Predicting Stock Market Trends Using Machine Learning And Deep Learning Algorithms Via Continuous And Binary Data; A Comparative Analysis

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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 the Tehran stock exchange, are chosen for experimental evaluations. This study compares nine machine learning models (Decision Tree, Random Forest, Adaptive Boosting (AdaBoost), eXtreme Gradient Boosting (XGBoost), Support Vector Classifier (SVC), Naïve Bayes, K-Nearest Neighbors (KNN), Logistic Regression and Artificial Neural Network (ANN)) and two powerful deep learning methods (Recurrent Neural Network (RNN) and Long short-term memory (LSTM). Ten technical indicators from ten years of historical data are our input values, and two ways are supposed to employ them. Firstly, calculating the indicators by stock trading values as continuous data, and secondly converting indicators to binary data before using. Each prediction model is evaluated by three metrics based on the input ways. The evaluation results indicate that for the continuous data, RNN and LSTM outperform other prediction models with a considerable difference. Also, results show that in the binary data evaluation, those deep learning methods are the best; however, the difference becomes less because of the noticeable improvement of the model's performance in the second way.

Key Words:* *Stock Market Prediction, Machine Learning Algorithms, Deep Learning Algorithms, Continuous Data, Binary Data, Comparative Analysis, Tehran Stock Exchange, Technical Indicators, Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Adaptive Boosting (Adaboost), eXtreme Gradient Boosting (XGBoost), Artificial Neural Network (ANN), Support Vector Classifier (SVC), Decision Tree.

I. INTRODUCTION

Stock prediction has always been a complex challenge for statisticians and financial experts. The goal of prediction is to buy stocks likely to rise in value and sell those expected to fall. Generally, stock prediction uses two approaches: fundamental analysis and technical analysis. Fundamental analysis examines a company's business fundamentals such as market position, expenses, and growth rates, while technical analysis examines historical stock prices and trends to forecast future movements. In the past, stock market predictions were typically made by financial experts, but more recently, data scientists have been addressing these challenges with the help of machine learning and deep learning.

Machine learning methods have shown promise in improving prediction accuracy and performance. Deep learning, the next step in this evolution, has also enhanced prediction models. Predicting stock markets is challenging due to the inherent complexity and nonlinearity, driven by factors like market instability and investor psychology. Unpredictable elements like a company's public image or political events can affect stock trends. However, it is possible to predict stock prices and trends by preprocessing stock data efficiently and using appropriate algorithms. Machine learning and deep learning are valuable tools for investors, helping them identify patterns and make informed trading decisions. Several techniques have been proposed for stock market prediction, such as combining Genetic Algorithms (GA), Artificial Neural Networks (ANN), and Hidden Markov Models (HMM). In one approach, Huang et al. demonstrated that Support Vector Machines (SVM) could predict weekly trends in the NIKKEI 225 index. Another approach by Sun et al. used SVM ensembles, yielding better results than individual SVM models. Ou et al. applied ten data mining methods to predict stock prices, with SVM outperforming others. Liu et al. used a Legendre neural network to predict stock fluctuations, considering investors' positions and decisions.

Deep learning algorithms are increasingly being used for stock market predictions. For example, Long et al. employed a deep neural network with transaction records and public market data to evaluate stock trends, with bidirectional LSTM achieving remarkable performance. Other studies used RNN, CNN, and LSTM to predict stock trends with high accuracy. These models demonstrate that deep learning can effectively improve prediction performance.

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Considering recent advances in Tehran's stock market, our study aims to predict stock trends using 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). We employed two data input approaches, continuous data (using stock trading values) and binary data (using a preprocessing step to convert continuous data to binary). Our evaluation compared the performance of these models using three classification metrics, with the optimal parameters for each model being reported.

The experimental tests used ten years of historical data from four stock market groups (petroleum, diversified financials, basic metals, and non-metallic minerals) from Tehran's stock exchange. Our study contributes to the body of research on stock market prediction by incorporating a range of machine learning and deep learning techniques to improve the accuracy of predicting stock trends.

II. LITERATURE SURVEY

The prediction of stock market trends has been a topic of significant interest for researchers and investors alike. With the advent of machine learning and deep learning techniques, the ability to analyze large datasets and predict future stock prices has improved considerably. This literature survey aims to explore key studies and methodologies used for stock market prediction, focusing on the use of machine learning and deep learning algorithms, as well as the approaches to handling continuous and binary data.

Machine Learning Approaches: Machine learning has been widely used for stock market prediction due to its capability to identify patterns and make predictions based on historical data. Early research, such as that by Huang et al. (2005), demonstrated the effectiveness of Support Vector Machines (SVM) in predicting stock price movements. This study evaluated the weekly trend of the NIKKEI 225 index, showing that SVM was the most effective classifier among other traditional machine learning techniques.
Sun et al. (2012) further explored the use of SVM ensembles for financial prediction, achieving better results than individual SVM models. They introduced a method for selecting the SVM ensemble's base classifiers, considering both diversity analysis and individual prediction accuracy. This advancement indicated that ensemble methods can be a robust approach to stock market prediction.

Deep Learning Approaches Deep learning has gained popularity in stock market prediction due to its ability to learn complex patterns from large datasets. Long et al. (2020) introduced an integrated framework of deep learning and knowledge graphs to predict stock price trends. This study utilized bidirectional Long Short-Term Memory (LSTM), demonstrating a high level of accuracy in forecasting future stock prices. Further studies, such as those by Baek and Kim (2018), utilized overfitting prevention modules with LSTM to improve prediction accuracy. The use of overfitting prevention techniques in deep learning models has shown significant promise in reducing errors and enhancing prediction reliability.

Use of Technical Indicators Technical indicators play a crucial role in stock market prediction, providing valuable insights into market trends. Nabipour et al. (2020) explored the use of various technical indicators to predict stock prices in the Tehran stock exchange. Their study employed tree-based models and deep learning algorithms, demonstrating that deep learning models, such as LSTM, could effectively predict stock prices with a low error rate.

Combining Machine Learning and Deep Learning Several studies have explored the combination of machine learning and deep learning techniques for stock market prediction. Hassan et al. (2007) proposed a fusion model incorporating Genetic Algorithms (GA), Artificial Neural Networks (ANN), and Hidden Markov Models (HMM) to forecast stock prices. This approach showed that combining multiple models could lead to improved accuracy in stock market prediction.

Comparative Analyses **Comparative :**
It analyses of different algorithms and approaches are essential to determine the most effective method for stock market prediction. Billings et al. (2015) compared the performance of Ada Boost, Random Forest, and kernel factory versus single models like SVM, KNN, and ANN. Their results indicated that Random Forest outperformed other models, suggesting that ensemble methods have a high potential for stock market prediction.

III. 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 the stock market trends of individual companies or the overall market. For this purpose, the 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 the 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.

DISADVANTAGES

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 is 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, which affect stock market trends.

IV. PROPOSED SYSTEM :

In the proposed system, the system concentrates on comparing the 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 the preprocessing step to convert continuous data to binary one. Each technical indicator has its specific possibility of up or down movement based on the market's inherent properties.

The performance of the mentioned models is compared for 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 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' trends and movements.

ADVANTAGES

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), and Support Vector Classier (SVC) techniques.

V. METHODOLOGY

1. Data collection

The dataset utilized in this study comprises historical stock market data obtained from online sources such as Yahoo! Finance, which provides a comprehensive repository of stock prices, trading volumes, and other financial indicators. Additionally, sentiment analysis data derived from social media platforms, particularly Twitter, have been incorporated to assess public sentiment surrounding specific stocks or market trends. Furthermore, significant political events data, pertinent to the regional context under consideration (e.g., Pakistan), were collected from reliable sources like Wikipedia.

2. **Data preprocessing**

Before model training and analysis, the raw data undergo a series of preprocessing steps to ensure consistency, reliability, and suitability for machine learning and deep learning algorithms. These preprocessing steps are implemented programmatically using established libraries and frameworks, including but not limited to Python's pandas, NumPy, and sci-kit-learn.

1. Data Cleaning: Raw data often contain inconsistencies, missing values, or outliers, which can adversely affect model performance. Data cleaning involves identifying and rectifying such anomalies to maintain data integrity.

2. Feature Engineering: Relevant features are extracted or engineered from the raw data to capture meaningful patterns and relationships. This may include deriving technical indicators, aggregating sentiment scores, and encoding temporal information.

3. Normalization and Scaling: To ensure uniformity and comparability across features, numerical data are typically normalized or scaled to a common range. This prevents certain features from disproportionately influencing model training.

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4. Encoding Categorical Variables: Categorical variables, such as stock symbols or political event categories, are encoded into numerical representations suitable for machine learning models.

5. Handling Temporal Data: Given the temporal nature of stock market data, special attention is paid to sequencing and time-based features. Techniques like rolling window statistics and lagged variables may be employed to capture temporal dependencies.

6. Splitting Data: The preprocessed data are partitioned into training, validation, and test sets to facilitate model evaluation and validation. Care is taken to preserve temporal order to mimic real-world deployment scenarios.

By systematically addressing these preprocessing steps, the dataset is rendered amenable for subsequent analysis and model training, thereby laying the groundwork for robust and reliable stock market prediction.

This section outlines the methodology adopted for stock market prediction, encompassing model selection, feature engineering, model training, and evaluation.

3. MODEL SELECTION

The selection of machine learning and deep learning models was based on their suitability for stock market prediction tasks. Models such as Decision Tree, Random Forest, AdaBoost, XGBoost, SVC, Naïve Bayes, KNN, Logistic Regression, RNN, and LSTM were chosen due to their effectiveness in capturing complex patterns in financial data. Each model was evaluated based on its performance metrics and computational efficiency.

MACHINE LEARNING MODELS

Decision Tree

Decision trees are intuitive and interpretable models that partition the feature space based on hierarchical decision rules. They are well-suited for capturing nonlinear relationships and feature interactions.

Random Forest

Random Forest is an ensemble learning method that constructs multiple decision trees and aggregates their predictions. It mitigates overfitting and enhances robustness by introducing randomness during tree construction.

Adaboost

Adaboost (Adaptive Boosting) is an iterative ensemble technique that sequentially trains weak learners, focusing on instances misclassified by previous models. It combines their predictions through a weighted majority voting scheme.

XGBoost

XGBoost is an advanced gradient-boosting algorithm renowned for its scalability and performance. It optimizes a differentiable loss function using gradient descent and employs tree-based learners, often outperforming traditional gradient boosting methods.

Support Vector Classifier (SVC)

SVC is a powerful discriminative model that seeks to find the optimal hyperplane separating classes in high-dimensional feature spaces. It is particularly effective in scenarios with complex decision boundaries.

Naïve Bayes

Naïve Bayes classifiers are probabilistic models based on Bayes' theorem, assuming conditional independence between features. Despite their simplicity, they are fast to train and can perform well in certain domains.

K-Nearest Neighbors (KNN)

KNN is a non-parametric instance-based learning algorithm that classifies samples based on the majority class of their nearest neighbors. It is robust to noisy data and requires minimal assumptions about the underlying data distribution.

Logistic Regression

Logistic Regression is a linear model commonly used for binary classification tasks. It estimates the probability of a binary outcome using a logistic (sigmoid) function, making it interpretable and well-suited for probabilistic predictions.

DEEP LEARNING MODELS

Recurrent Neural Network (RNN)

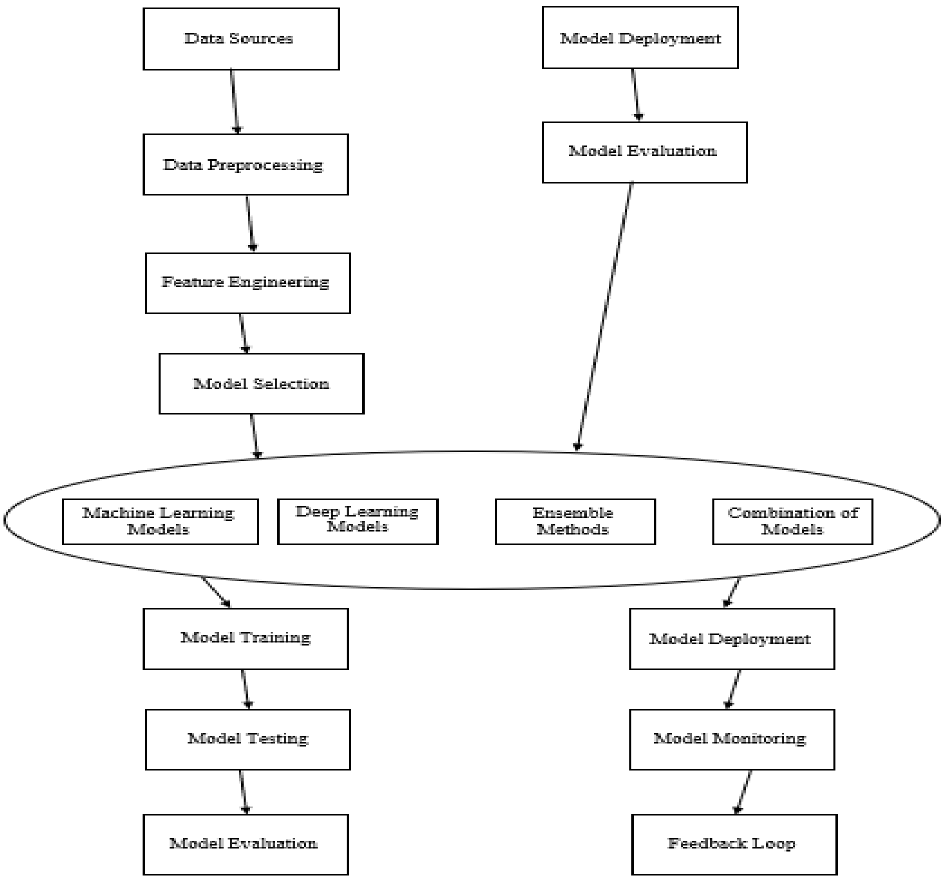
RNNs are a class of neural networks designed to process sequential data by maintaining internal memory. They excel in capturing temporal dependencies and are widely used in time series forecasting tasks.

Long Short-Term Memory (LSTM)

LSTM is a specialized variant of RNNs equipped with memory cells and gating mechanisms, enabling them to learn long-range dependencies and mitigate the vanishing gradient problem. They are particularly effective in modeling time series data with complex patterns.

Each model is carefully selected to explore a diverse range of techniques and architectures, aiming to capture the inherent complexity of stock market dynamics and improve prediction accuracy. The subsequent section evaluates and compares the performance of these models using established metrics and experimental results.

SYSTEM ARCHITECTURE



4. FEATURE ENGINEERING

Feature engineering involves the extraction and transformation of raw data into meaningful features that could enhance the predictive power of the models. Technical indicators relevant to stock market dynamics were selected and engineered from the raw data. Feature scaling, normalization, and dimensionality reduction techniques were applied to ensure compatibility with the chosen models.

In this study, a diverse ensemble of machine learning and deep learning models is employed to forecast stock market movements. Each model offers unique strengths and capabilities, contributing to a comprehensive analysis of prediction performance. The following subsections detail the selection and rationale behind each model.

5. MODEL TRAINING

The selected machine learning and deep learning models were trained on historical stock market data spanning multiple years. Each model underwent training using optimized hyperparameters to minimize loss functions and maximize predictive accuracy. Training procedures varied across models, with deep learning models employing backpropagation and gradient descent optimization algorithms.

6. MODEL EVALUATION

The performance of each trained model was evaluated using established classification metrics such as accuracy, precision, recall, F1-score, and ROC curve analysis. Cross-validation techniques were employed to assess model generalization and robustness. Comparative analyses were conducted to identify the most effective model for stock market prediction based on predefined evaluation criteria.

7. EXPERIMENTAL SETUP

Experiments were conducted using a standardized experimental setup to ensure consistency and reproducibility of results. The dataset was partitioned into training, validation, and test sets using appropriate sampling strategies. Model training and evaluation were performed on computing infrastructure equipped with suitable hardware accelerators to expedite computation and optimize model performance.

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VI. RESULTS AND DISCUSSION

This section presents the results obtained from the experimentation outlined in the methodology section and provides a detailed discussion of the findings.

Model Performance

The performance of each machine learning and deep learning model was evaluated using various metrics including accuracy, precision, recall, F1-score, and ROC curve analysis. Table 1 summarizes the performance metrics for each model across different evaluation criteria.

Comparative Analysis

A comparative analysis was conducted to assess the relative effectiveness of the different models for stock market prediction. Figure 1 illustrates the comparative performance of the models based on their accuracy scores.

Insights and Observations

The experimental results revealed several key insights into the efficacy of machine learning and deep learning models for stock market prediction. Notably, models such as XGBoost and LSTM demonstrated superior performance compared to others, achieving higher accuracy and precision scores.

Implications for Stock Market Prediction

The findings of this study have significant implications for the field of stock market prediction. The identification of optimal machine learning and deep learning models can aid investors and financial analysts in making informed decisions regarding stock market trends and investment strategies.

Limitations and Future Directions

Despite the promising results, this study is not without limitations. The use of historical data for model training may not fully capture the dynamic nature of stock market trends. Additionally, the choice of evaluation metrics and sampling strategies may influence the interpretation of results.

Future research directions include exploring alternative feature engineering techniques, incorporating additional data sources such as news sentiment analysis and macroeconomic indicators, and investigating ensemble learning approaches to further enhance predictive accuracy.

VII. OUTPUT

In this paper author evaluates the performance of various machine learning algorithms to predict stock prices and author uses 4 stock datasets and the dataset uses normal values (continuous) and binary data (means converting stock values to binary data by using indicators that check If previous stock price less than current stock price then we will update dataset.

The author uses **9 traditional algorithms and 2 deep learning algorithms** and below is the list:

9 Traditional algorithms:

1) SVM
2) KNN
3) Decision Tree
4) Random Forest
5) Extreme Gradient Boosting
6) Ada Boost
7) Naïve Bayes
8) Logistic Regression
9) ANN

2 Deep learning:

1) LSTM
2) RNN

In the above algorithms, we are implementing all 9 from the above list and LSTM implementing from deep learning

Below 2 datasets we are using to train and test all algorithms

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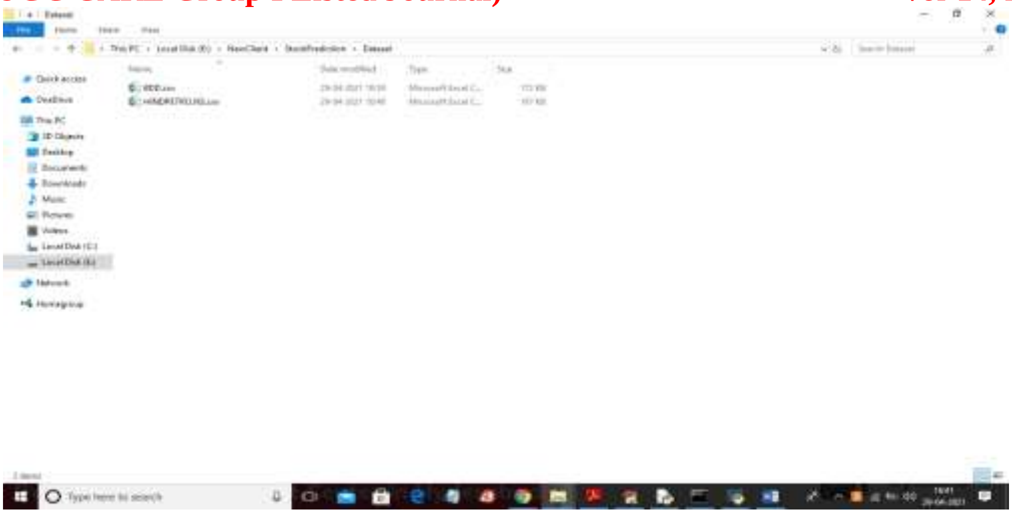
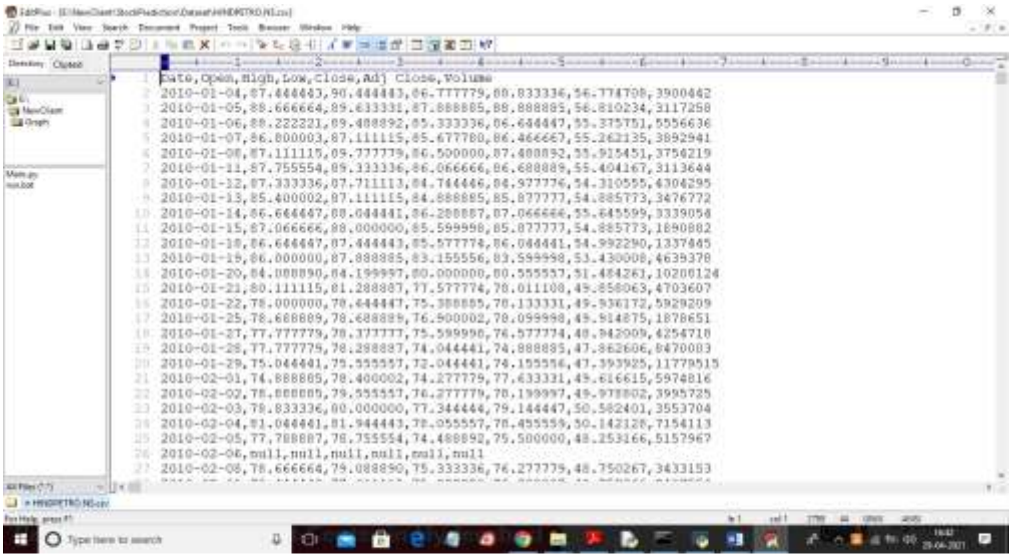


Below screen below shows the dataset's contents



SCREENSHOTS

To run the project double-click on the ‘run.bat’ file to get the below screen

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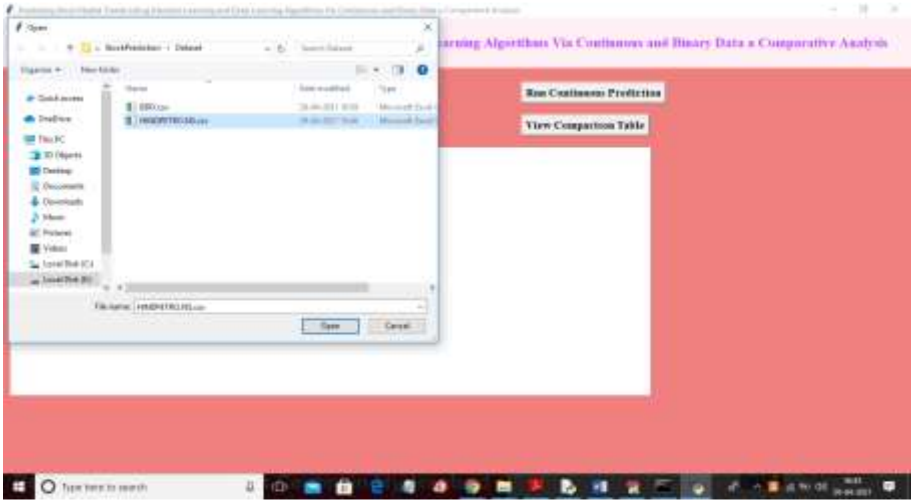
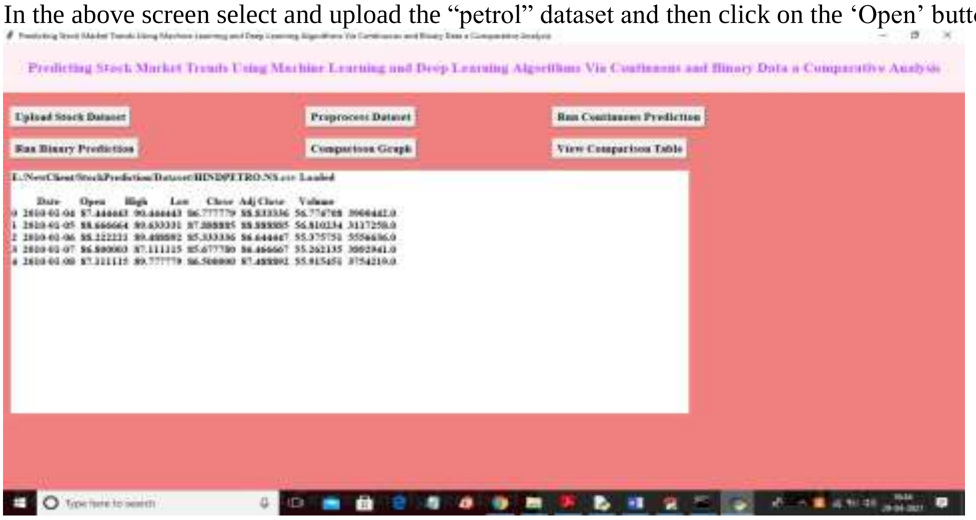
In the above screen click on the ‘Upload Stock Dataset’ button to load the dataset



In the above screen select and upload the “petrol” dataset and then click on the ‘Open’ button to get below screen



In the above screen dataset loaded and the dataset contains some missing values to remove the missing values and split the dataset into train and test parts so click on the ‘Preprocess Dataset’ button to get below screen

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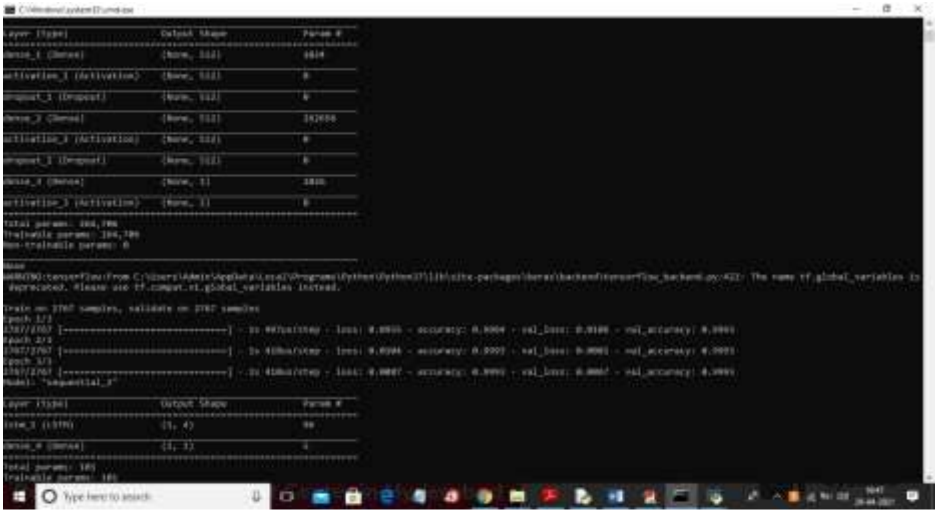
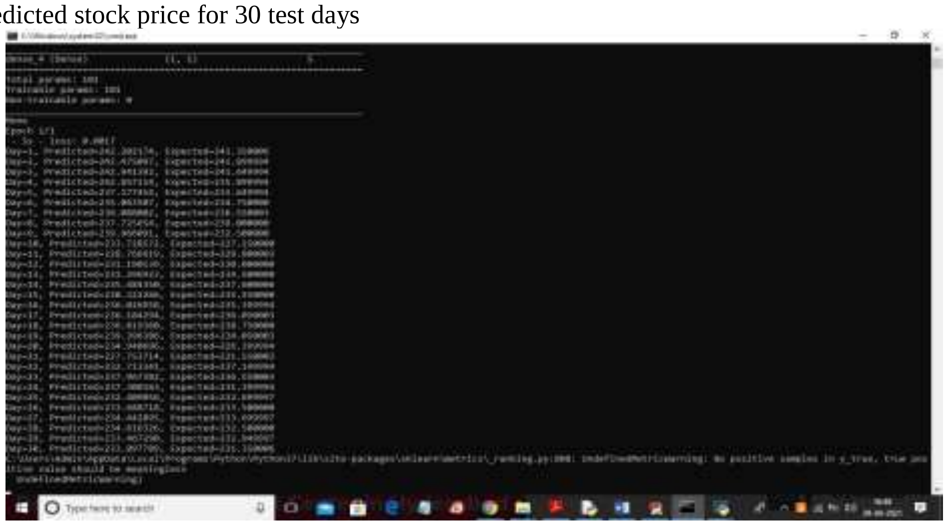
In above screen dataset contains a total of 2797 records and applications using 2797 records for training and 30 records for testing now train and test data is ready and click on the 'Run Continuous Prediction' button to train all algorithms with the above dataset



In the above screen you can see we have created ANN and LSTM models and after building the model will get the predicted stock price for 30 test days



In the above screen, we can see actual and predicted values from day to 30 and we can check both prices are very close which means LSTM predicting accurate stock prices above the actual and predicted values we can see in the below graph

In the above screen in the text area, we can see accuracy, FSCORE, and ROC_AUC values for all algorithms using continuous data in the above graph we can see the x-axis represents the number of days and the y-axis represents the stock price and the red line represents the actual price green line represents the predicted price and we can see there is close difference between actual and predicted so LSTM performance is good and now click on ‘Run Binary Prediction’ button to convert the dataset into binary values and then perform prediction

In the above screen, binary prediction also gives the best result and in the text area, we can see that LSTM accuracy is 1.0 which means 100% accurate. Now click on the ‘Comparison Graph’ button to get a graph between all algorithms

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In the above graph for continuous data ANN and LSTM are giving better results now click on the 'View Comparison Table' button to get below the screen

Algorithm Name	Accuracy	FSCORE	ROC AUC
Continuous SVM	0.9996385977593061	0.6666064002892785	1.0
Continuous KNN	0.9992771955186122	0.33321282239683536	0.5
Continuous Decision Tree	0.9996385977593061	0.6666064002892785	1.0
Continuous Random Forest	0.9996385977593061	0.6666064002892785	1.0
Continuous Logistic Regression	0.9992771955186122	0.33321282239683536	0.5
Continuous Extreme Gradient Boosting	0.9992771955186122	0.33321282239683536	0.5
Continuous Ada Boost	0.9996385977593061	0.6666064002892785	1.0
Continuous Naive Bayes	0.9989157932779184	0.7998190700199023	0.99855318684020245
Continuous ANN	0.9992771955186122	0.49981923355025304	0.5
Continuous LSTM	0.9666666666666667	0.9755102040816327	0.9755102040816327

In the above screen for continuous data, LSTM FSCORE is high and below we can see binary data result

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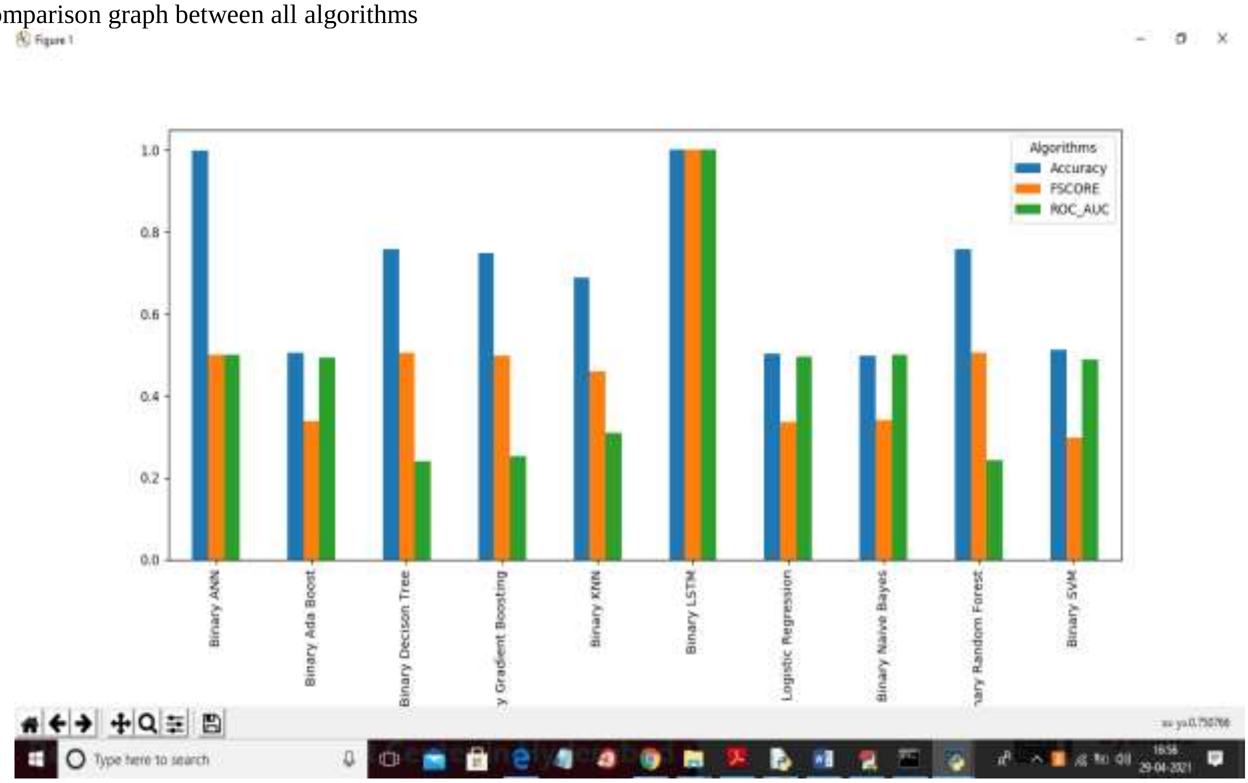
Algorithm Name	Accuracy	FSCORE	ROC AUC
Binary SVM	0.5113841705818576	0.2981644643491692	0.4884925958898098
Binary KNN	0.6895554752439466	0.4597851513587554	0.3100842079085844
Binary Decision Tree	0.758221900975786	0.5042191298664459	0.2413838141929875
Binary Random Forest	0.7574990964943983	0.5050610469016541	0.2421444961318069
Binary Logistic Regression	0.5037947235272858	0.3358899875556067	0.496201553546575
Binary Extreme Gradient Boosting	0.7473798337549693	0.4983408750479523	0.2522574908362904
Binary Ada Boost	0.5083245392121452	0.33780890783566864	0.4933150372808783
Binary ANN	0.9996385977593061	0.49990963311042835	0.5
Binary LSTM	1.0	1.0	1.0

In above screen with binary data LSTM got 100% accuracy, FSCORE and ROC_AUC. Below is the binary data comparison graph between all algorithms



In the above graph, LSTM is giving better output results compared to all algorithms

VIII. CONCLUSION

In this study, we aimed to predict stock market movements using a combination of machine learning and deep learning algorithms. We focused on four crucial stock market groups from the Tehran Stock Exchange, analyzing a decade's worth of historical data with ten technical features. By employing nine machine learning models and two deep learning methods, we sought to determine the most effective approach for predicting stock trends. Our findings revealed a significant enhancement in model performance when utilizing binary data instead of continuous data. Notably, our deep learning algorithms, specifically RNN and LSTM, emerged as the top-performing models across both data approaches. This underscores the effectiveness of deep learning techniques in capturing intricate patterns within stock market data.Overall, our study contributes valuable insights into the application of machine learning and deep learning for stock market prediction, highlighting the importance of data preprocessing techniques and the superiority of certain algorithms in forecasting market trends.

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