Requirements

- Software tool: Anaconda Navigator
- IDE: Jupyter Notebook
- Python 3

### 4.2 About the Software and Packages

- **Jupyter Notebook**

Jupyter Notebook provides an interactive computing environment ideal for data exploration, experimentation, and visualization. Its integration with Python allows for seamless coding, documentation, and sharing of code and results, facilitating collaboration and reproducibility.

- **Scikit-learn**

Scikit-learn is a versatile machine learning library in Python, offering a wide range of algorithms and tools for building predictive models, including regression, classification, clustering, and dimensionality reduction. Its user-friendly interface and extensive documentation make it suitable for implementing various machine learning techniques in the proposed system.

- **NLTK (Natural Language Toolkit)**

NLTK is a leading platform for natural language processing (NLP) in Python, providing tools and resources for text analysis, tokenization, stemming, tagging, and sentiment analysis. It offers pre-trained models and datasets, making it ideal for extracting sentiment from textual data sources, such as news articles and social media.

- **TensorFlow and Keras**

TensorFlow is an open-source machine learning framework developed by Google, while Keras is a high-level neural networks API that runs on top of TensorFlow. Together, they offer a powerful platform for building and training deep learning models, such as Long Short-Term Memory (LSTM) networks, essential for capturing complex patterns and dependencies in sequential data, such as time-series financial data.

- **Matplotlib and Seaborn**

Matplotlib and Seaborn are Python libraries for creating static, animated, and interactive visualizations. They offer a wide range of plotting functions and styles, making



it easy to generate informative and visually appealing plots, charts, and graphs to analyze and communicate the results of the proposed system.

- **HTML and CSS:**

HTML (Hypertext Markup Language) and CSS (Cascading Style Sheets) are fundamental technologies used for creating and styling web pages. While not directly involved in the backend development of the proposed system, HTML and CSS may be utilized for designing user interfaces, such as dashboards or visualization tools, to present the results of the analysis in a user-friendly and visually appealing manner. These technologies enable the creation of interactive and responsive web interfaces that enhance the overall user experience and facilitate the interpretation of results.

### **4.3 About the programming language**

**Python:** Python serves as the main programming language for our project. It's popular for its simplicity and readability, making it easy to understand and write code. Python's versatility allows us to tackle various tasks, from analyzing data to building machine learning models and even developing web applications. With a vast collection of libraries like Pandas for data manipulation, Scikit-learn for machine learning, and TensorFlow for deep learning, Python provides powerful tools to achieve our project goals. Its user-friendly syntax and active community support make it accessible to developers of all skill levels, ensuring efficient development and continuous innovation for our system.

## CHAPTER 5

### SYSTEM DESIGN

The stock price forecasting system is designed to leverage various machine learning algorithms in identifying trends and predicting future price movements. The process involves several sequential stages: initially, relevant data is gathered including historical stock prices, market indicators, and company financial reports. Pre-processing steps are then applied to handle missing or anomalous values, while feature engineering may create new variables representing market conditions. The data is labelled to define target outcomes, such as price directionality or volatility.

Machine learning algorithms like logistic regression, decision trees, or random forests are selected based on an analysis of the inherent characteristics of stock market data. The model is then trained on a subset of the dataset and evaluated on separate test data to assess predictive performance. Continuous monitoring and updates are conducted to adapt the model to evolving market data and emerging trends.

#### 5.1 Architecture

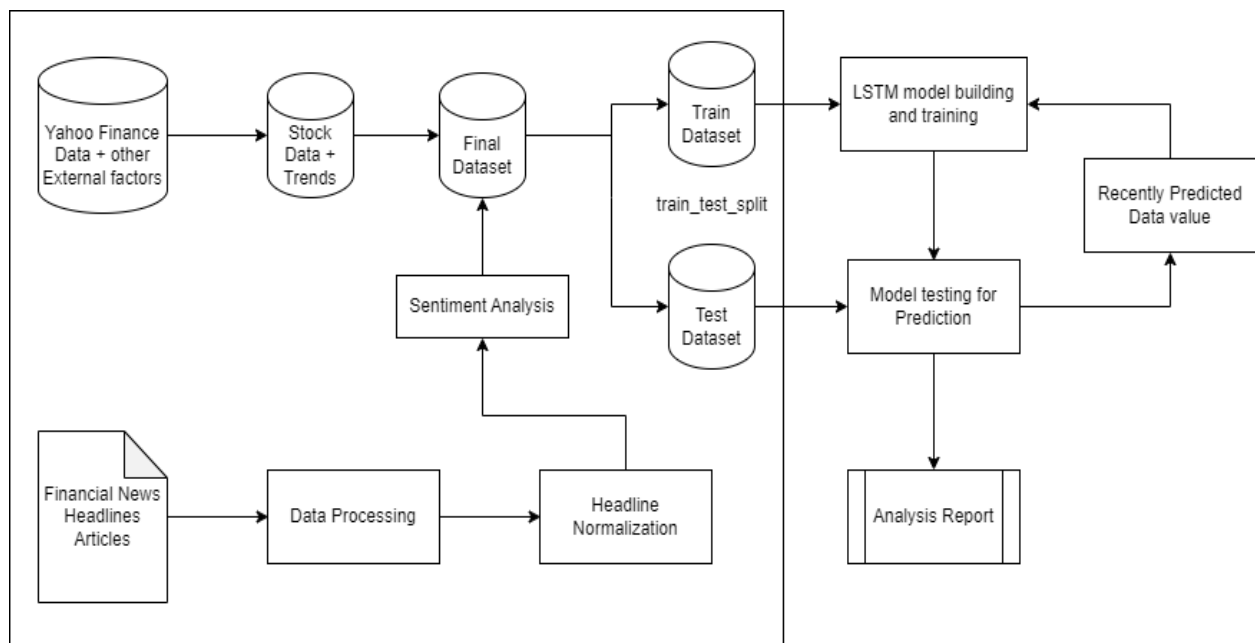


Figure 5.1 Block Diagram

In crafting our stock rate prediction model, we've adhered to a methodological framework that combines conventional financial evaluation strategies with modern system getting to know algorithms. This complete approach was chosen to make sure the efficacy and reliability of our forecasting system amidst the elaborate dynamics of monetary markets. Our technique unfolds in a chain of meticulously achieved ranges, every aimed at refining our predictive models and imparting actionable insights for buyers and economic analysts alike.

To construct our stock price forecasting algorithm, we followed a methodological method that mixes conventional economic evaluation techniques with today's device learning algorithms. This complete technique was selected to make certain the efficiency and reliability of our forecasting system in the complex dynamics of financial markets. Our method unfolds in a chain of carefully designed steps, every of which aims to refine our forecasting models and provide usable insights for buyers and economic analysts alike.

Our approach carries numerous critical methods and techniques, that have been actively implemented for the duration of the development of the device. Initially, we started out our records series journey via acquiring ancient inventory costs from reliable financial statistics providers. At the identical time, we gathered important economic records such as gold charges, petroleum prices and USD to INR alternate costs from real sources. Rigorous pre-processing procedures have been used to cleanse and standardize the dataset after records collection, handling missing values, inconsistencies, and many others. And for this step essential to make certain records integrity and consistency, laying a solid foundation for next studies.

The integration of outputs from machine learning fashions and sentiment evaluation constituted a critical step in our technique. By fusing insights from diverse sources, we aimed to create a comprehensive set of inputs for very last prediction, enriching the predictive abilities of our system. Through this integration, we sought to offer stakeholders with unique forecasts and beneficial insights into marketplace dynamics.

## **1. Data Collection**

- Stock Prices: Historical stock prices are collected from reliable financial data sources. This data includes daily closing prices, trading volumes, and other relevant metrics.
- Economic Factors: Data on gold prices, petroleum prices, and USD to INR exchange rates is gathered from authoritative sources to capture the broader economic landscape.

## **2. Data Preprocessing**

- Cleaning: Raw data is cleaned to handle missing values, outliers, and other irregularities.
- Scaling: Data is normalized or scaled to ensure that all features contribute equally to the model training process.

## **3. Machine Learning Models**

### **a. Linear Regression**

Purpose: Linear Regression is employed to version the relationship among the stock prices and selected functions linearly.

Training: The version is skilled the use of ancient facts and monetary elements, with a focus on minimizing the distinction between expected and real final charges.

### **b. Random Forest**

Purpose: Random Forest is chosen for its potential to handle non-linear relationships and complex interactions amongst functions.

Training: Multiple selection is skilled, and their outputs are blended to decorate prediction accuracy.

### **c. K-Nearest Neighbours (KNN)**

Purpose: KNN is utilized for its simplicity and effectiveness in shooting local patterns within the facts.

Training: The algorithm shops instances of historical records and predicts the inventory charge primarily based on the bulk of okay-nearest facts points.

### **d. Convolutional Neural Networks**

Purpose: CNNs seize spatial hierarchies and nearby styles in sequential statistics.

Training: The model learns to extract features from enter facts through convolutional layers and modify their weights to minimize prediction errors.

### **e. Artificial Neural Networks (ANN)**

Purpose: ANN is a powerful tool for shooting patterns and dependencies in the records.

Training: The neural community is educated the usage of historical facts, adjusting weights to reduce the distinction among expected and real prices.

f. Long Short-Term Memory (LSTM)

Purpose: LSTM is employed quick-term dependencies and patterns in time-series facts.

Training: The version is skilled to research from sequences of ancient stock charges.

## **4. Sentiment Analysis**

- Text Data Collection: News articles records are collected to come across marketplace sentiment.
- Sentiment Analysis: Natural Language Processing (NLP) strategies are implemented to research the sentiment of the amassed textual information.

## **5. Integration**

- Feature Fusion: The outputs from machine gaining knowledge of models and sentiment analysis are mixed, creating a complete set of inputs for the final prediction.

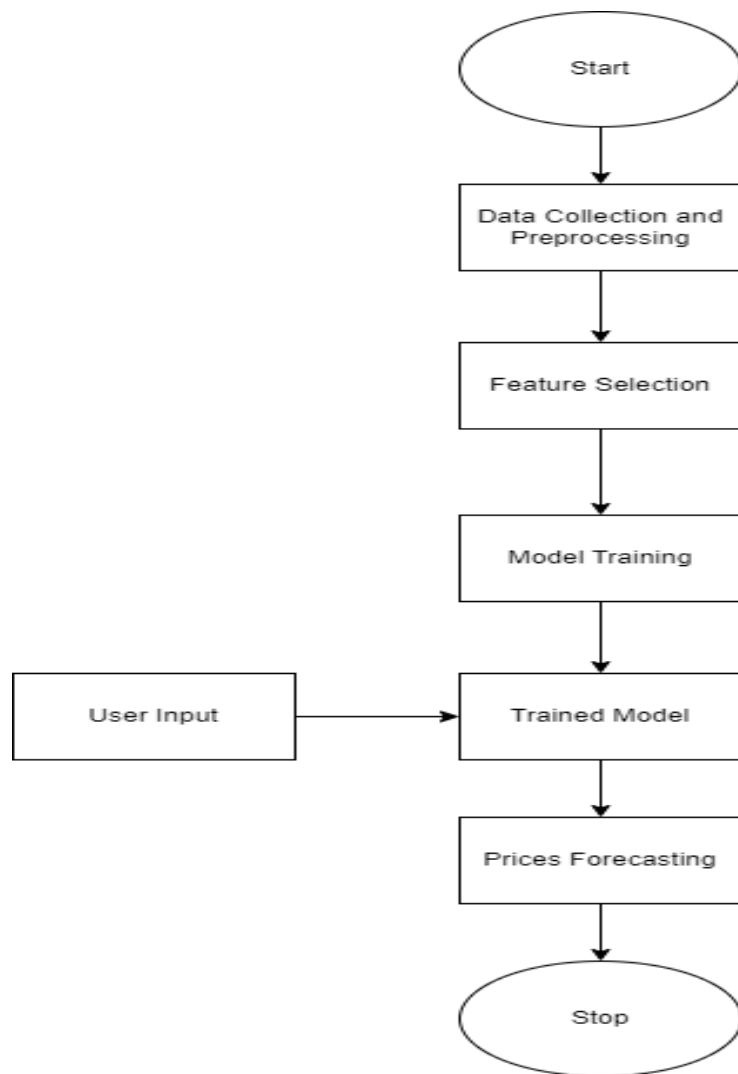
## **6. Model Evaluation**

- Metrics: Various metrics, along with Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Square Error (MSE), are used to evaluate the performance of each model.
- Back testing: The fashions are returned examined towards historical facts to assess their effectiveness in a simulated buying and selling environment.

## **7. Deployment**

- API Integration: The device may be integrated with APIs for day-by-day facts updates and seamless deployment in a production surroundings.
- User Interface: A user-friendly interface affords stakeholders with insights into predictions, version performance, and monetary elements affecting stock charges.

## 5.2 Methodology



**Fig 5.2 Methodology diagram**

### Step 1: Data Collection and Preprocessing

- Gather relevant data from various sources including historical stock prices, gold prices, petroleum prices, and USD to INR exchange rates.
- Clean the data by handling missing values, removing duplicates, and ensuring consistency in formatting.
- Preprocess the data by normalizing or scaling numerical features and encoding categorical variables.
- Split the data into training and testing sets for model evaluation.

## **Step 2: Feature Selection**

- Identify the most relevant features for stock price prediction, considering factors such as historical stock prices, economic indicators, and market sentiment.
- Use techniques like correlation analysis, feature importance scores, or domain knowledge to select the most informative features.
- Reduce dimensionality if needed to improve model performance and reduce computational complexity.

## **Step 3: Model Training**

- Choose suitable system studying algorithms including Linear Regression, Random Forest, or Artificial Neural Networks for schooling.
- Train the selected model(s) the usage of the education records, permitting them to research patterns and relationships within the features.
- Tune hyperparameters using strategies like grid seek or random search to optimize version performance.
- Evaluate the trained models with the use of metrics including Mean Squared Error (MSE) or Root Mean Squared Error (RMSE) to evaluate their predictive accuracy.

## **Step 4: Trained Model**

- Once the machine studying model has been skilled on ancient statistics and evaluated for its predictive overall performance, it is prepared to be applied for making predictions.
- When a person inputs applicable statistics, which include recent stock prices, economic signs, or another factor influencing stock price, this information is fed into the educated model.
- The trained model methods the entered facts through its learned patterns and relationships to generate predictions approximately future stock costs.
- Depending on the complexity of the model and the amount of input data provided, the prediction process can be immediately or may require some computational time.

## **Step 5: Prices Forecasting**

- After the trained model has processed the user input data, it generates forecasts or predictions for future stock prices.
- These forecasts are typically expressed as numerical values representing the predicted prices for specific time periods, such as tomorrow's closing price or next week's average price.
- The forecasting procedure might also include producing self-belief intervals or uncertainty estimates to suggest the reliability of the predictions.
- Once the forecasts are generated, they can be presented to the user through the system's interface, permitting traders and financial analysts to make informed decisions based on the expected stock expenses.

By following these steps, the stock price prediction system leverages the trained machine learning model to generate forecasts that can assist users in navigating the complexities of the stock market and making strategic investment decisions.



## CHAPTER 6

# SYSTEM IMPLEMENTATION

A thorough analysis of the inherent characteristics of stock market data is conducted to select the most appropriate machine learning algorithms, such as logistic regression, decision trees, or random forests, best suited for the given prediction task. The selected model is rigorously trained on a representative subset of the cleaned and engineered dataset and its predictive performance is evaluated on separate unseen test data to ensure generalizability. Continuous monitoring and periodic model updates are conducted to automatically adapt the system to evolving financial market behaviour and emerging trends. This helps maintain predictive accuracy over time as new data becomes available.

## 6.1 Pseudo Code Explanation

### Patch 1: Data Retrieval and Preprocessing

FUNCTION download\_data(ticker, start\_date, end\_date):

    TRY:

        data = GET\_DATA\_FROM\_YFINANCE(ticker, start\_date, end\_date)

        data = SELECT\_COLUMN(data, 'Close')

    RETURN data

    CATCH Exception AS e:

        PRINT\_ERROR\_MESSAGE("Error downloading data for {ticker}: {e}")

    RETURN EMPTY\_SERIES\_WITH\_NAME(ticker)

DEFINE dataframes = []

FOR EACH ticker IN tickers:

    dataframe = download\_data(ticker, start\_date, end\_date)

    APPEND dataframe TO dataframes

### **Explanation**

- The `download_data` function retrieves stock data for a given ticker symbol within a specified date range. It handles exceptions and returns an empty series if there's an error.
- Ticker symbols, start date, and end date are defined.
- The dataframes are merged into a single dataframe, and columns are renamed.
- The merged data is saved to a CSV file.

### **Patch 2: Data Analysis**

IMPORT Libraries

IMPORT Data

DEFINE tickers = ['FRSH', 'NEM', 'XOM', 'INR=X']

DOWNLOAD Data for tickers using yfinance, covering the last 20 years

MERGE Dataframes for tickers

HANDLE Missing Values

SAVE Merged Data to 'merged\_data.csv'

PRINT Summary Statistics of Data

### **Explanation:**

- Import necessary libraries for data analysis.
- Define a list of tickers (stock symbols) to collect data for.
- Download historical stock price data using Yahoo Finance API (yfinance) for the specified tickers, covering the last 20 years.
- Merge the downloaded dataframes into one dataframe, handling any missing values.
- Save the merged data to a CSV file for further use.
- Print summary statistics of the dataset to gain insights into the distribution and characteristics of the data.

### Patch 3: Model Building and Evaluation

```
DEFINE X_train, X_test, y_train, y_test = SPLIT_DATA(X, y, test_size=0.2, random_state=42)

# Long Short-Term Memory (LSTM)

DEFINE scaler_lstm = INITIALIZE_MINMAX_SCALER()

X_train_lstm, X_test_lstm, y_train_lstm, y_test_lstm = CREATE_LSTM_SEQUENCES(X, y,
scaler_lstm)

DEFINE model_lstm = INITIALIZE_LSTM_MODEL()

COMPILE_MODEL(model_lstm, optimizer='adam', loss='mean_squared_error')

FIT_MODEL(model_lstm, X_train_lstm, y_train_lstm, epochs=50, batch_size=32)

y_pred_lstm = PREDICT(model_lstm, X_test_lstm)

y_pred_lstm_inv = INVERSE_TRANSFORM(y_pred_lstm, scaler_lstm)

y_test_inv_lstm = INVERSE_TRANSFORM(y_test_lstm, scaler_lstm)

DEFINE rmse_lstm = CALCULATE_RMSE(y_test_inv_lstm, y_pred_lstm_inv)

PRINT("LSTM RMSE: ", rmse_lstm)
```

#### Explanation

- Splits the data into training and testing sets.
- Initializes and fits models for linear regression, random forest, k-nearest neighbors, CNN, ANN, and LSTM.
- Calculates evaluation metrics for each model.
- Prints the evaluation metrics for comparison.

### Patch 4: Sentiment Analysis

```
IMPORT Libraries for Sentiment Analysis (nltk, finnhub, csv)

FETCH Company News and Historical Stock Prices for a Specified Ticker ('FRSH')
```

PROCESS and PREPARE Data: Combine News Headlines, Summaries, and Stock Prices

SAVE Processed Data to CSV for Sentiment Analysis

DOWNLOAD Vader Lexicon for Sentiment Analysis

READ Processed Data from CSV

APPLY Sentiment Analysis using Vader Sentiment Intensity Analyzer

SAVE Sentiment Scores (Headline and Content) to CSV

PREPARE Data for Machine Learning Model: Features (Headline Sentiment, Content Sentiment) and Target Variable (Close Price)

SPLIT Data into Train, Validation, and Test Sets

TRAIN a RandomForestRegressor Model on the Training Set

EVALUATE Model Performance on the Test Set: Calculate MSE, RMSE, MAE, and Error Percentage

VISUALIZE Predicted vs Actual Close Prices

### **Explanation**

- Import necessary libraries for sentiment analysis including nltk, finnhub, and csv.
- Fetch company news and historical stock prices for a specified ticker ('FRSH') using relevant APIs (Finnhub and Yahoo Finance).
- Process and prepare the data by combining news headlines, summaries, and corresponding stock prices.
- Save the processed data to a CSV file for sentiment analysis.
- Download the Vader Lexicon, a lexicon for sentiment analysis, using the NLTK library.
- Read the processed data from the CSV file.
- Apply sentiment analysis to the news headlines and summaries using the Vader Sentiment Intensity Analyzer.
- Save the sentiment scores (headline and content) to a CSV file for further analysis.

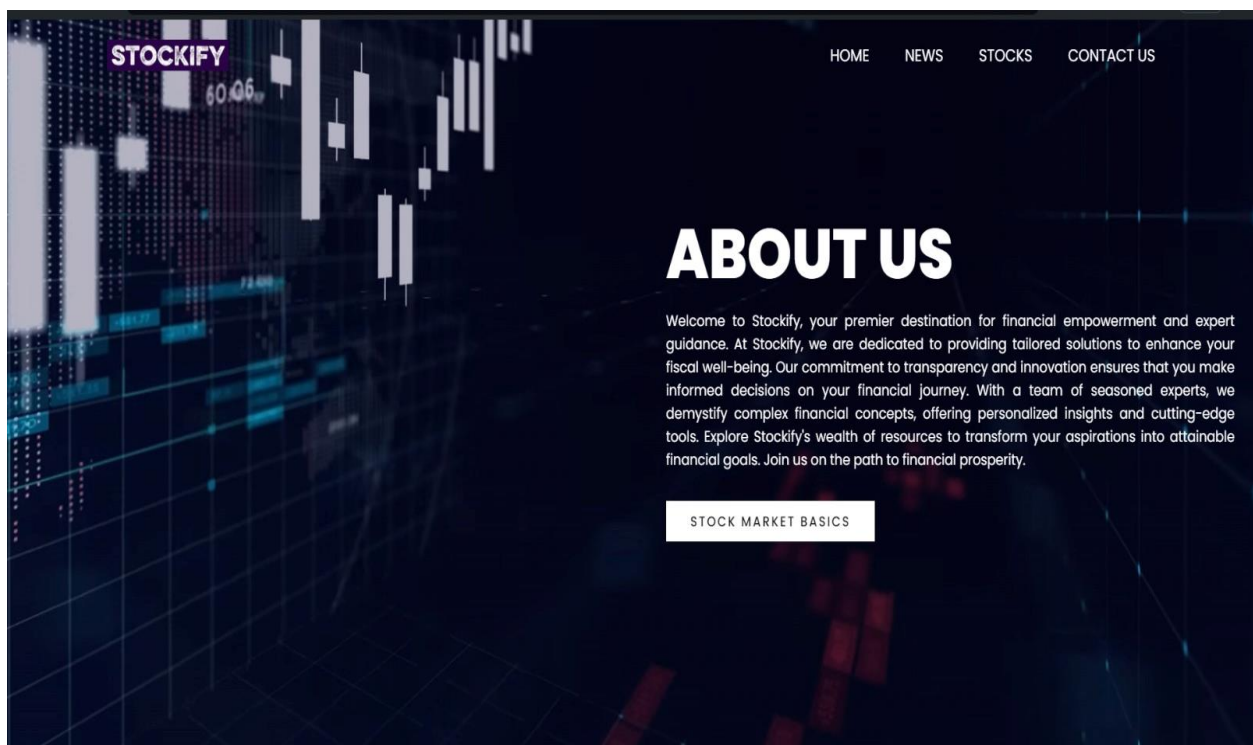
- Prepare the data for machine learning modeling by selecting features (headline sentiment, content sentiment) and the target variable (close price).
- Split the data into training, validation, and test sets.
- Train a RandomForestRegressor model on the training set.
- Evaluate the model's performance on the test set by calculating metrics such as mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and error percentage.
- Visualize the predicted vs actual close prices to assess the model's performance visually.

## CHAPTER 7

# EXPERIMENTAL RESULT AND ANALYSIS

This section begins with a concise presentation of the results and showcases the visual aspects of the interface along with a sample output. It also discusses the findings obtained through our investigation.

## 7.1 Screenshot



**Fig 7.1 The Home Page**

The starting page for users that provides essential information and functionalities. It provides essential information to help visitors understand the products, and services in a clear and concise manner.

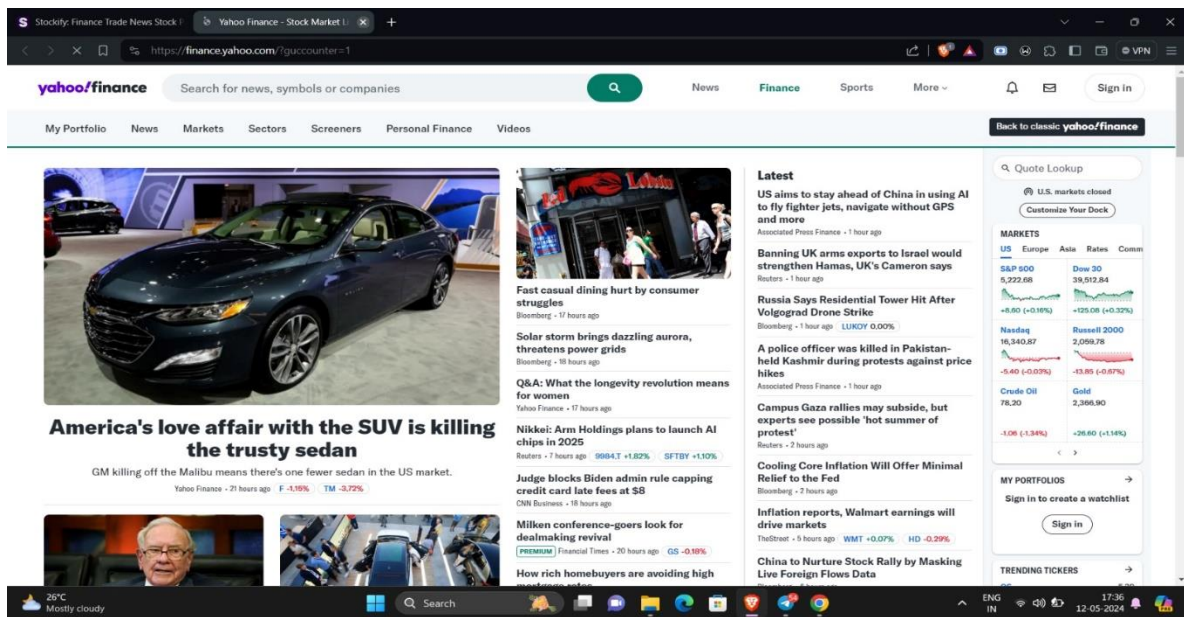


Fig 7.2 The News Page

The News web page offers real-time market updates and summaries of the stocks that is redirected to official website of Yahoo Finance. Users can access key market statistics, performance trends, and evaluation to gain insights into market sentiment and trends.

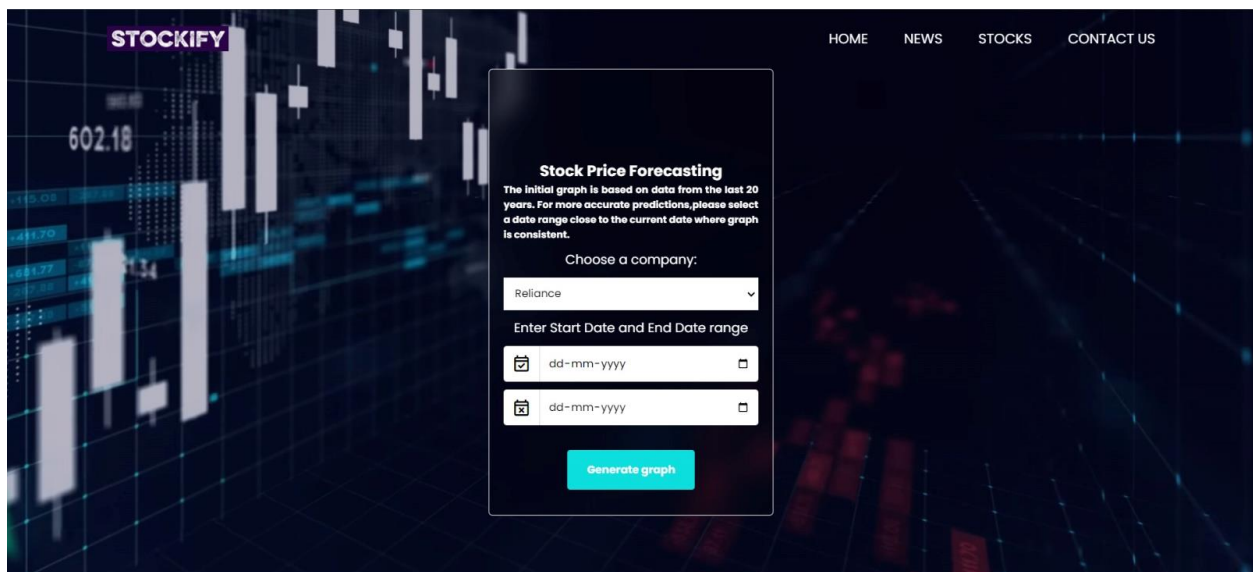
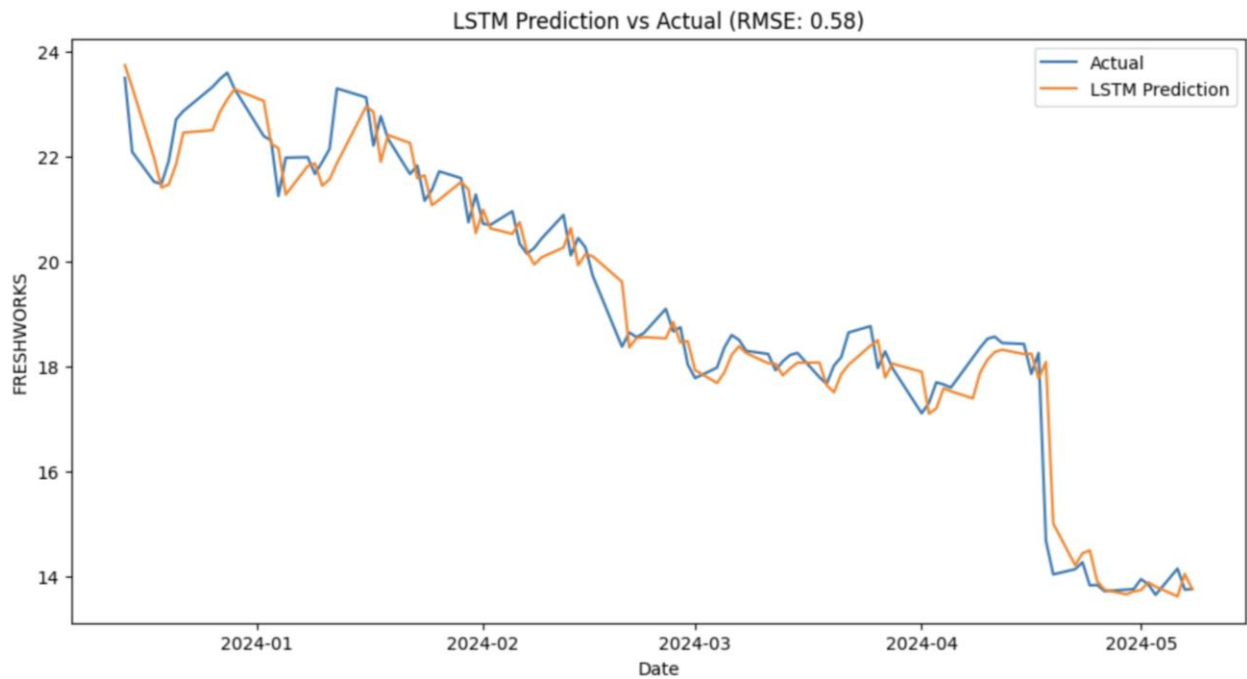


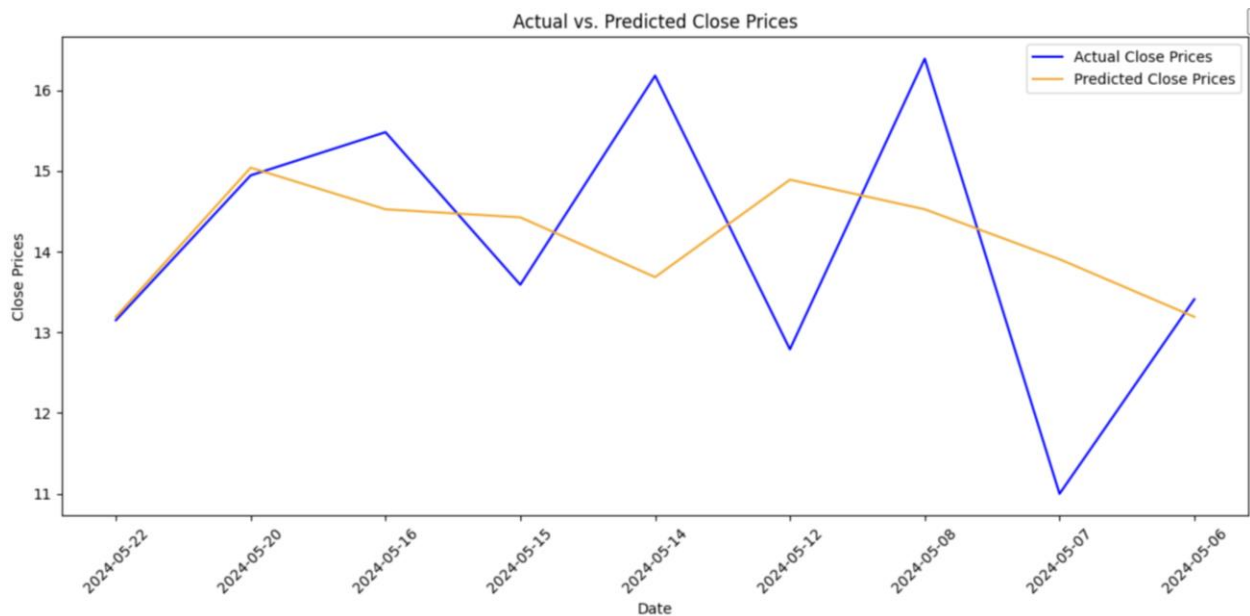
Fig 7.3 Stock Form page

The stock form page allows users to input particular parameters and dates to generate predictions of stocks. A dropdown menu or search bar wherein users can pick out the dates they want to predict.



**Fig 7.4 LSTM Analysis**

The graph received from LSTM assessment on stock prediction platform visualizes the stock over a detailed time horizon. The horizontal axis of the graph represents time, with dates beginning from the begin to the stop of the prediction duration. The Y-axis values suggest the predicted expenses of the stock(s) at each corresponding time component along the X-axis.



**Fig 7.5 Sentiment Analysis**

The above graph received from sentiment analysis visualizes the sentiments extracted from textual data, which include news articles, social media posts, or economic opinions, the usage of sentiment



analysis strategies. The graph normally gives sentiment rankings over the years, with the x-axis representing the timeline and the y-axis indicating the close price.

**Table 7.1 Validation Table**

	<b>Validation Size (%)</b>	<b>MSE</b>	<b>MAE</b>	<b>RMSE</b>	<b>Error %</b>
<b>0</b>	<b>5</b>	<b>1.00817</b>	<b>0.670647</b>	<b>1.00408</b>	<b>5.79639</b>
<b>1</b>	<b>10</b>	<b>0.752473</b>	<b>0.56404</b>	<b>0.867452</b>	<b>4.68523</b>
<b>2</b>	<b>15</b>	<b>0.791916</b>	<b>0.608994</b>	<b>0.889897</b>	<b>4.47476</b>
<b>3</b>	<b>20</b>	<b>1.2599</b>	<b>0.875628</b>	<b>1.12245</b>	<b>5.64592</b>

Based at the validation outcomes, the model plays relatively properly across distinct validation set sizes, with decrease MSE, MAE, RMSE, and errors probabilities indicating higher predictive overall performance.

**Table 7.2 Error Table**

Model	MSE	RMSE	MAE	Error Percentage
Linear Regression	23.20	4.81	3.54	18.30
Random Forest	10.10	3.17	1.64	8.51
K-Nearest Neighbours	26.25	5.09	3.30	17.06
Convolutional Neural Network	18.06	4.25	3.10	16.03
Artificial Neural Network	11.66	3.41	2.58	13.35
LSTM	0.72	0.85	0.58	2.96

The table provides insight into the predictive efficacy of each model using metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Error Percentage.

Lower values in these metrics indicate greater predictive accuracy. The Error Percentage specifically offers a relative measure of error compared to the average actual stock prices. This table serves as a performance report for various regression models applied to predict stock prices using features such as gold and petroleum prices and currency values.

## **CHAPTER 8**

### **CONCLUSION AND FUTURE SCOPE**

Predicting stock prices is a sophisticated endeavour that relies upon advanced data analytics techniques, sophisticated machine learning algorithms, and a nuanced understanding of economic principles. To glean meaningful insights, it is imperative to leverage diverse data sources, including economic indicators and platforms such as Yahoo Finance and Finnhub. Developing effective forecasting tools necessitates careful attention to data quality, thoughtful feature engineering processes, and the judicious selection of appropriate algorithms.

The dynamic nature of financial markets demands continuous adaptation and refinement of models. Regular evaluation and updates are necessary to ensure the models accurately capture ever-changing market dynamics. Looking ahead, as technology continues to progress, there is potential for artificial intelligence, deep learning techniques, and sophisticated data analytics to further refine and improve the precision and agility of stock price forecasting models. This progress can empower market participants with enhanced insights, aiding in more informed and strategic decision-making processes.

Despite these challenges, the advancements in machine learning, deep learning, and natural language processing techniques continue to drive innovation in stock price forecasting. By addressing the limitations and refining existing methodologies, researchers and practitioners can further improve the effectiveness and reliability of predictive models, ultimately enhancing decision-making processes in the financial industry.

## REFERENCES:

- [1] Yue-Gang Song, Yu-Long Zhou, Ren-Jie Han. Neural networks for stock price prediction. Last accessed 2018.
- [2] Lorenzo Malandri, Frank Xing, Carlotta Orsenigo, Carlo Vercellis. Public Mood-Driven Asset Allocation: The Importance of Financial Sentiment in Portfolio Management. Last accessed 2018.
- [3] Xinyi Li, Yinchuan Li, Hongyang Yang, Liuqing Ypang, Xiao-Yang Liu. DP-LSTM: Differential Privacy-inspired LSTM for Stock Prediction Using Financial News. Last accessed 2019.
- [4] Mehar Vijh, Deeksha Chandola, Vinay Anand Tikkiwal, Arun Kumar. Stock Closing Price Prediction using Machine Learning Techniques. Last accessed 2019.
- [5] Sidra Mehtab, Jaydip Sen. A Robust Predictive Model for Stock Price Prediction Using Deep Learning and Natural Language Processing. Last accessed 2019.
- [6] Dev Shah, Haruna Isah, Farhana Zulkernine. Predicting the Effects of News Sentiments on the Stock Market. Last accessed 2019.
- [7] Sidra Mehtab, Jaydip Sen and Abhishek Dutta. Stock Price prediction Using Machine Learning and LSTM-Based Deep Learning Models. Last accessed 2021.
- [8] Narayana Darapaneni, Anwesh Reddy Paduri, Himank Sharma, Milind Manjrekar, Nutan Hindlekar, Pranali Bhagat, Usha Aiyer, Yogesh Agarwal. Stock Price Prediction using Sentiment Analysis and Deep Learning for Indian Markets. Last accessed 2022.
- [9] Dr. Rais Mulla, Dinesh Bharambe, Swastik Gupta, Khemraj Bohra, Preeta Tiwari. Visualizing and Forecasting Stocks Using Dash. Last accessed 2022.
- [10] Xiaobin Tang, Nuo Lei, Manru Dong and Dan Ma. Stock Price Prediction Based on Natural Language Processing. Last accessed 2022.
- [11] <https://finance.yahoo.com/>
- [12] <https://www.nseindia.com/>
- [13] <https://chat.openai.com/>
- [14] <https://centerpointsecurities.com/stock-market-algorithms/>
- [15] <https://www.geeksforgeeks.org/long-short-term-memory-networks-explanation/>

## APPENDICES





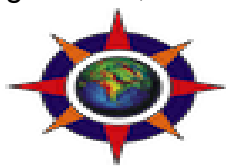






# **PES INSTITUTE OF TECHNOLOGY & MANAGEMENT**

NH-206, Sagar Road, Shivamogga – 577204



## **VISION OF THE INSTITUTE**

---

*To be the most preferred institution for engineering & management education, research and entrepreneurship by creating professionally superior and ethically strong global manpower.*

---

## **MISSION OF THE INSTITUTE**

---

*To prepare students for professional accomplishments and responsible global citizenship while fostering continuous learning and to provide state-of-the-art education through the committed and highly skilled faculty by partnering and collaborating with industry and r&d institutes.*

---

## **DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING**

### **VISION OF THE DEPARTMENT**

---

*To be a leader in providing education with skilled technical knowledge imbining professional ethics to the students in the field of computer science and engineering.*

---

### **MISSION OF THE DEPARTMENT**

---

**Mission 1:** *Imparting quality education to students by ensuring a learning environment through qualified faculty and good infrastructure*

**Mission 2:** *Empower students to attain strong technical and ethical skills for a successful career in industry, academics, research and entrepreneurship through active engagement with all the stakeholders.*

---



# **PES INSTITUTE OF TECHNOLOGY & MANAGMENT**

NH-206, Sagar Road, Shivamogga – 577204



## **Department of Computer Science & Engineering**

### **Program Educational Objectives (PEOs)**

---

**PEO1:** *The ability to conceptualize, analyze, design and develop it solutions of varying complexities by leveraging advances in computer technology*

**PEO2:** *The ability to apply standard practices and strategies in software project development and management using industry-wide bench marked framework to deliver a sustainable quality product*

**PEO3:** *The ability to work as a team player in cross-cultural environment adhering to work ethics with a passion for entrepreneurship and a zest for higher studies*

---

### **Program Specific Outcomes (PSOs)**

---

**PSO1:** *To develop ability to interpret the fundamental concepts and methodologies of computer systems.*

**PSO2** *To use the mathematical concepts to crack problems using suitable mathematical analysis, data structures and algorithms.*

**PSO3:** *Develop ability to grasp the software development lifecycle and methodologies of software system, possess competent skills and knowledge of software design process. familiarity and practical proficiency with a broad area of programming concepts and provide new ideas and innovations towards res*

---

# Application of LSTM and Sentiment Analysis in Stock Price Forecasting

Vinutha H M<sup>1</sup>, Harsh Mishra<sup>2</sup>, Shaishav<sup>3</sup>, Sumit Raj<sup>4</sup>, Trupthi K<sup>\*5</sup>

<sup>1</sup>Assistant Professor, Dept. of Computer Science, PES Institute of Technology and Management, Karnataka, India

<sup>2345</sup>UG Student, Dept. of Computer Science, PES Institute of Technology and Management, Karnataka, India

\*Corresponding author: [trupthi2003@gmail.com](mailto:trupthi2003@gmail.com)

**Abstract** - Stock price prediction presents inherent difficulties due to the complexity and variability of market forces. However, integrating long short-term memory (LSTM) neural networks with sentiment analysis techniques may help to ameliorate such challenges by increasing forecasting precision. By reviewing past stock performance data and concurrently incorporating sentiment metrics derived from news and social media coverage, this hybrid model strives to account for temporal dependencies within the market while also gauging prevailing investor perspectives. Specifically, the model aims to capture trends and patterns over extended time periods from historical price information using LSTM algorithms. In parallel, it seeks to measure overall reaction and opinion regarding each stock from current media and social sharing using sentiment analysis. By combining these LSTM and sentiment analysis approaches, the model pursues a comprehensive methodology to benefit from both the market's movements over the longer term and real-time sentiment among market participants.

**Keyword:** Machine Learning models, LSTM, Sentiment analysis, Stock forecasting, Stock trends, Neural networks.

## I. INTRODUCTION

Stock price forecasting is a complex process that involves analyzing various data sources and employing different methodologies to predict future movements in a stock's value. Historical stock prices serve as foundational data set, providing insights into trends and patterns. Trading volume, representing market interest and liquidity, is another critical factor [1]. Technical analysis utilizes past price charts to identify trends and employ indicators including moving average and RSI. Combining these approaches can provide more holistic view of a stock's potential future trajectory. Quantitative models, particularly those leveraging machine learning algorithms, have gained prominence in recent years. Time series analysis treats stock prices as sequential data, considering their temporal dependencies. Algorithmic trading, employing automated strategies based on predefined rules, is another avenue for leveraging quantitative models. Forecasting refers to making predictions about future stock price movements. Analysts analyze historical data to identify patterns and trends to estimate how stock's value may change over time. Forecasting can use technical analysis, fundamental analysis, or quantitative modeling [2]. Time

series analysis is a core technique used by analysts to better understand the dynamics of financial markets. It involves reviewing historical stock price data points to discern identifiable patterns, trends and behaviors. Methods like moving averages and regression analysis help uncover trends in the data, providing a more holistic perspective on market influences [3]. Analysts employ methods such as moving averages and regression analysis to discern trends, offering a holistic market perspective. Sentiment analysis also plays an important role in forecasting by helping to gauge investor emotion and opinion. Understanding shifts in sentiment is valuable as it can help anticipate changes in stock price and trends, given investor sentiment has a notable impact on market movements and dynamics. Analysts will evaluate qualitative sources of information such as news reports, social media posts and analyst notes to assess overall market sentiment [4]. Understanding shifts in sentiment is valuable as it can help anticipate changes in stock price and trends, given investor sentiment has a notable impact on market movements and dynamics. Positive sentiment promotes bullish behavior and upward prices while negative sentiment triggers bearish behavior and downward trends. Sentiment analysis seeks to quantify emotional responses to better inform forecasts. It provides valuable perspective on emotional drivers of behavior. Incorporating sentiment insights enhances the capability of forecasting models to predict future stock price movements.

## II. RELATED WORK

Long-term Short-term Memory (LSTM) neural networks represent a category of recurrent neural networks that enhance traditional RNNs through improved retention of long-term memory and mitigation of the vanishing gradients phenomenon [5]. LSTM neural networks can dynamically ascertain whether an output should function as the subsequent input based on preserving significant information across time. Researchers have increasingly examined stock price forecasting techniques as stock markets have expanded globally. The goal of this examination is to analyze and attempt to predict fluctuations and variations in stock prices that are influenced by various factors [6]. These influential factors include economic conditions, political environments, governmental policies, natural or human-made disasters, investor behaviors, and other elements [4]. In a recent study, Darapaneni and Agarwal forecasted stock price movements by integrating historical pricing data with sentiment data obtained from sources such as news articles and social media posts [7]. They utilized linear regression and random forest machine

learning models to generate projections of future stock prices [5]. Interestingly, they also introduced macroeconomic indicators such as gold and oil prices and currency exchange rates into their models. They used the root mean squared error metric to gauge each model's accuracy. Their study provided stock-specific forecasting results and highlighted the relative predictive performance of each model for different stocks. In the recent research, Vijha and Kumar introduced advanced artificial intelligence techniques [8], specifically artificial neural networks and random forests, to enhance the efficiency of predicting a stock's closing price on the following trading day. This analysis utilized key financial metrics, including opening, highest, lowest, and closing prices for five companies across different industries [9].

### III. PROPOSED SYSTEM

TradingView is an online platform for analyzing financial markets. It provides customizable charts to analyze price movements of stocks, forex, cryptocurrencies, and commodities. The platform offers technical analysis indicators and drawing tools to aid trading decisions. Basic use is free, subscriptions unlock additional features and real-time. Successfully developing a model meeting this challenge could equip traders and investors with a reliable resource for obtaining accurate stock price predictions. Unlike Trading View’s delayed or limited access to real-time data for free users, our system ensures continuous updates with the latest market information. By incorporating mechanisms for daily data integration and model retraining, users can access up-to-date predictions, enhancing the timeliness and accuracy of their trading decisions.

### IV. METHODOLOGY

In building this stock price prediction system, we leverage a range of tools and APIs to streamline data collection and processing. Historical stock prices are collected from reliable financial data sources including platforms like Yahoo Finance to furnish the necessary source material for modeling purposes.

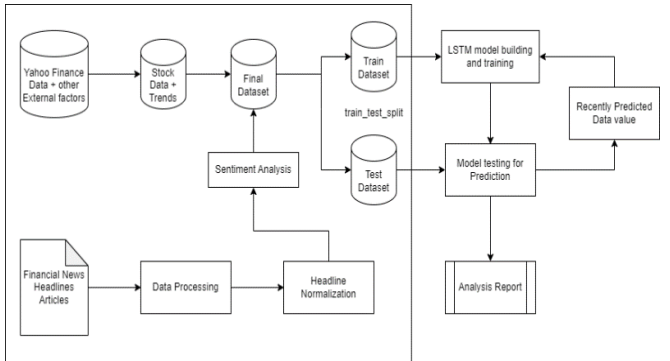


Fig. 1. System Architecture

The collected data may include historical stock prices, economic indicators, financial news. First, preprocess the data by addressing any missing values, outliers, or features requiring normalization. Next, divide the full dataset into

separate training and testing subsets. Finally, select an appropriate modeling technique, here we used LSTM, and train the model using historical data [10]. Continuous monitoring and periodic updates are essential for maintaining accuracy in a dynamic financial environment. Several evaluation metrics are used to analyze model performance, including various matrices, and the range between predicted and actual target values within the test set.

Model	MSE	RMSE	MAE	Error %
Linear Regression	119513.9547	345.7079	294.5776	27.9167
Random Forest	3946.30177	62.8196	32.82127	3.11043
KNN	177151.0295	375.7123	254.4853	24.1172
ANN	48075.37253	219.2609	148.3170	14.0558
LSTM	646903.19751	804.3029	697.311	65.898

Table 1. Error Table

The table provides insight into the predictive efficacy of each model using various metrics and Error Percentage. Lower values in these metrics indicate greater predictive accuracy.

### V. RESULTS

Upon completion of training, the model's predictive performance is assessed by comparing its predictions against the actual target values contained in the held-out test data. This evaluation involves calculating metrics to assess how well the trained model performs when faced with new, unseen data.

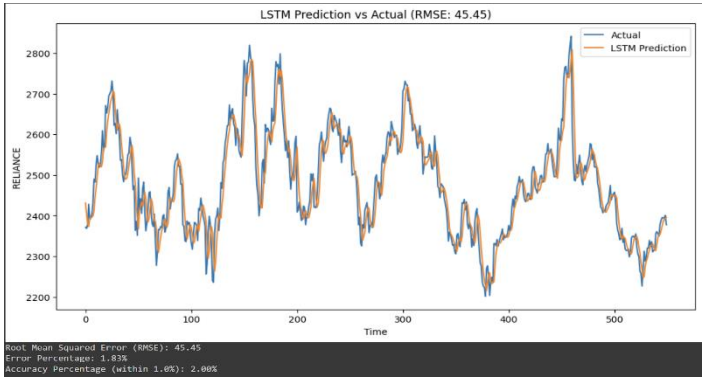


Fig. 2. LSTM Analysis

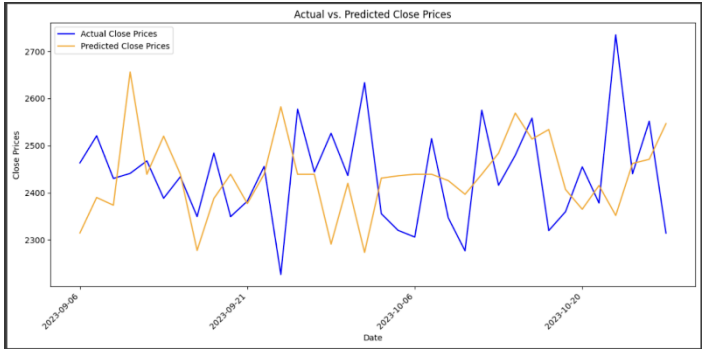


Fig. 3. Sentiment Analysis

After prediction, it was found that LSTM gave closest stock prices when compared to sentiment data on this particular database.

## VI. CONCLUSION

Predicting stock prices is a sophisticated task that relies on advanced data analytics, machine learning algorithms, and economic understanding. Developing effective forecasting tools requires careful attention to data quality, thoughtful feature engineering, and the selection of appropriate algorithms. Regular evaluation and updates are necessary to ensure the models accurately capture changing market dynamics. Looking ahead, as technology advances, there's potential for artificial intelligence, deep learning, and data analytics to further refine and improve the precision and agility of stock price forecasting models. This progress can empower market participants with enhanced insights, aiding in more informed and strategic decision-making processes.

## FUTURE WORK

This work presents an opportunity for expansion by incorporating additional data sources beyond news articles, social media feeds, earnings reports, analyst opinions, and macroeconomic indicators. The inclusion of alternative data points could enhance results of sentiment analysis to ensure compliance with evolving regulations pertaining to financial projections and automated trading platforms.

## REFERENCES

- [1] Yue-Gang Song, Yu-Long Zhou, Ren-Jie Han. *Neural networks for stock price prediction*. Last accessed 2018.
- [2] Lorenzo Malandri, Frank Xing, Carlotta Orsenigo, Carlo Vercellis. *The Importance of Financial Sentiment in Portfolio Management*. Last accessed 2018.
- [3] Xinyi Li, Yinchuan Li, Hongyang Yang, Liuqing Ypang, Xiao-Yang Liu. DP-LSTM: Differential Privacy-inspired LSTM for Stock Prediction Using Financial News. Last accessed 2019.
- [4] Sidra Mehtab, Jaydip Sen. *A Robust Predictive Model for Stock Price Prediction Using Deep Learning and Natural Language Processing*. Last accessed 2019.
- [5] Dev Shah, Haruna Isah. *Predicting the Effects of News Sentiments on the Stock Market*. Last accessed 2019.
- [6] Sidra Mehtab, Jaydip Sen and Abhishek Dutta. *Stock Price prediction Using ML and LSTM-Based Deep Learning Models*. Last accessed 2021.
- [7] Narayana Darapaneni, Anwesh Reddy Paduri, Himank Sharma, Milind Manjrekar, Pranali Bhagat, Yogesh Agarwal. *Stock Price Prediction using Sentiment Analysis and Deep Learning for Indian Markets*. Last accessed 2022.
- [8] Mehar Vijha, Deeksha Chandola, Vinay Anand Tikkiwal, Arun Kumar. *Stock Closing Price Prediction using Machine Learning Techniques*. Last accessed 2019.

- [9] Dr. Rais Mulla, Dinesh Bharambe, Swastik Gupta, Khemraj Bohra, Preeta Tiwari. *Visualizing and Forecasting Stocks Using Dash*. Last accessed 2022.

- [10] Xiaobin Tang, Nuo Lei, Manru Dong and Dan Ma. *Stock Price Prediction Based on Natural Language Processing*. Last accessed 2022.

## BIOGRAPHIES-



Vinutha H M  
Assistant Professor  
Dept. of CSE,  
PESITM, Shimoga



Harsh Mishra  
UG Student  
Dept. of CSE,  
PESITM, Shimoga



Shaishav  
UG Student  
Dept. of CSE,  
PESITM, Shimoga




Sumit Raj  
UG Student  
Dept. of CSE,  
PESITM, Shimoga





Trupthi K  
UG Student  
Dept. of CSE,  
PESITM, Shimoga


## PROFILE DETAILS


	<p>Guide: Ms. Vinutha H M Assistant Professor, Department of CS&amp;E, PESITM, Shivamogga.</p> <p>Email: <a href="mailto:vinuthahm@pestrust.edu.in">vinuthahm@pestrust.edu.in</a> Phone No: 6360148846</p>
---	--

## TEAM MEMBERS

	<p>Ms. Trupthi K 4PM20CS119 CSE 8<sup>th</sup> B PESITM, Shivamogga Email: <a href="mailto:trupthik2003@gmail.com">trupthik2003@gmail.com</a> Phone No: 9108741642</p>
---	--

	<p>Mr. Shaishav 4PM20CS090 CSE 8<sup>th</sup> B PESITM, Shivamogga Email: <a href="mailto:trupthik2003@gmail.com">trupthik2003@gmail.com</a> Phone No: 9801094555</p>
---	---

	<p>Mr. Harsh Mishra 4PM20CS039 CSE 8<sup>th</sup> A PESITM, Shivamogga Email: <a href="mailto:mishraharsh2222@gmail.com">mishraharsh2222@gmail.com</a> Phone No: 8709228329</p>
---	---

	<p>Mr. Sumit Raj 4PM20CS115 CSE 8<sup>th</sup> B PESITM, Shivamogga Email: <a href="mailto:sumitrajsky00@gmail.com">sumitrajsky00@gmail.com</a> Phone No: 6204286223</p>
---	--