A

Project Report

On

PREDICTING STOCK MARKET TRENDS USING MACHINE LEARNING DEEP LEARNING ALGORITHMS VIA CONTINUOUS AND BINARY DATA A COMPARATIVE ANALYSIS

Submitted in partial fulfilment of the requirements for the award of Degree

BACHELOR OF TECHNOLOGY

in

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

by

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2021-2025

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING(AI&ML)

CERTIFICATE

This is to certify that the project entitled **"PREDICTING STOCK MARKET TRENDS USING MACHINE LEARNING AND DEEP LEARNING ALGORITHMS VIA CONTINUOUS AND BINARY DATA A COMPARATIVE ANALYSIS"** being submitted by **GOPU SANJANA (217R1A7318), PARKALA HARSHA VARDHAN REDDY (217R1A7350), KOKKONDA SUJAY (217R1A7329) i**n partial fulfillment of the requirements for the award of the degree of B. Tech in Computer Science and Engineering (AI&ML) to the Jawaharlal Nehru Technological University Hyderabad, is a record of bonafide work carried out by them under ourguidance and supervision during the year 2024-25.

The results embodied in this thesis have not been submitted to any other University or Institute for the award of any degree or diploma.

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INTERNAL GUIDE	

EXTERNAL EXAMINER

Submitted for viva voice Examination held on

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ABSTRACT

The nature of stock market movement has always been ambiguous for investors because of various influential factors. This study aims to significantly reduce the risk of trend prediction with machine learning and deep learning algorithms. Four stock market groups, namely diversified financials, petroleum, non-metallic minerals and basic metals from Tehran stock exchange, are chosen for experimental evaluations. The objective of this project is to compare the effectiveness of machine learning (ML) and deep learning (DL) algorithms in predicting stock market trends using continuous and binary data. The continuous data includes historical stock prices, trading volumes, and moving averages, while the binary data encompasses market sentiment indicators, buy/sell signals, and earnings reports.

The algorithms employed in this study range from ML methods such as Linear Regression, Decision Trees, Random Forests, and Support Vector Machines to DL techniques like Recurrent Neural Networks (RNNs), and Long Short-Term Memory networks (LSTMs).The methodology involves preprocessing data to handle missing values, normalization, and feature extraction, followed by splitting the data into training, validation, and test sets. Various ML and DL models are trained on both continuous and binary datasets, with their performance evaluated.

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1.INTRODUCTION

1.INTRODUCTION

1.1 PROJECT SCOPE

The project aims to conduct a comparative analysis of machine learning (ML) and deep learning (DL) algorithms for predicting stock market trends using continuous and binary data. The scope includes collecting and preprocessing historical stock market data, implementing and tuning various ML algorithms such as Linear Regression, Support Vector Machines, Random Forests, and Gradient Boosting Machines, and DL models including Recurrent Neural Networks and Long Short-TermMemory networks models. The models will be trained and evaluated using metrics likeMean Squared Error for continuous data predictions and Accuracy, Precision, Recall, and F1 Score for binary data predictions. A detailed comparative analysis will be conducted to assess the performance of these models, examining the impact of data types. The project will leverage Python for implementation, aiming to provide valuable insights into the efficiency of ML and DL techniques in stock market prediction.

1.2 PROJECT PURPOSE

The purpose of this project is to systematically evaluate and compare the effectiveness of machine learning (ML) and deep learning (DL) algorithms in predicting stock market trends using both continuous and binary data. The project aimsto identify which approaches provide the most accurate and reliable predictions. This analysis will help in understanding the strengths and weaknesses of various algorithms, contributing to more informed decision-making in financial markets. Additionally, the project seeks to uncover the impact of different data types on model performance, offering a comprehensive understanding of how to best utilize available data for stock market forecasting.

1.3 PROJECT FEATURES

The project features a comprehensive approach to stock market trend prediction, incorporating both machine learning (ML) and deep learning (DL) algorithms. Key feature include the collection and preprocessing of extensive historical stock market data, covering both continuous data (such as stock prices and trading volumes) and binary data (such as buy/sell signals and news sentiment). The project will implement and fine-tune a variety of ML models, including Linear Regression, Support Vector Machines, Random Forests, and Gradient Boosting Machines, alongside DL models like Recurrent Neural Networks, Long Short-Term Memory networks, Convolutional Neural Networks, and Transformer-based models. Each model's performance will be rigorously evaluated using metrics suitable for both continuous and binary predictions. Additionally, the project will conduct a detailed comparative analysis to assess the relative performance of these models. The use of advanced tools and libraries such as Python, will facilitate efficient model development and analysis. Overall, the project aims to provide actionable insights into the most effective techniques for stock market prediction.

2.SYSTEM ANALYSIS

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SYSTEM ANALYSIS

The system analysis encompasses a detailed examination of several critical components. Initially, the project involves the collection of diverse stock market data from reputable financial sources, which includes continuous data like stock prices and trading volumes, and binary data such as buy/sell signals and sentiment from news. This data is stored in a secure and scalable database system to ensure its integrity and accessibility. Data preprocessing is a key phase, involving the cleaning of datasets to address missing values and outliers, normalization to standardize feature scales, and feature engineering to derive meaningful variables from raw data. For continuous and binary data, various ML models and DL models are employed to leverage their advanced capabilities in handling sequential and complex data patterns. The analysis includes a comparative evaluation of these models, assessing their strengths and limitations in predicting stock market trends.

2.1 PROBLEM DEFINITION

The problem addressed in this project is the challenge of accurately predicting stock market trends using machine learning (ML) and deep learning (DL) algorithms, given the complexity and volatility of financial markets. Traditional forecasting methods often struggle to capture the intricate patterns and fluctuations inherent in stock price movements. This project seeks to overcome these limitations by applying a range of ML and DL techniques to analyze both continuous data (such as stock prices and trading volumes) and binary data (such as buy/sell signalsand news sentiment). The goal is to determine which algorithms and data types provide the most reliable predictions. The project aims to enhance the accuracy of stock market predictions, providing a more effective tool for investors and analystsin navigating the dynamic financial landscapes.

2.2 EXISTING SYSTEM

Stock market trends can be affected by external factors such as public sentiment and political events. The goal of this research is to find whether or not public sentiment and political situation on a given day can affect stock market trends of individual companies or the overall market. For this purpose, sentiment and Situation features are used in a machine learning model to find the effect of public sentiment and political situation on the prediction accuracy of algorithms for 7 days in future. Besides, interdependencies among companies and stock markets are also studied. For the sake of experimentation, stock market historical data are downloaded from Yahoo! Finance and public sentiments are obtained from Twitter. Important political events data of Pakistan are crawled from Wikipedia. The raw text data are then pre-processed, and the sentiment and situation features are generated to create the final data sets.

Ten machine learning algorithms are applied to the final data sets to predict the stock market future trend. The experimental results show that the sentiment feature improves the prediction accuracy of machine learning algorithms by 0–3%, and the political situation feature improves the prediction accuracy of algorithms by about 20%. Furthermore, the sentiment attribute is most effective on day 7, while the political situation attribute is most effective on day 5. SMO algorithm is found to show the best performance, while ASC and Bagging show poor performance. The interdependency results indicate that stock markets in the same industry show a medium positive correlation with each other.

2.2.1 DISDAVANATGES OF EXISTING SYSTEM

- In the existing work, the system in which Stock market prediction is full of challenges, and data scientists usually confront some problems when they try to develop a predictive model.
- This system has less performance in which it is clear that there are always unpredictable factors
- such as the public image of companies or the political situation of countries.

2.3 PROPOSED SYSTEM

In the proposed system, the system concentrates on comparing prediction performance of nine machine learning models (Decision Tree, Random Forest, Adaboost, XGBoost, SVC, Naïve Bayes, KNN, Logistic Regression and ANN) and two deep learning methods (RNN and LSTM) to predict stock market movement. Ten technical indicators are utilized as inputs to our models. The proposed study includes two different approaches for inputs, continuous data and binary data, to investigate the effect of preprocessing; the former uses stock trading data (open, close, high and low values) while the latter employs preprocessing step to convert continuous data to binary one. Each technical indicator has its specific possibility of up or down movement based on market inherent properties.

The performance of the mentioned models is compared for the both approaches with three classification metrics, and the best tuning parameter for each model (except Naïve Bayes and Logistic Regression) is reported. All experimental tests are done with ten years of historical data of four stock market groups (petroleum, diversified financials, basic metals and non-metallic minerals), that are totally crucial for investors, from the Tehran stock exchange. We believe that this study is a new research paper that incorporates multiple machine learning and deep learning methods to improve the prediction task of stock groups' trend and movement.

2.3.1 ADVANATGES OF PROPOSED SYSTEM

- In the proposed system, each of the algorithms can effectively solve stock prediction problems.
- The system is more effective due to the presence of eXtreme Gradient Boosting (XGBoost), Support Vector Classifier (SVC) techniques.

2.4 FEASIBILITY STUDY

An important outcome of preliminary investigation is the determination that the system the request is feasible. This is possible only if it is feasible within limited resources and time. The different feasibility that have to be analyzed are

- Economic Feasibility
- Technical Feasibility
- Operational Feasibility

2.4.1 ECONOMIC FEASIBILITY

The economic feasibility of predicting stock market trends using machine learning (ML) and deep learning (DL) algorithms, analyzed through both continuous and binary data, is favorable. Initial expenses include acquiring high-quality data, which can be obtained through subscriptions or purchases from financial databases. Computational costs for training sophisticated ML and DL models, such as those involving GPUs or cloud services, are manageable due to flexible pricing options. Open-source tools like Python reduce software costs. The potential return on investment is significant, as enhanced prediction accuracy can lead to improved investment strategies and increased financial returns. With a growing demand for advanced forecasting solutions, the project stands to benefit economically by providing valuable insights that can drive better decision-making. Overall, the cost-benefit analysis indicates that the financial investment required is justified by the anticipated gains and the project's potential impact on financial forecasting.

2.4.2 TECHNICAL FEASIBILITY

Predicting stock market trends using machine learning and deep learning involves leveraging both continuous and binary data, each with its own technical feasibility. Continuous data, such as stock prices and trading volumes, enables the use of sophisticated models like LSTM to capture intricate patterns and temporal dependencies. These models, while powerful, require extensive preprocessing and are sensitive to noise. In contrast, binary data, which simplifies the prediction task to categorical outcomes (e.g., price up or down), can be handled by simpler classification models like logistic regression or decision trees. While these models are easier to implement interpret, they may miss nuanced market trends captured by continuous data. Thus, while continuous data allows for a more detailed analysis, binary data offers robustness and simplicity, making the choice between them dependent on the analysis's complexity and data requirements.

2.4.3 OPERATIONAL FEASIBILITY

Operational feasibility for it requires robust infrastructure for handling and processing high-frequency, real-time data, as well as advanced models like LSTM or Transformer networks that need significant computational resources and fine-tuning. In contrast, binary data simplifies operational demands, allowing the use of less complex models and less intensive data processing. These models are typically easier to deploy and maintain but might not capture the full spectrum of market dynamics. Therefore, while continuous data offers deeper insights and requires more sophisticated operational support, binary data provides a more streamlined and manageable approach for prediction tasks.

2.5 HARDWARE & SOFTWARE REQUIREMENTS

2.5.1 HARDWARE REQUIREMENTS

Hardware interfaces specify the logical characteristics of each interface between the software product and the hardware components of the system. The following are some hardware requirements.

- Processor - Pentium-IV
- RAM - 8GB and above
- Hard Disk - 20 GB
- Key Board - Standard Windows Keyboard
- Mouse - Optical
- Monitor - LED

2.5.2 SOFTWARE REQUIREMENTS

Software Requirements specifies the logical characteristics of each interface and software components of the system. The following are some software requirements.

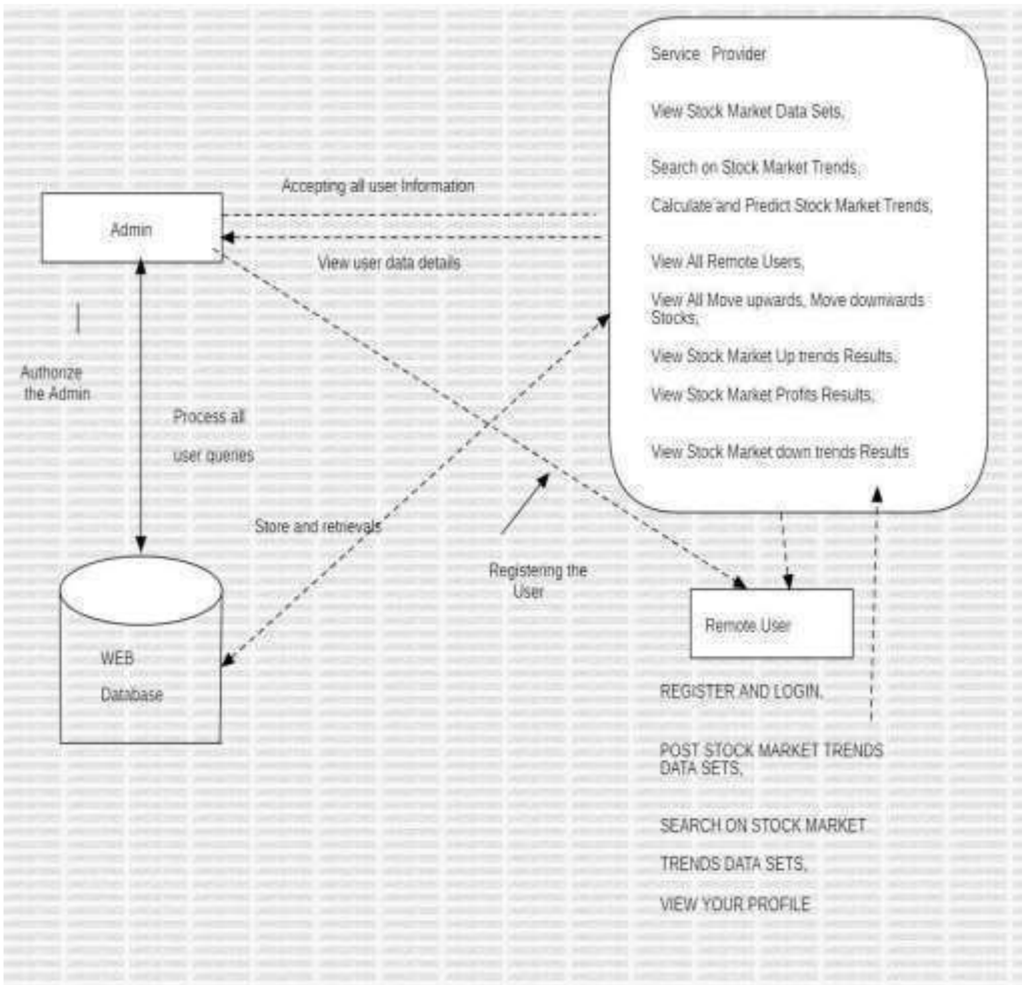
- Operating system : Windows 10 and above.
- Coding Language : Python.
- Front-End : HTML, CSS JavaScript.
- Back-End : Django-ORM.
- Data Base : MySQL.
- Web Server : XAMPP Server

3.ARCHITECTURE

3. ARCHITECTURE

3.1 PROJECT ARCHITECTURE

This project architecture shows the procedure followed classification starting from input to final prediction



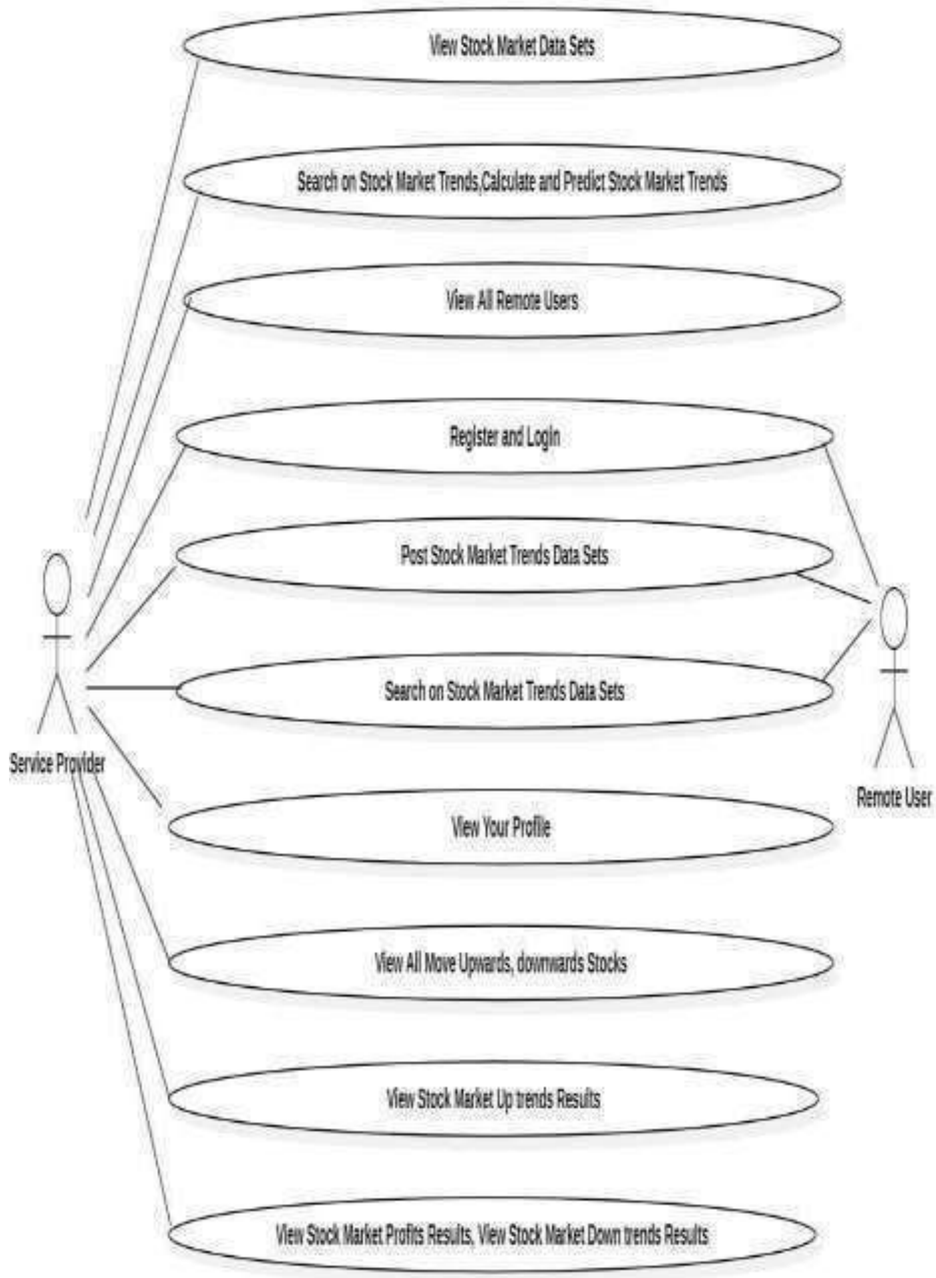
3.1 Architecture Diagram

DESCRIPTION

An architecture diagram for predicting stock market trends using machine learning and deep learning algorithms, focused on a comparative analysis of continuous and binary data, features several interconnected layers. At the base is the Data Collection Layer, which gathers raw stock market data from various sources. This feeds into the Data Preprocessing Layer, where the Data Preprocessor component cleans, normalizes, and encodes data, differentiating between continuous and binary data types. The processed data then enters the Modeling Layer, containing two main components: Machine Learning Model and Deep Learning Model. Each model type is encapsulated within its respective module, implementing specific algorithms like regression, classification, neural networks, and deep learning techniques. Both models interact with the Training and Validation Module, which handles the training process, hyperparameter tuning, and cross-validation. Next is the Prediction Layer, where trained models generate stock market trend predictions. The Evaluation Layer assesses the performance of these predictions using metrics like accuracy, precision, recall, and mean squared error. Finally, the ComparisonLayer consolidates evaluation results, enabling a comparative analysis betweenmachine learning and deep learning models on continuous and binary data. This architecture ensures a systematic approach to analyzing and predicting stock market trends, highlighting the strengths and weaknesses of differentalgorithmic approaches on varied data types.

3.2 USE CASE DIAGRAM

In the use case diagram, we have basically one actor who is the user in the trained model. A use case diagram is a graphical depiction of a user's possible interactions with a system. A use case diagram shows various use cases and different types of users the system has. The Use cases are represented by either circles or ellipses.



3.2 Use Case Diagram

DESCRIPTION

The use case diagram for predicting stock market trends using machine learning and deep learning algorithms via continuous and binary data for a comparative analysis involves several key actors and interactions. The primary actors include the Data Scientist, who designs and implements the predictive models, and the Stock Market Analyst, who utilizes the predictions to inform investment decisions.

The system interacts with a Data Source to gather historical stock market data and relevant financial indicators. Key use cases involve Data Collection, where data is retrieved from the
source; Data Preprocessing, involving cleaning and transforming the data into suitable formats; Model Training, where both machine learning and deep learning models are trained on continuous and binary data; Model Evaluation, which compares the performance of the models; and Prediction Generation, where the trained models produce stock market trend predictions.

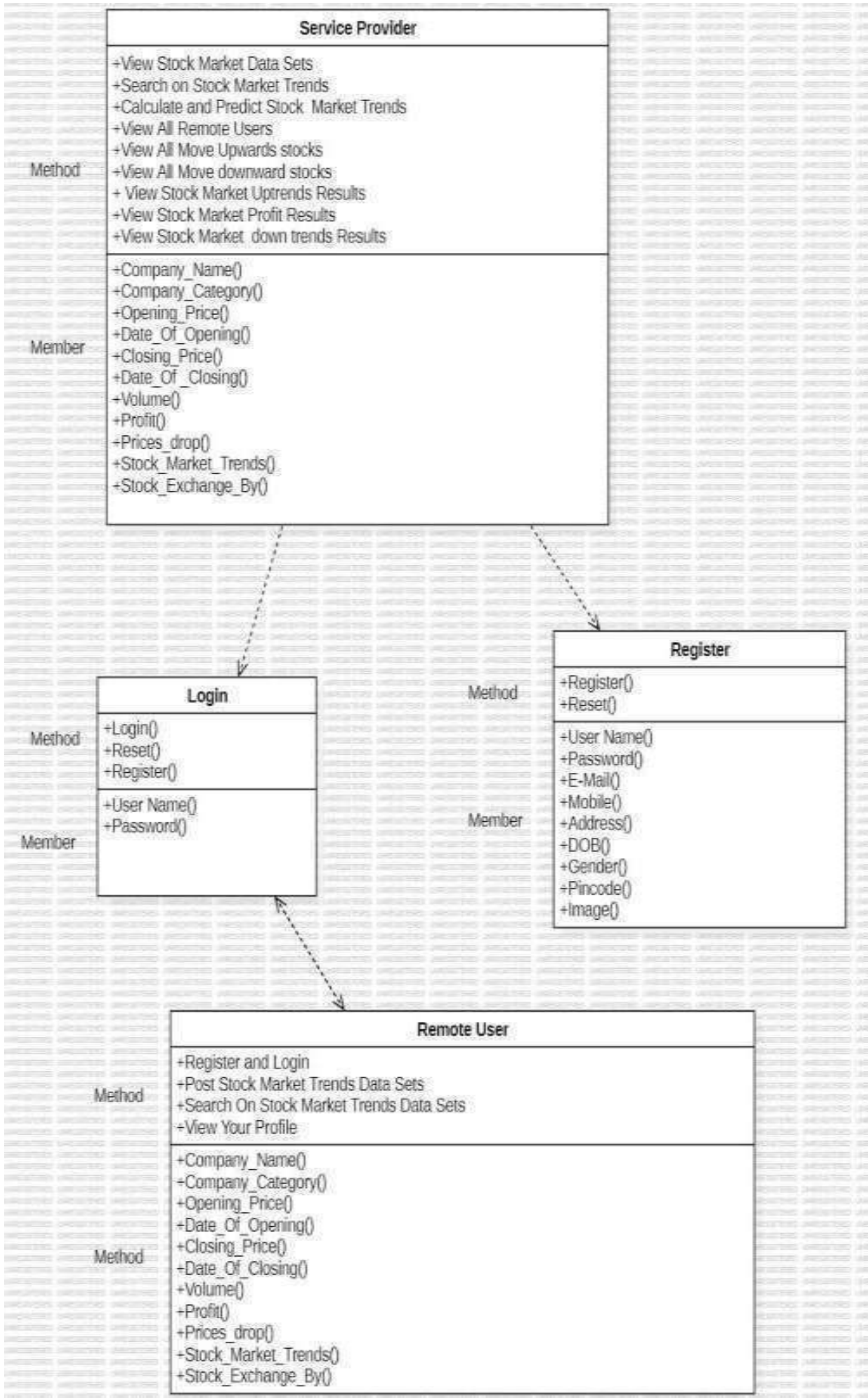
The comparative analysis use case is crucial, as it evaluates the effectiveness of the algorithms on different data types, providing insights into their respective strengths and weaknesses. This system enables continuous improvement and adaptation of predictive strategies based on comprehensive performance assessments.

3.3 CLASS DIAGRAM

Class diagram is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among objects.

DESCRIPTION

A class diagram for predicting stock market trends using machine learning and deep learning algorithms in a comparative analysis of continuous and binary data involves several key components. The primary class, Stock Market Predictor, includes attributes for input data, model selection, and prediction outputs. This class interacts with the Data Preprocessor class, responsible for data cleaning, normalization, and encoding. Two subclasses, Machine Learning Model and Deep Learning Model, inherit from the Predictive Model superclass, which defines common methods such as train, validate, and predict. The Evaluation class assesses model performance using metrics like accuracy, precision, recall, and mean squared error. Additionally, a Comparison class facilitates the comparative analysis of the models, storing results and generating reports. The Data Handler class manages the data flow, distinguishing between continuous and binary datasets and ensuring they are processed accordingly. Together, these classes encapsulate the workflow from data preprocessing to model training, evaluation, and comparison, providing a structured approach to stock market trend prediction.



3.3 Class Diagram

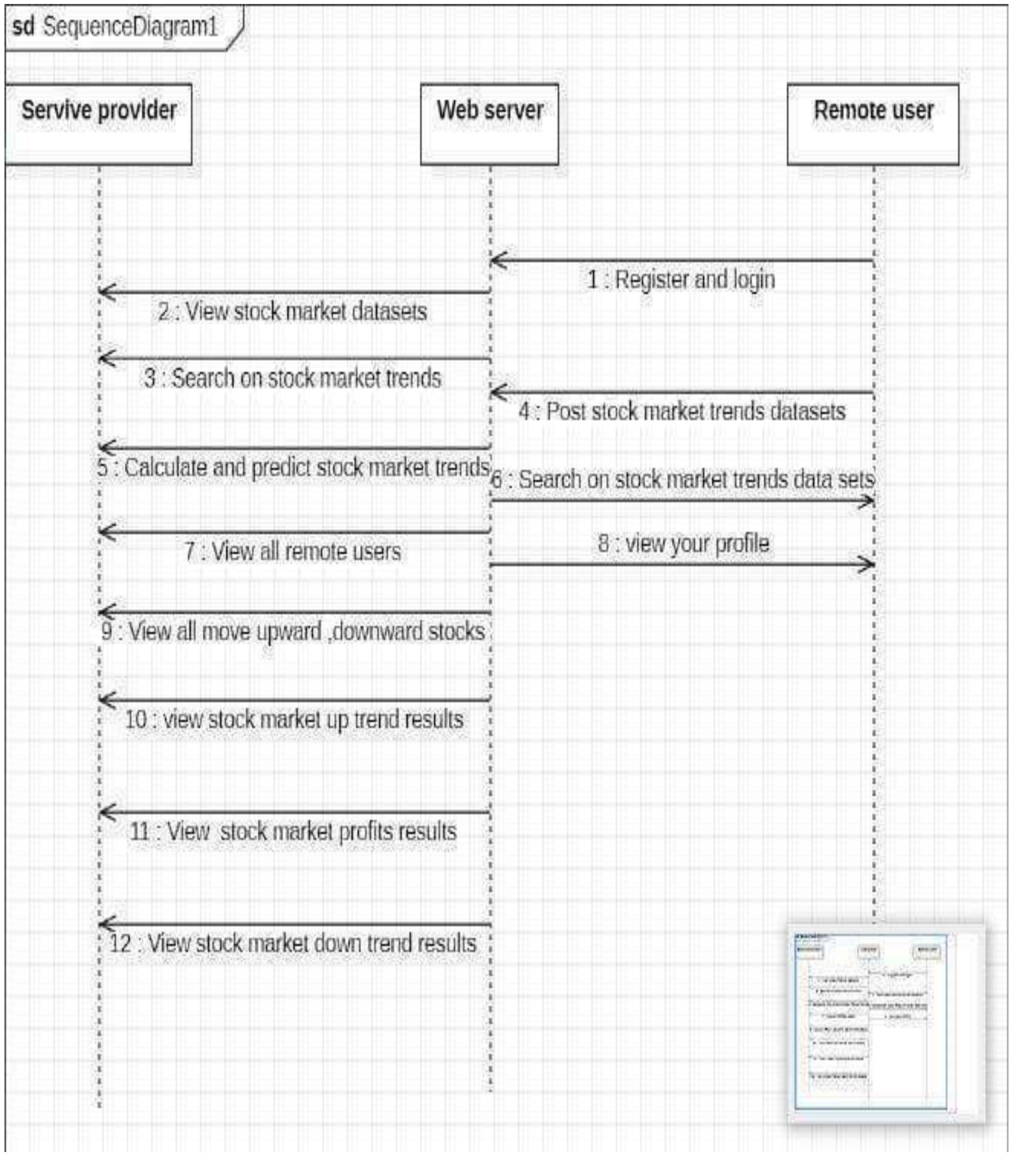
3.4 SEQUENCE DIAGRAM

A sequence diagram shows object interactions arranged in time sequence. It depicts the objects involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of the scenario. Sequence diagrams are typically associated with use case realizations in the logical view of the system underdevelopment.

DESCRIPTION

A sequence diagram for predicting stock market trends using machine learning and deep learning algorithms, focusing on a comparative analysis of continuous and binary data, starts with the User initiating the process. The user requests data from the Data Collection System, which retrieves raw stock market data and sends it to the Data Preprocessor. The preprocessor cleans, normalizes, and encodes the data, distinguishing between continuous and binarytypes, and then forwards the processed data to the Predictive Model superclass.

From here, the sequence splits into two parallel paths: one for the Machine Learning Model and one for the Deep Learning Model. Each model class receives the processed data and sends it to the Training and Validation Module, which trains the models, performs hyperparameter tuning, and cross-validates the results. Once training is complete, both models pass their trained instances to the Prediction Module, which generates stock market trend predictions. The predictions are then sent to the Evaluation Module, where the performance of each model is assessed using metrics such as accuracy, precision, recall, and mean squared error. The evaluation results are forwarded to the Comparison Module, which consolidates and compares the performance metrics of the machine learning and deep learning models on continuous and binary data.



3.4 Sequence Diagram

4.IMPLEMENTATION

4.IMPLEMENTATION

4.1 DECISION TREE

Decision Tree is a common supervised learning approach employed for both regression and classification problems. The goal of technique is forecasting a target by using easy decision rules shaped from the dataset and related features. Being easy to interpret or able to solve problems with different outputs are two advantages of using this model; on the contrary, constructing over-complex trees that cause over-fitting is a typical disadvantage

4.2 RANDOM FOREST

Great number of decision trees make a random forest model. The model basically averages the forecast result of trees, which is named a forest. Also, the algorithm includes three random ideas, selecting training data randomly when forming trees, randomly choosing some subsets of variables when dividing nodes and deeming only a subset of all variables for splitting every node in each basic decision tree. Every basic tree learns from a random sample of the dataset during the training process of a random forest.

4.3 ADABOOST

The process of converting some weak learners to a powerful one is named Boosting method. AdaBoost is a specific type of Boosting that is an ensemble model to progress the predictions of every learning technique. The goal of boosting is to train weak learners sequentially to adjust their previous predictions. This model is a meta-predictor which starts by fitting a model on the basic dataset before fitting additional copies of it on the same dataset. During the process of training, samples' weights are modified based on the current forecasting error; therefore, the consequent model focuses on tough items.

4.4 XG BOOST

XGBoost is a recent ensemble model based on decision trees. This employs the rules of Boosting for weak learners similarly. XGBoost was presented for better performance and speed compared

to other tree-based models. Regularization for preventing overfitting, In-built cross-validation capability, proficient handling Missing data, catch awareness, parallelized tree building and tree pruning are significant benefits of the XGBoost method.

4.5 SUPPORT VECTOR MACHINE (SVM)

Support Vector Machines (SVMs) are a set of supervised learning approaches that can be employed for classification and regression problems. The classifier version is named SVC. The method's purpose is finding a decision boundary between two classes with vectors. The boundary must be far from any point in the dataset, and support vectors are the signs of observation coordinates with a gap named margin. SVM is a boundary that best separates two classes by employing a line or hyperplane. The decision boundary is defined in Equation 1 where SVMs can map input vectors xi Rd into a high dimensional feature space 8 (xi) H, and 8 is mapped by a kernel function K (xi, xj).

4.6 NAIVE BAYES

Naive Bayes classifier is a member of probabilistic classifiers based on Bayes' theorem with strong independence assumptions between the features given the value of the class variable. This method is a set of supervised learning algorithms. The following relationship is stated in Equation5 by Bayes' theorem where y is class variable, and x1 through xn are dependent feature vectors. P(y |x1 , . . . , xn) =P(y)ni Q=1 P(xi|y)P(x1,...,xn)(5) Naive Bayes classifier can be highly fast in comparison with more sophisticated algorithms. The separation of the class distributions means that each one can be independently evaluated.

4.7 K- NEAREST NEIGHBORS

Two properties usually are suggested for KNN, lazy learning and non-parametric algorithm, because there is not any assumption for underlying data distribution by KNN. The method follows some steps to find targets: Dividing dataset into training and test data, selecting the value of K, determining which distance function should be used, choosing a sample from test data (as a new sample) and computing the distance to its n training samples, sorting distances gained and taking k-nearest data samples, and finally, assigning the test class to the sample on the majority vote of its k neighbors.

4.8 LOGISTIC REGRESSION

Logistic regression is used to assign observations to a separated set of classes as a classifier. The algorithm transforms its output to return a probability value with the logistic sigmoid function, and predicts the target by the concept of probability. Logistic Regression is similar to Linear Regression model, but the Logistic Regression employs sigmoid function, instead of a logistic one, with more complexity. The hypothesis behind logistic regression tries to limit the cost function between 0 and 1.I. ANNs are a prominent subset of machine learning algorithms that are usually single or multi-layer nets which are fully connected together.

4.9 RECURRENT NEURAL NETWORK

A very significant version of neural networks is recognized as RNN, which is widely employed in different problems. In a typical neural network, the input passes through some layers, and output is created. It is proposed that two consecutive inputs are totally independent; however, the condition is not true in all processes. For instance, to forecast the stock market at a certain period, it is vital to observe the prior samples. RNN is named recurrent due to it doing the same task for each item of a sequence.

4.10 LONG - SHORT TERM MEMORY

LSTM is a particular type of RNN with an extensive range of uses such as document classification, time series analysis, voice and speech recognition. Opposite to feed forward networks, the predictions (created by RNNs) are dependent on prior estimations. In experimental works, RNNs are not applied broadly due to include a few lacks that result in impractical estimations. Without investigation of too much detail, LSTM solves the problems by employing assigned gates for forgetting old information and learning new ones. The LSTM layer is made of our neural network layers that interact in a specific method. A usual LSTM unit involves three different parts, a cell, an output gate and a forget gate. The main task of the cell is recognizing values over random time intervals and the task of controlling the information flow into the cell and out of it belongs to the gates.

4.11 DATASET DESCRIPTION

The dataset comprises historical stock prices, including open, high, low, close, and adjusted close prices, along with trading volume for various companies over several years. Additionally, it incorporates technical indicators such as moving averages, relative strength index (RSI), and moving average convergence divergence (MACD) to capture market momentum and trend. Economic indicators like interest rates, inflation rates, and GDP growth are also included to reflect macroeconomic conditions influencing stock performance. The dataset is structured to support both continuous predictions, where the exact future stock prices are forecasted, and binary classification, where the market movement direction (up or down) is predicted. For the continuous prediction task, regression models like Linear Regression, Random Forest Regressor, and Long Short-Term Memory (LSTM) networks are employed. For binary classification, algorithms such as Logistic Regression, Support VectorMachines (SVM), are utilized.

4.12 PERFORMANCE METRICS

The performance metrics for evaluating the effectiveness of machine learning and deep Learning algorithms in predicting stock market trends vary based on whether the task is continuous prediction or binary classification. For continuous prediction, metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) are utilized. These metrics measure the accuracy of predicted stock prices by comparing them to actual values, with lower error values indicating better model performance. In the case of binary classification, where the goal is to predict the direction of stock price movement (up or down), metrics like Accuracy, Precision, Recall, F1-Score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC) are employed. Accuracy measures the overall correctness of the predictions, while Precision and Recall provide insights into the model's ability to identify true positives and minimize false positives and negatives. The F1-Score, which is the harmonic mean of Precision and Recall, offers a balanced measure of the model's performance, especially when dealing with imbalanced datasets. The AUC-ROC metric evaluates the model's discriminatory power, with higher values indicating better performance in distinguishing between upward and downward movements.

Precision=True Positives/(True Positives+ False Positives)

Recall=True Positives/(True Positives + False Negatives)

F1=2 × (Precision ×Recall/ Precision + Recall)

By analyzing these performance metrics, the comparative study aims to highlight the relative strengths and limitations of different machine learning and deep learning algorithms in the context of stock market trend prediction, providing a nuanced understanding of their effectiveness in various scenarios.

4.13 SAMPLE CODE

```
from django.db.models import Count, Avg from django.shortcuts import
render, redirect from django.db.models import Count
from django.db.models import Q
import datetime from Remote_User.models
import
ClientRegister_Model,stock_market_model,predicting_stock_markettrends_m
odel def service provider login(request):
if request.method == "POST":
admin = request.POST.get('username') password =
request.POST.get('password')
if admin == "SProvider" and password =="SProvider":
stock_market_model.objects.all().delete()
predicting_stock_markettrends_model.objects.all().delete()
return redirect('View_Remote_Users')
 return render(request,'SProvider/serviceproviderlogin.html') def view reading
questions(request,chart_type):
dd = {} pos,neu,neg =0,0,0
poss=None
Topic=predicting_stock_markettrends_model.objects.values('ratings').annotate
(dcount=Count('ra tings')).order_by('-dcount')
 for t in topic: topics=t['ratings']
pos_count=predicting_stock_markettrends_model.objects.filter(topics=topics).
values('names').an notate(t
piccount=Count('ratings'))poss=s_count
for pp in pos_count: senti= pp['names']
if senti == 'positive': pos= pp['topiccount']
elif senti == 'negative': neg = pp['topiccount']
elif senti == 'neutral': neu = pp['topiccount'] dd[topics]=[pos,neg,neu] return
render(request,'SProvider/viewtreandingquestions.html',{'object':topic,'dd':dd,'
```

```
art_type':chart_t ype})
def Search_StockMarket(request): # Search if request.method == "POST":
kword = request.POST.get('keyword')
print(kword)
obj = stock_market_model.objects.all().filter(Company_Name
contains=kword)
obj1     =   stock_market_model.objects.get(Company_Name
contains=kword) opening=int(obj1.Opening_Price)
closing=int(obj1.Closing_Price) trends=closing-opening if(opening<closing):
val='Profit' Stock_Market_Trends='Uptrends'
 if(opening>closing): val = 'prices drop'
  Stock_Market_Trends = 'downtrends' if (opening == closing):
val = 'Horizontal'
Stock_Market_Trends = 'HorizontalTrends'
        return render(request, 'SProvider/Search_StockMarket.html', {'objs':
obj,'trends': trends,'val': val,'Stock_Market_Trends': Stock_Market_Trends})
   return render(request, 'SProvider/Search_StockMarket.html') def
View_All_StockMarket_Prediction_Details(request):
pl=0 pl1=0
obj1 = stock_market_model.objects.values( 'Company_Name',
'Company_Category' 'Opening_Price', 'Date_Of_Opening',
'Closing_Price', 'Date_Of_Closing', 'volume',
'Profit', 'prices_drop',
'Stock_Market_Trends',
'Stock_Exchange_By')
 predicting_stock_markettrends_model.objects.all().delete() for t in obj1:
Company_Name=t['Company_Name']
Company_Category=t['Company_Category']
Opening_Price=int(t['Opening_Price'])
Date_Of_Opening=t['Date_Of_Opening']
Closing_Price=int(t['Closing_Price']) Date_Of_Closing=t['Date_Of_Closing']
volume=t['volume']
```

Profit=t['Profit'] prices_drop=t['prices_drop']
Stock_Market_Trends=t['Stock_Market_Trends']

Stock_Exchange_By=t['Stock_Exchange_By']

Total =Closing_Price-Opening_Price if (Opening_Price < Closing_Price):

val = 'Profit'

Stock_Market_Trends = 'Up trends' final str=val+':'+Stock_Market_Trends

if (Opening_Price > Closing_Price): val = 'prices drop'

Stock_Market_Trends='downtrends'

final str = val + ':' + Stock_Market_Trends if (Opening_Price ==

Closing_Price):

val = 'Horizontal'

Stock_Market_Trends = 'Horizontal Trends' final str = val + ':' +

Stock_Market_Trends

if (Total > 0): pl = Total

predicting_stock_markettrends_model.objects.create(names=Company_Name,

Company_Category=Company_Category,

Opening_Price=Opening_Price,
predicting_stock_markettrends_model.objects.all().delete() for t in obj1:

Company_Name=t['Company_Name']

Company_Category=t['Company_Category']

Opening_Price=int(t['Opening_Price'])

Date_Of_Opening=t['Date_Of_Opening']

Closing_Price=int(t['Closing_Price']) Date_Of_Closing=t['Date_Of_Closing']

volume=t['volume']

Profit=t['Profit'] prices_drop=t['prices_drop']

Stock_Market_Trends=t['Stock_Market_Trends']

Stock_Exchange_By=t['Stock_Exchange_By']

Total =Closing_Price-Opening_Price if (Opening_Price < Closing_Price):

val = 'Profit'

Stock_Market_Trends = 'Up trends' final str=val+':'+Stock_Market_Trends

if (Opening_Price > Closing_Price): val = 'prices drop'

```
Stock_Market_Trends='downtrends
final str = val + ':' + Stock_Market_Trends if (Opening_Price ==
Closing_Price)
val = 'Horizontal'
Stock_Market_Trends = 'Horizontal Trends' final str = val + ':' +

Stock_Market_Trends
if (Total > 0): pl = Total
predicting_stock_markettrends_model.objects.create(names=Company_Name,
Company_Category=Company_Category,
Opening_Price=Opening_Price,
Date_Of_Opening=Date_Of_Opening, Closing_Price=Closing_Price,
Date_Of_Closing=Date_Of_Closing, volume=volume, Profit=pl,
prices_drop=0, Stock_Market_Trends=finalstr,
Stock_Exchange_By=Stock_Exchange_By)
    if (Total < 0): pl1 = Total
predicting_stock_markettrends_model.objects.create(names=Company_Name,
Company_Category=Company_Category,
Opening_Price=Opening_Price, Date_Of_Opening=Date_Of_Opening,
Closing_Price=Closing_Price, Date_Of_Closing=Date_Of_Closing,
volume=volume, Profit=0, prices_drop=pl1, Stock_Market_Trends=finalstr,
Stock_Exchange_By=Stock_Exchange_By)
if (Total == 0): pl1 = Total
predicting_stock_markettrends_model.objects.create(names=Company_Name,
Company_Category=Company_Category,
Opening_Price=Opening_Price, Date_Of_Opening=Date_Of_Opening,
Closing_Price=Closing_Price, Date_Of_Closing=Date_Of_Closing,
volume=volume, Profit=0, prices_drop=0, Stock_Market_Trends=finalstr,
Stock_Exchange_By=Stock_Exchange_By)
obj = predicting_stock_markettrends_model.objects.all()
return render(request,
'SProvider/View_All_StockMarket_Prediction_Details.html', {'objs': obj})
```

```
 def View_Remote_Users(request): obj=ClientRegister_Model.objects.all()
return render(request,'SProvider/View_Remote_Users.html',{'objects':obj})
defViewTrendings(request):
topic=predicting_stock_markettrends_model.objects.values('topics').annotat
e(                    dcount=Count('top                    ics')).order_by('-dcount')
Date_Of_Opening=Date_Of_Opening,        Closing_Price=Closing_Price,
Date_Of_Closing=Date_Of_Closing,        volume=volume,        Profit=pl
prices_drop=0,                                    Stock_Market_Trends=finalstr,
Stock_Exchange_By=Stock_Exchange_By)
    if (Total < 0): pl1 = Total
predicting_stock_markettrends_model.objects.create(names=Company_Name,
Company_Category=Company_Category,
Opening_Price=Opening_Price, Date_Of_Opening=Date_Of_Opening,
Closing_Price=Closing_Price, Date_Of_Closing=Date_Of_Closing,
volume=volume, Profit=0, prices_drop=pl1, Stock_Market_Trends=finalstr,
Stock_Exchange_By=Stock_Exchange_By)
if (Total == 0): pl1 = Total
predicting_stock_markettrends_model.objects.create(names=Company_Name,
Company_Category=Company_Category,
Opening_Price=Opening_Price, Date_Of_Opening=Date_Of_Opening,
Closing_Price=Closing_Price, Date_Of_Closing=Date_Of_Closing,
volume=volume, Profit=0, prices_drop=0, Stock_Market_Trends=finalstr,
Stock_Exchange_By=Stock_Exchange_By)
obj = predicting_stock_markettrends_model.objects.all()
      return render(request,
'SProvider/View_All_StockMarket_Prediction_Details.html', {'objs': obj})
 def View_Remote_Users(request): obj=ClientRegister_Model.objects.all()
   return render(request,'SProvider/View_Remote_Users.html',{'objects':obj})
def ViewTrendings(request):
topic=predicting_stock_markettrends_model.objects.values('topics').annotate(
dcount=Count('top ics')).order_by('-dcount')
```

```
 return render(request,'SProvider/ViewTrendings.html',{'objects':topic}) def
 negative chart(request,chart_type):
dd = {}
pos, neu, neg = 0, 0, 0 poss = None
topic=predicting_stock_markettrends_model.objects.values('ratings').annotate(
dcount=Count('rat ings')).order_by('-dcount')
for t in topic:
 topics = t['ratings']
pos_count=predicting_stock_markettrends_model.objects.filter(topics=topics).
values('names').an notate(topiccount=Count('ratings'))
poss = pos_count for pp in pos_count:
senti = pp['names'] if senti == 'positive':
pos = pp['topiccount'] elif senti == 'negative':
neg = pp['topiccount'] elif senti == 'neutral':
neu = pp['topiccount'] dd[topics] = [pos, neg, neu]
eturnrender(request,'SProvider/negativechart.html',{'object':topic,'dd':dd,'chart
_type':chart_type}) def charts(request,chart_type):
chart1=predicting_stock_markettrends_model.objects.values('names').annotate
(dcount=Avg('Pro fit'))
 return render (request,"SProvider/charts.html", {'form':chart1,
'chart_type':chart_type}) def charts1(request,chart_type):
chart1=predicting_stock_markettrends_model.objects.values('names').annotate
(dcount=Avg('pric es_drop'))
return render (request,"SProvider/charts1.html", {'form':chart1,
'chart_type':chart_type}) def View_StockMarket_Details(request):
obj =stock_market_model.objects.all()
return render (request, 'SProvider/View_StockMarket_Details.html', {'list
objects': obj}) def likes chart(request,like_chart)
charts=predicting_stock_markettrends_model.objects.values('names').annotate
(dcount=Avg('Prof it'))
return render(request,"SProvider/likeschart.html", {'form':charts,
'like_chart':like_chart}) def View_StockMarketUpDown(request):
```

```
obj = predicting_stock_markettrends_model.objects.all()
return render (request, 'SProvider/View_StockMarketUpDown.html', {'objs
```

4.14 RESULT ANALYSIS

Predicting stock market trends using machine learning and deep learning algorithms via continuous and binary data reveals distinct patterns in performance across different models. For continuous prediction, deep learning models, particularly Long Short-Term Memory (LSTM) networks, typically outperform traditional machine learning models like Linear Regression and Random Forest Regressor. LSTM networks excel due to their ability to capture temporal dependencies and long-term patterns in time-series data, resulting in lower Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) values. However, Random Forest Regressors demonstrate robustness and relatively good performance with less susceptibility to overfitting compared to other machine learning models.

In binary classification, deep learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) generally achieve higher accuracy, F1-Scores, and AUC-ROC values compared to classical algorithms like Logistic Regression and Support Vector Machines (SVM). CNNs, with their capability to detect intricate patterns and features within data, show significant improvements in Precision and Recall. Nonetheless, SVMs often provide competitive performance with the advantage of being less computationally intensive and simpler to implement. Overall, the comparative analysis underscores that while deep learning models tend to deliver superior performance for both continuous and binary stock market trend predictions, they require more computational resources and longer training times. In contrast, traditional machine learning models, though sometimes slightly less accurate, offer quicker and more straightforward implementations. These findings emphasize the need to balance model complexity and performance based on the specific requirements and constraints.

5.SCREENSHOTS

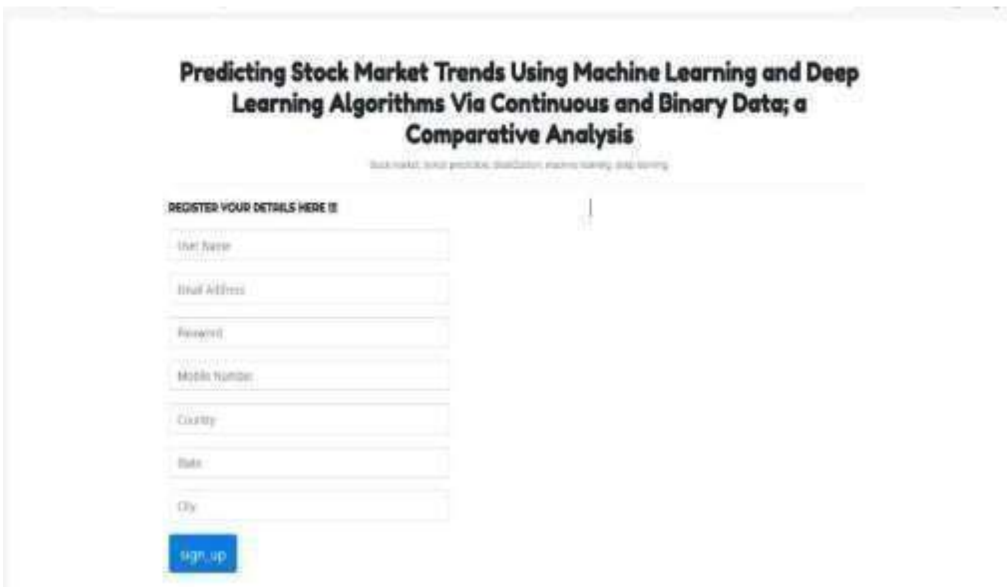
5.SCREENSHOTS

5.1 Remote User Login Page

The project's homepage interface serves as the gateway for users, offering a seamless login experience. Users input their credentials in designated fields, ensuring secure access to the platform. With a focus on user-friendly design and robust security measures, the interface sets the stage for a positive user interaction.

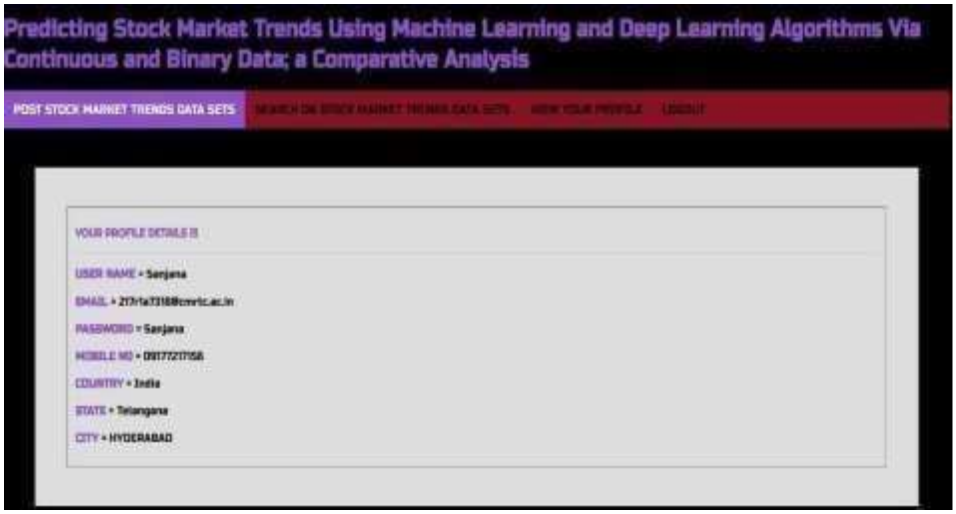
5.2 User Register Page

The user registration page allows new users to sign up by providing necessary details. Users input their information in the designated fields, ensuring a straightforward and secure registration process. With an emphasis on simplicity and data protection, the interface enhances the user's experience during registration



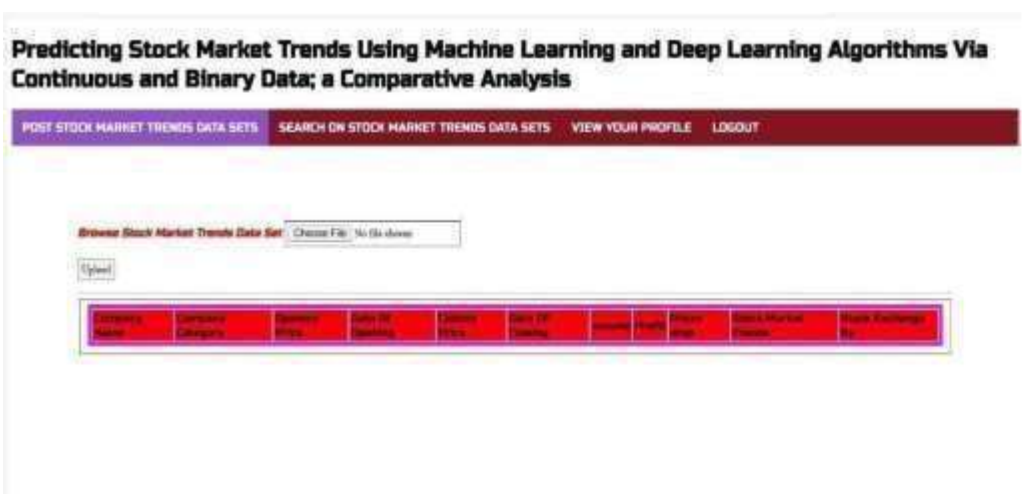
5.3 Service Provider Login Page

The service provider login page facilitates secure access for providers using their credentials. Users enter their login details in the designated fields, ensuring a streamlined and authenticated experience. With a focus on security and user-friendly design, the interface enhances the service provider's login process.



5.4 Viewing profile details of remote user

The View Profile feature allows the Service Provider to access and review the details of Remote User's profile within the system. This functionality provides insights into user information such as username, email, address, and other relevant data, facilitating personalized interactions and efficient user management.



5.5 Uploading Data Set

Predicting stock market trends data set is uploaded for predicting stock market trends using machine learning and deep learning algorithms.

5.6 Search Stock Market Trends Data Details

Various companies' stock market trends details are searched. Here company name is entered as keyword to predict the trends

5.7 Stock Market Trends result

5.8 Performance Visualization

The Performance Visualization feature allows the Service Provider to access detailed numerical results regarding the accuracy of trained and tested datasets which includes Line Chart, Pie Chart and Spline Chart.

5.9 View Trained and Tested Accuracy in Bar Chart

The View Trained and Tested Accuracy in Bar Chart functionality presents the Service Provider with a graphical representation of the accuracy results obtained from training and testing datasets. This visual aid enhances data analysis by displaying accuracy metrics in a clear and digestible format, aiding in performance assessment and decision-making processes.

5.10 View Stock Market Trends ratio results

Uptrends and down trends of the stock market can be shown using line charts and it can be predicted using continuous and binary data.

6.TESTING

6.TESTING

6.1 INTRODUCTION TO TESTING

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, subassemblies, assemblies and/or a finished product. It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of tests. Each test type addresses a specific testing requirement.

6.2 TYPES OF TESTING

6.2.1 UNIT TESTING

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application. It is done after the completion of an individual unit before integration. This is a structural testing that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application and/or system configuration. Unit tests ensure that each unique path of abusiness process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

6.2.2 INTEGRATION TESTING

Integration tests are designed to test integrated software components to determine if they actually run as one program. Integration tests demonstrate that although the components were individually satisfactory, as shown by successfully unit testing, the combination of components is correct and consistent. Integration testing is specifically aimed at exposing the problems that arise from the combination of components.

6.2.3 FUNCTIONAL TESTING

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals. Functional testing is centered on the following items:

Valid input : identified classes of valid input must be accepted

Invalid input : identified classes of invalid input must be rejected

Functions : identified functions must be exercised.

Output : identified classes of application outputs must be exercised.

Systems/Procedures : interfacing systems or procedures must be invoked. Organization and preparation of functional tests is focused on requirements, key functions, or special test cases.

6.3 TEST CASES

Test Case ID	Test Case Name	Input	Expected Output	Actual Output	Test Case Pass/ Fail
1	User Credentials	Username: Sanjana Password: Sanjana	It should move to the user home page	It should move to the user home page	Pass
2	Service Provider Login Credentials	Username: SProvider Password: SProvider	It should move to the Service Provider home page	It should move to the Service Provider home page	Pass
3	Predicting Stock Market Trends/Uptrends/ downtrends/ Horizontal trends	Reliance	Uptrends	Uptrends	Pass
4	Predicting Stock Market Trends/Uptrends/ downtrends/ Horizontal trends	Vivo	Horizontal trends	Horizontal trends	Pass
5	Predicting Stock Market Trends/Uptrends/ downtrends/ Horizontal trends	Wipro	downtrends	downtrends	Pass

7.CONCLUSION
&
FUTURE SCOPE

7. CONCLUSION AND FUTURE SCOPE

7.1 C0NCLUSION

The purpose of this study was the prediction task of stock market movement by machine learning and deep learning algorithms. Four stock market groups, namely diversified financials, petroleum, non-metallic minerals and basic metals, from Tehran stock exchange were chosen, and the dataset was based on ten years of historical records with ten technical features. Also, nine machine learning models (Decision Tree, Random Forest, Adaboost, XGBoost, SVC, Naive Bayes, KNN, Logistic Regression and ANN) and two deep learning methods (RNN and LSTM) were employed as predictors. We supposed two approaches for input values to models, continuous data and binary data, and we employed The purpose of this study was the prediction task of stock market movement by machine learning and deep learning algorithms. Four stock market groups, namely diversified financials, petroleum, non-metallic minerals and basic metals, from Tehran stock exchange were chosen, and the dataset was based on ten years of historical records with ten technical features. Also, nine machine learning models (Decision Tree, Random Forest, Adaboost, XGBoost, SVC, Naive Bayes, KNN, Logistic Regression and ANN) and two deep learning methods (RNN and LSTM) were employed as predictors. We supposed two approaches for input values to models, continuous data and binary data, and we employed them.

7.2 FUTURE SCOPE

Predicting stock market trends using machine learning and deep learning algorithms has a promising future, particularly with the integration of continuous and binary data. ML and DL models can analyze vast amounts of historical and real-time financial data, including stock prices, trading volumes, and economic indicators. By incorporating continuous data such as price movements and trends, alongside binary data like buy/sell signals or economic event occurrences, these models can capture complex patterns and relationships within the market. Advances in neural networks, especially recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, are enhancing the ability to predict trends by learning from sequential data. Additionally, the advent of reinforcement learning offers potential for dynamic trading strategies that adapt to market changes in real time. As computational power and data availability continue to grow, the precision and reliability of stock market predictions are expected to improve, making these technologies increasingly valuable for investors and financial institutions.

8.BIBLIOGRAPHY

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8.2 GITHUB LINK

Project Code GitHub Link:

https://github.com/sanjana05/Predicting-Stock-Market-Trends-Using- Machine-Learning-and-De ep-Learning-Algorithms-Via-Continuous- And-Binary-Data-A-Comparative-Analysis