IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 4, April 2025
Impact Factor: 7.67

Predicting Market Performance Using Machine and Deep Learning Techniques

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Abstract: *Stock market movements have long been characterized by uncertainty due to the influence of numerous dynamic factors. This study aims to reduce the risk associated with trend prediction by leveraging a combination of machine learning (ML) and deep learning (DL) algorithms. Four key sectors from the Tehran Stock Exchange—diversified financials, petroleum, non-metallic minerals, and basic metals—are selected for empirical evaluation. The study examines 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)) alongside two advanced deep learning techniques: Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM). Input features are derived from ten technical indicators based on ten years of historical data, applied through two approaches: (1) as raw continuous data calculated from stock trading values, and (2) as binarized data through thresholding. Each model's performance is evaluated using three standardized metrics under both data formats. Results indicate that RNN and LSTM significantly outperform traditional ML models when using continuous data. Although these DL models also maintain a leading position in binary data evaluations, the performance gap narrows due to notable improvements in ML models when using binarized inputs. This comparative analysis highlights the effectiveness of deep learning in capturing complex temporal patterns in financial data and demonstrates the impact of data representation on predictive accuracy.*

Keywords: Machine Learning, Deep Learning, Stock Market Prediction, Data Representation, Tehran Stock Exchange.

I. INTRODUCTION

The stock market has always been a complex and volatile domain influenced by a wide range of economic, political, psychological, and technical factors. Predicting stock trends is an inherently challenging task due to the non-linear, dynamic nature of financial markets. Investors and analysts have long sought reliable methods to forecast future trends to maximize returns and minimize risks. Traditional statistical approaches often fall short in capturing the intricacies and temporal dependencies present in stock market data. This has led to the growing application of intelligent computational techniques, particularly machine learning (ML) and deep learning (DL) models, which offer the capability to identify patterns and relationships within large volumes of data.

Machine learning models have gained popularity in financial forecasting due to their ability to learn from historical data and make generalizations for unseen scenarios. Supervised learning algorithms such as Decision Trees, Random Forests, Support Vector Classifiers, and Logistic Regression have shown promising results in various classification tasks, including financial trend prediction. Ensemble methods like AdaBoost and XGBoost enhance predictive accuracy by combining multiple weak learners, whereas algorithms like K-Nearest Neighbors and Naïve Bayes offer simplicity and computational efficiency. Moreover, Artificial Neural Networks (ANNs), a fundamental form of deep learning, mimic the human brain's structure and have been widely applied in stock prediction studies due to their ability to model complex non-linear relationships.

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Despite the success of traditional ML techniques, deep learning models, particularly those designed to process sequential data, have shown even greater potential in stock market forecasting. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are particularly well-suited for time-series prediction tasks because they retain information across time steps, which is crucial for capturing temporal dependencies in stock price data. These models not only consider the current data input but also integrate contextual information from previous time intervals, enabling them to generate more accurate forecasts compared to standard ML models.

An important aspect of predictive modeling in financial contexts is the selection and representation of input features. Technical indicators—such as moving averages, relative strength index (RSI), and stochastic oscillators—are widely used to derive insights from price and volume data. However, the way these indicators are presented to models can significantly influence performance. While using raw continuous data allows models to learn subtle variations and patterns, converting indicators into binary form (e.g., signaling buy/sell conditions) simplifies the problem and may reduce noise, potentially improving the generalization capability of certain algorithms.

This study adopts a dual-perspective approach to investigate the effectiveness of various ML and DL algorithms in predicting stock market trends. We focus on four major stock groups—diversified financials, petroleum, non-metallic minerals, and basic metals—from the Tehran Stock Exchange. Ten technical indicators derived from a decade of historical data serve as inputs, formatted in both continuous and binary forms. The comparative analysis includes nine ML algorithms and two DL models, evaluated using multiple performance metrics to assess accuracy and robustness across different data representations.

The objective is not only to identify the most effective model for stock trend prediction but also to examine the impact of data representation—continuous versus binary—on model performance. The results aim to provide insights for both researchers and practitioners into the optimal use of modern AI tools in financial forecasting. By systematically evaluating a broad range of algorithms and feature encoding strategies, this study contributes to the growing body of literature that supports the integration of intelligent systems in stock market analysis and investment decision-making.

II. EXISTING SYSTEM

The traditional approaches to stock market trend prediction primarily relied on statistical models such as linear regression, autoregressive integrated moving average (ARIMA), and generalized autoregressive conditional heteroskedasticity (GARCH). While these models offered foundational insights into price movements and volatility, they often assumed linear relationships and failed to capture the complex, non-stationary, and highly volatile nature of financial markets. Moreover, they lacked the flexibility to adapt to real-time fluctuations and market anomalies. As a result, their predictive performance was limited, especially in high-frequency trading environments where rapid decision-making is critical. With the emergence of technical indicators like Moving Averages, MACD, RSI, and Bollinger Bands, many prediction systems began to integrate these features to enhance forecasting capabilities. However, most of these systems still relied on rigid rule-based logic or single-model approaches that could not adapt effectively to dynamic patterns in the data.

In recent years, machine learning techniques have been introduced to overcome these limitations. Studies have explored algorithms such as Support Vector Machines (SVM), Decision Trees, and Random Forests to improve prediction accuracy. These models can handle non-linear relationships and learn patterns directly from historical data without needing explicit programming of rules. While machine learning brought significant improvements, it still has limitations when handling sequential and temporal dependencies, especially in time-series data like stock prices. To address this gap, deep learning models—particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks—have been proposed due to their ability to retain memory across time steps and model sequential dependencies effectively. However, many existing systems use these models with a single format of data input, typically continuous values, without exploring the potential of alternative representations such as binary encoding. There is also limited comparative analysis across a wide range of ML and DL models using different input formats. This highlights a key gap that the proposed system in this study aims to fill.

III. PROPOSED SYSTEM

The proposed system aims to enhance the accuracy and reliability of stock market trend prediction by implementing a comparative framework that combines both machine learning and deep learning algorithms. This study uniquely explores how different data representations—continuous and binary—affect the performance of predictive models. By utilizing technical indicators derived from historical trading data, the system is designed to analyze patterns and trends across various market sectors. The focus is on four stock groups from the Tehran Stock Exchange: diversified financials, petroleum, non-metallic minerals, and basic metals. These sectors were chosen due to their market significance and data availability, offering a diverse testing ground for evaluating model robustness.

To extract relevant patterns, ten widely used technical indicators are calculated from ten years of historical stock data. These indicators serve as input features and are prepared in two formats. In the first approach, raw continuous values are used directly as inputs, allowing models to learn subtle trends and variations in trading behavior. In the second approach, indicators are converted into binary form based on predefined thresholds (e.g., if an RSI value is above 70, it is labeled as 1, otherwise 0). This transformation simplifies the data, potentially reducing noise and enhancing the generalization ability of certain models. The goal of using both data types is to assess how input representation affects each model's ability to capture market signals and forecast trends effectively.

The system incorporates a comprehensive set of prediction algorithms, including 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)—as well as two deep learning models: Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM). Each algorithm is trained and tested using both continuous and binary input formats. This dual approach ensures a fair and balanced comparison, shedding light on which algorithms perform best under different data conditions.

The deep learning models, particularly RNN and LSTM, are expected to outperform traditional ML models when working with continuous time-series data, due to their inherent capacity to retain temporal memory and model sequence dependencies. RNNs maintain hidden states that capture past information, while LSTMs go a step further by using gated mechanisms to preserve long-term dependencies and mitigate vanishing gradient problems. These features are especially useful in stock market prediction, where understanding previous trends is essential to forecasting future movements. However, the performance gap is anticipated to narrow when binary inputs are used, as the simplified data may benefit algorithms that perform well on classification tasks.

Each model’s performance is evaluated using three key metrics—accuracy, precision, and F1-score—to ensure a comprehensive assessment of prediction capability. These metrics provide insights into not only how well the model predicts overall trends, but also how balanced and reliable its predictions are across different market conditions. Cross-validation is applied during model training to prevent overfitting and to validate the consistency of results. The system also records computational time and training efficiency to gauge the practicality of deploying each model in real-world scenarios.

Ultimately, this proposed system offers a holistic framework for stock trend prediction by merging technical analysis with advanced AI techniques. By comparing a broad spectrum of algorithms across different data formats and market sectors, this study contributes meaningful insights into which models are most suitable for various forecasting contexts. Moreover, the findings highlight the importance of thoughtful data representation, as even high-performing models like LSTM may experience shifts in performance based on how input data is structured

IV. LITERATURE REVIEW

Patel et al. (2015) – “Predicting Stock and Stock Price Index Movement Using Decision Tree, Naïve Bayes, and Random Forest”

This study focused on applying three machine learning models—Decision Tree, Naïve Bayes, and Random Forest—to predict stock index movement in the Indian market. The authors used technical indicators such as RSI, MACD, and Bollinger Bands derived from historical data to serve as inputs. Their results showed that Random Forest outperformed the other two algorithms in terms of accuracy and robustness. One of the key insights from this paper was the significance of feature selection and data preprocessing in improving model performance. However, the study was limited to only three models and did not consider temporal relationships in the data, which are crucial for time-series forecasting.

Fischer & Krauss (2018) – "Deep Learning with Long Short-Term Memory Networks for Financial Market Predictions"

In this influential study, the authors employed LSTM networks to predict stock price movements based on historical prices and technical indicators from the S&P 500. The LSTM model demonstrated significantly better accuracy than traditional machine learning techniques like logistic regression and random forests. The strength of this study lies in its use of deep learning to capture time-dependent features, which are often missed by conventional models. It clearly illustrated how memory-based architectures such as LSTM can handle the sequential nature of stock data. The study set a strong precedent for future research in applying deep learning to financial forecasting.

Chen et al. (2019) – "Stock Market Prediction Using Deep Learning and Technical Indicators: A Hybrid Approach"

Chen and colleagues proposed a hybrid framework combining LSTM with Convolutional Neural Networks (CNN) to predict stock movements. They integrated multiple technical indicators into their model, which processed data both temporally (with LSTM) and spatially (with CNN). The hybrid model outperformed individual LSTM and CNN models, suggesting that a combination of deep learning architectures can yield better results. Although the study offered high prediction accuracy, it required considerable computational power and training time. It also raised questions about the interpretability of such complex models, an ongoing concern in finance applications.

Hiransha et al. (2018) – "NSE Stock Market Prediction Using Deep-Learning Models"

This study focused on comparing deep learning models—RNN, LSTM, and CNN—for stock price prediction on the National Stock Exchange (NSE) of India. The authors used historical closing prices as input without incorporating external features or indicators. LSTM once again outperformed the other models, mainly due to its capability to capture long-term dependencies. However, the CNN model also produced competitive results, especially in capturing short-term fluctuations. The paper emphasized the importance of model selection in time-series data and supported the use of LSTM in financial time-series forecasting.

Ballings et al. (2015) – "Evaluating Multiple Classifiers for Stock Price Direction Prediction"

This research paper evaluated several machine learning classifiers including SVM, Random Forest, Neural Networks, and KNN for predicting the direction of stock prices. Using a dataset of S&P 500 stocks, the study highlighted that ensemble methods like Random Forest consistently outperformed individual classifiers. The authors also discussed the role of data preprocessing, such as normalization and balancing class distribution, in improving prediction results. This study contributed to the literature by offering a comprehensive comparison of multiple ML models and suggesting that no single model is universally superior—it depends on the data and context

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V. WORKING OF SYSTEM

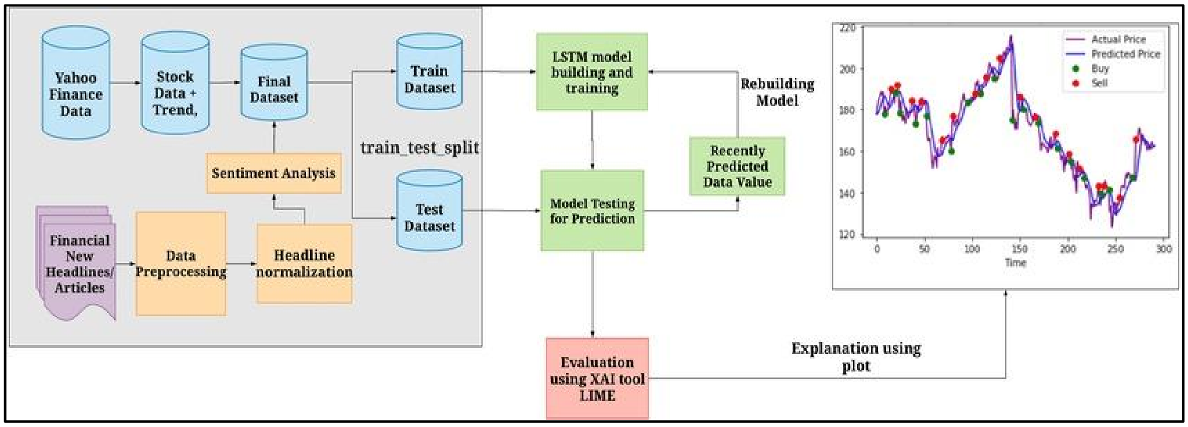

Fig. 1 System Architecture

The proposed system operates through a structured pipeline comprising several key stages, from data acquisition and preprocessing to model training, evaluation, and result comparison. Below is a step-by-step explanation of how the system functions:

1. Data Collection

The first step involves collecting historical stock market data from the Tehran Stock Exchange. Data is gathered for four major stock groups: diversified financials, petroleum, non-metallic minerals, and basic metals. For each group, ten years of data is compiled, including daily stock prices (open, high, low, close), trading volume, and other relevant market metrics.

2. Technical Indicator Generation

From the raw stock data, the system calculates ten widely used **technical indicators**. These indicators are mathematical formulations based on price and volume that help identify patterns and trends. Common examples include:

- Moving Average (MA)
- Relative Strength Index (RSI)
- Moving Average Convergence Divergence (MACD)
- Bollinger Bands
- Stochastic Oscillator
- Rate of Change (ROC)
- Average True Range (ATR)
- Commodity Channel Index (CCI)
- Momentum
- On-Balance Volume (OBV)

These indicators form the **feature set** (input variables) for training the predictive models.

3. Data Representation: Continuous vs Binary

To explore the effect of feature representation, two different forms of input data are prepared:

Continuous Data: The raw numerical values of technical indicators are used directly. This preserves all the quantitative variation and enables models to learn from subtle changes.

Binary Data: Each technical indicator is converted into a binary signal based on domain-specific thresholds. For instance, RSI > 70 may be encoded as '1' (overbought), and RSI < 30 as '0' (oversold). This simplification reduces data noise and frames the problem more as a classification task

Each version of the data (continuous and binary) is stored separately for model training and evaluation.

4. Model Training

The system uses **eleven models**:

Machine Learning Models (9): Decision Tree, Random Forest, AdaBoost, XGBoost, SVC, Naïve Bayes, KNN, Logistic Regression, and ANN

Deep Learning Models (2): Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM)

Each model is trained twice:

Once on **continuous** data

Once on **binary** data

The target variable (label) is typically the **direction of price movement** (e.g., up = 1, down = 0) for the next day or next time step.

5. Model Evaluation

To assess and compare the models, the following **evaluation metrics** are used:

Accuracy: Percentage of correct predictions

Precision: Ratio of true positives to all predicted positives

F1-Score: Harmonic mean of precision and recall

Cross-validation is used during model training to ensure results are not overfitted to a particular data split. The models are evaluated on both continuous and binary datasets, and performance metrics are recorded for analysis.

6. Result Comparison and Analysis

The final step involves comparing all model performances side by side to determine:

Which models perform best overall

Whether continuous or binary input leads to higher accuracy

How deep learning models (RNN, LSTM) compare to classical ML models

Which algorithms are best suited for which data types

The system concludes by identifying trends in performance across data types and model types. Typically, **LSTM and RNN outperform** other models with continuous data due to their temporal learning capabilities. With binary data, the **performance gap narrows**, and some traditional ML models improve significantly.

VI. ALGORITHMS USED

This study employs a total of **11 predictive algorithms** — 9 from the **Machine Learning** category and 2 from **Deep Learning**. Each algorithm brings different strengths in terms of classification accuracy, learning complexity, and ability to handle different data representations (continuous vs binary).

1. Decision Tree

A tree-structured classifier where internal nodes represent features, branches represent decision rules, and leaf nodes represent outcomes (predicted class labels). It's easy to interpret and works well with both categorical and numerical data.

Strengths: Fast, interpretable

Limitations: Prone to overfitting

2. Random Forest

An ensemble method that builds multiple decision trees and combines their outputs through majority voting. It reduces overfitting and increases accuracy.

Strengths: Robust to noise, handles non-linear data

Limitations: Computationally intensive

Adaptive Boosting (AdaBoost)
A boosting algorithm that combines multiple weak learners (typically decision stumps) into a strong classifier. It gives more weight to misclassified instances.
Strengths: Works well with imbalanced data
Limitations: Sensitive to noisy data

4. eXtreme Gradient Boosting (XGBoost)
A powerful and scalable implementation of gradient boosting, known for its speed and performance in structured data.
Strengths: High accuracy, handles missing values
Limitations: Requires careful hyperparameter tuning

5. Support Vector Classifier (SVC)
A supervised learning model that tries to find the optimal hyperplane that maximizes the margin between two classes.
Strengths: Effective in high-dimensional spaces
Limitations: Slow with large datasets, sensitive to parameter choice

6. Naïve Bayes
A probabilistic classifier based on Bayes' Theorem assuming independence between features.
Strengths: Simple, fast, and effective for binary and multiclass classification
Limitations: Assumes independence between predictors, which is rare in financial data

7. K-Nearest Neighbors (KNN)
A non-parametric algorithm that classifies new data points based on the majority label among its 'k' nearest neighbors.
Strengths: Easy to implement, no training phase
Limitations: Slow prediction time, sensitive to data scaling

8. Logistic Regression
A statistical method used for binary classification that models the probability of a class using a logistic function.
Strengths: Interpretable, fast
Limitations: Assumes linear relationship between features and log-odds

9. Artificial Neural Network (ANN)
A model inspired by the human brain that consists of layers of interconnected nodes (neurons). It learns complex non-linear mappings between inputs and outputs.
Strengths: Handles complex relationships
Limitations: Requires large data, longer training time

10. Recurrent Neural Network (RNN)
A deep learning model designed for sequential data. RNNs maintain a memory of previous inputs through internal loops.
Strengths: Captures temporal dependencies in stock data
Limitations: Struggles with long sequences due to vanishing gradient

11. Long Short-Term Memory (LSTM)
An advanced version of RNN with gates that regulate the flow of information, allowing it to remember long-term dependencies.
Strengths: Excellent at time-series prediction, avoids vanishing gradient
Limitations: Computationally expensive

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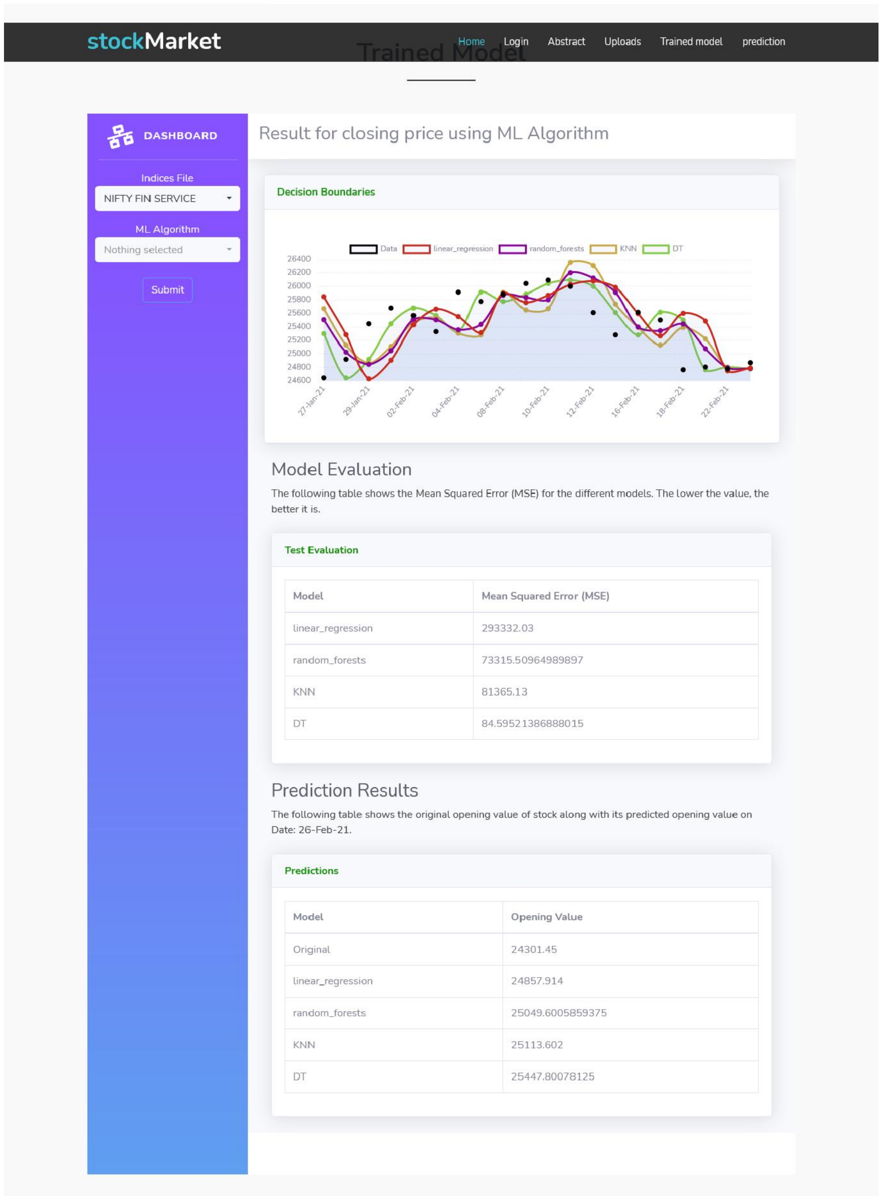
Each algorithm is evaluated on its performance using both continuous and binary representations of input data. The combination of these diverse models ensures a holistic comparison across different learning paradigms.

VII. RESULT



VIII. CONCLUSION

This study presents a comprehensive comparative analysis of various machine learning and deep learning algorithms for predicting stock market trends using both continuous and binary representations of technical indicator data. By experimenting with eleven models across four major stock sectors from the Tehran Stock Exchange, the results clearly demonstrate that deep learning techniques—particularly LSTM and RNN—consistently outperform traditional models when trained on continuous data due to their ability to capture temporal dependencies. However, when technical indicators are transformed into binary form, the performance gap narrows significantly, highlighting that input representation plays a critical role in predictive accuracy. The enhanced performance of some machine learning models on binary data also suggests their suitability in classification-focused market prediction tasks. This dual-perspective evaluation not only improves forecasting accuracy but also contributes valuable insights into the appropriate selection of models and data preparation strategies, ultimately aiding investors and analysts in making more informed, data-driven decisions.

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