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Predicting Stock Market Trends Using Machine Learning and Deep Learning Algorithms: A Comparative Analysis of Continuous and Binary Data

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Abstract: *Predicting the stock market is a crucial yet difficult undertaking because of its inherent complexity and nonlinearity. In order to forecast trends, this study examines the predictive capabilities of machine learning and deep learning models utilizing continuous and binary data. We used historical data from the Tehran Stock Exchange (2009 to 2019) for four stock market groups: petroleum, non-metallic minerals, basic metals, and diversified financials. Three metrics were used to evaluate two deep learning algorithms (Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM)) and nine machine learning models (Decision Tree, Random Forest, AdaBoost, XGBoost, Support Vector Classifier (SVC), Naïve Bayes, K-Nearest Neighbors (KNN), Logistic Regression, and Artificial Neural Network (ANN)). Findings indicate that deep learning techniques perform better than conventional machine learning models, particularly when dealing with continuous data. Additionally, binary data conversion significantly improved the predictive accuracy of all models, narrowing the performance gap between deep learning and machine learning approaches.*

Keywords: Stock Market Prediction, Machine Learning Models, Deep Learning Algorithms, Binary Data, Continuous Data, Trend Forecasting, Tehran Stock Exchange, Decision Tree (DT), Random Forest (RF), AdaBoost, XGBoost

I. INTRODUCTION

Economists, scholars, and investors have long been interested in stock market prediction because of its potential to reduce risks and increase profits. Making wise investment decisions can be facilitated by insightful information that can be obtained via accurate market trend forecasting. However, because of the influence of numerous factors such market psychology, political developments, public emotion, and macroeconomic indicators, stock price prediction is intrinsically difficult. Developing models that regularly produce accurate forecasts is challenging due to the extremely volatile and nonlinear character of stock movements.

1.1 Traditional Approaches to Stock Market Prediction

Historically, two main approaches have been used to predict stock market trends:

Fundamental Analysis: This approach examines a company's financial statements, revenue, earnings, industry position, and macroeconomic factors in order to determine its inherent value. To decide if a company is overpriced or undervalued, analysts look at things like management effectiveness, future growth potential, and market competitiveness. Despite offering a thorough grasp of a business's financial situation, fundamental analysis frequently fails to account for the effects of abrupt shifts in the market and sentiment-driven volatility.

Technical Analysis: To predict future price movements, technical analysis uses past price patterns, trading volumes, and technical indicators. Traders forecast future price behavior by spotting trends, patterns, and market signals.

Bollinger Bands, the Relative Strength Index (RSI), and the Moving Average Convergence Divergence (MACD) are examples of popular technical indicators. Technical analysis may not fully account for market anomalies or unforeseen occurrences that have a substantial impact on stock prices, even while it can catch short-term price movements.

1.2 Emergence of Machine Learning and Deep Learning in Stock Prediction

Large datasets and the quick development of processing power have made machine learning (ML) and deep learning (DL) approaches extremely effective tools for stock market forecasting. ML models make use of algorithms that analyze past data to find patterns that can forecast future price movements. Decision Trees, Random Forest, Support Vector Machines (SVM), and ensemble models like XGBoost and AdaBoost are examples of frequently used machine learning models. These models can detect intricate, nonlinear connections between changes in stock prices and input data.

On the other hand, by identifying temporal correlations in sequential data, deep learning models like Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks enhance prediction abilities. RNNs are ideal for time-series data, like as stock prices, because they are built to process consecutive inputs by preserving internal memory. However, LSTM networks overcome RNNs' drawbacks, including vanishing gradients, by adding gates that regulate information flow over extended periods of time. Because of this, LSTM models have shown impressive results in identifying long-term dependencies and producing more precise forecasts of stock price movements.

1.3 Importance of Data Preprocessing in Prediction Models

The quality of the input data and preprocessing methods, in addition to the algorithm employed, affect how accurate predictive models are. Binary data (discrete representations of upward or downward trends) and continuous data (raw numerical values of stock indicators) are two examples of the various forms in which stock price data can be shown.

Continuous Data: A continuous depiction of stock movements can be obtained by using formulas to calculate technical indicators and raw historical stock data, such as open, close, high, and low prices. However, inconsistent model performance could result from the intricacy and unpredictability of continuous data.

Binary Data: By categorizing continuous data into upward (+1) or downward (-1) movements, the conversion method adds a preprocessing step that makes trend recognition easier. By lowering noise, this method enables models to concentrate on forecasting market direction rather than particular price values, which could improve prediction accuracy.

By converting highly changeable continuous data into more predictable patterns, binary data conversion can enhance model performance and help models more effectively detect market moves, according to studies. This study examines the effects of binary data conversion on ML and DL models' prediction accuracy.

1.4 Motivation for the Study

Few studies have examined the impact of data preparation (binary vs. continuous data) on prediction accuracy, despite the fact that prior research has compared the effectiveness of specific machine learning and deep learning models in stock market prediction. Additionally, even while RNN and LSTM models have become more popular for predicting financial time series, little is known about how well they perform in comparison to more conventional machine learning models, especially when using multiple data formats.

In order to close this gap, this study compares how well two deep learning models and nine machine learning models predict stock market patterns.

Examining how using binary and continuous data affects model accuracy.

Selecting the best preprocessing techniques and models for stock market forecasting.

By providing a comprehensive analysis of the impact of data preprocessing on model performance, this research contributes to the growing field of financial prediction using artificial intelligence.

1.5 Objectives of the Study

The primary objectives of this study are:

1. Assess and contrast the predicted accuracy of two deep learning models and nine machine learning models.
2. To examine how model performance is affected when continuous data is converted to binary data.
3. To use historical data from the Tehran Stock Exchange to determine the best prediction model for stock market movements.

II. LITERATURE REVIEW

In recent years, scholars and practitioners have paid close attention to the application of artificial intelligence (AI) in forecasting stock market developments. More precise forecasts are now possible because to the successful identification of intricate patterns in stock price fluctuations by both machine learning (ML) and deep learning (DL) approaches. With an emphasis on machine learning models, deep learning approaches, and the effect of data preprocessing on predictive accuracy, this part examines the corpus of extant work on stock market prediction.

2.1 Machine Learning Approaches for Stock Market Prediction

The capacity of machine learning algorithms to uncover hidden patterns in historical data has led to their widespread adoption in stock market prediction. Using input variables including opening and closing prices, trading volumes, and technical indicators, these models employ statistical methods to forecast changes in stock prices. When predicting stocks, some of the most popular machine learning algorithms are as follows:

2.1.1 Decision Trees and Random Forest

Decision Trees (DT) are frequently employed in problems involving regression and classification. In order to arrive at a leaf node that predicts the target variable, a decision tree divides data into branches according to feature thresholds. When employed alone, decision trees are less accurate for stock market prediction due to their propensity for overfitting, notwithstanding their interpretability.

By adding randomization during training, Random Forest (RF) aggregates the predictions of several decision trees in order to get around these restrictions. When predicting stock returns, Tsai et al. [13] showed that ensemble techniques like Random Forest performed better than individual classifiers, producing more accurate and consistent results.

2.1.2 AdaBoost and XGBoost

AdaBoost and XGBoost are examples of boosting algorithms that enhance model performance by iteratively fixing the mistakes caused by weak learners. While XGBoost uses gradient boosting to efficiently decrease loss functions, AdaBoost gives misclassified samples larger weights.

AdaBoost, Random Forest, and kernel-based models were compared by Ballings et al. [14] in order to forecast stock values in European markets. According to their research, AdaBoost and Random Forest outperformed conventional models in terms of predicted accuracy. Similar to this, Basak et al. [15] shown that by minimizing overfitting and improving tree architectures, XGBoost increased classification accuracy when predicting changes in stock prices.

2.1.3 Support Vector Machines (SVM)

In order to categorize data, supervised learning algorithms called Support Vector Machines (SVM) choose the best hyperplane to divide data points into distinct classes. Several studies have shown that SVM is a good tool for forecasting stock market trends.

In their evaluation of SVM's ability to forecast the weekly trend of the NIKKEI 225 index, Huang et al. [8] noted that SVM fared better than other classification models including neural networks and linear discriminant analysis. Their findings showed that SVM is a preferred model for classification jobs because it can accurately capture nonlinear correlations in stock price data.

2.1.4 Naïve Bayes and K-Nearest Neighbors (KNN)

The Bayes Theorem is applied by the probabilistic classifier Naïve Bayes (NB), which makes significant assumptions about feature independence. Despite its interpretability and computational efficiency, Naïve Bayes may not always be appropriate for complicated datasets, such as stock market data.

A non-parametric approach called K-Nearest Neighbors (KNN) uses the majority vote of k-nearest neighbors to determine class labels. When Patel et al. [25] used KNN to forecast stock market movements, they discovered that although the algorithm did well for short-term forecasts, it did not do as well for long-term trends.

2.1.5 Logistic Regression and Artificial Neural Networks (ANN)

A statistical model for binary classification issues is called logistic regression (LR). Despite its ease of use and interpretability, logistic regression might not work well with datasets that are high-dimensional or nonlinearly separable.

Conversely, Artificial Neural Networks (ANN) can capture complex associations in stock price data because they replicate the structure and operation of the human brain. When forecasting the direction of the Istanbul Stock Exchange index, Kara et al. [24] evaluated ANN and SVM models and discovered that ANN produced superior accuracy, particularly when working with larger datasets.

2.2 Deep Learning Models for Stock Market Prediction

For financial time-series prediction, deep learning models—in particular, Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks—have emerged as the go-to option. These models are excellent at learning sequential patterns and understanding temporal connections, which makes them perfect for predicting changes in stock prices.

2.2.1 Recurrent Neural Networks (RNN)

An artificial neural network type called an RNN is made specifically for sequence prediction. RNNs have an internal memory, which enables information to endure between time steps, in contrast to conventional neural networks. This feature makes RNNs ideal for examining time-series data, like stock prices, where historical observations impact present values.

However, the inability of RNNs to capture long-term relationships is caused by the problem of vanishing gradients. A hybrid RNN model for stock prediction was presented by Maqsood et al. [3], who used gated architectures to solve the vanishing gradient issue. According to their findings, RNNs were ineffective at capturing long-term price fluctuations but excelled at capturing short-term ones.

2.2.2 Long Short-Term Memory (LSTM)

A modified kind of RNN called LSTM introduces memory cells and gates to regulate the information flow, overcoming the drawbacks of vanishing gradients. Time-series forecasting benefits greatly from LSTM networks' ability to selectively store pertinent information over long sequences thanks to these gates (input, forget, and output).

LSTM models were used by Long et al. [17] to integrate transaction records and public market data in order to forecast stock price patterns. Bidirectional LSTM models fared better than other models in terms of robustness and prediction accuracy, according to their study. Similarly, by reducing model overfitting, Baek and Kim [21] showed that LSTM models with an overfitting prevention module had higher stock market forecast accuracy.

2.2.3 Hybrid Models: Combining Deep Learning and Ensemble Techniques

In order to enhance prediction performance, recent studies have investigated the application of hybrid models that integrate the advantages of ensemble and deep learning approaches. In order to predict stock prices, Weng et al. [16] used a hybrid model that combined LSTM and a boosting regressor. They showed that the hybrid strategy greatly decreased prediction errors when compared to standalone models.

A genetic algorithm-optimized LSTM model was created by Chung and Shin [22] and performed exceptionally well in forecasting stock price changes. Their results highlighted how crucial it is to combine deep learning models with optimization methods in order to improve forecast accuracy.

2.3 Impact of Data Preprocessing on Prediction Accuracy

In order to increase the accuracy of stock market prediction models, data preparation is essential. Noise and volatility are common in raw stock price data, which can make machine learning and deep learning algorithms less effective. There are two primary methods for preparing data:

2.3.1 Continuous Data Approach

Technical indicators are usually computed using continuous data, which is obtained from raw trade values (open, close, high, and low prices). To keep lesser values from being overshadowed by bigger ones, these indicators are then standardized. The intricacy of continuous data can result in inconsistent model performance, even though this method captures comprehensive information regarding price fluctuations.

2.3.2 Binary Data Conversion

Continuous numbers can be converted into binary representations that indicate either upward (+1) or downward (-1) trends via binary data conversion. Binary data improves model performance by reducing noise and distilling the data into recognizable trends.

By enabling models to concentrate on determining market direction rather than forecasting precise price levels, Patel et al. [26] showed that transforming continuous data to binary data greatly increased prediction accuracy. In a similar vein, Sun et al. [9] pointed out that by making the prediction task simpler, trend deterministic data preparation improved machine learning model accuracy.

2.4 Comparative Studies on Model Performance

A number of research have examined how well deep learning and machine learning models predict the stock market. When it came to forecasting changes in stock prices, Basak et al. [15] discovered that tree-based models like XGBoost and Random Forest performed better than linear models. When predicting stock index movements, Pang et al. [19] demonstrated that LSTM models outperformed conventional classifiers in terms of accuracy. According to Kelotra and Pandey [20], the prediction of stock price movements was enhanced when convolutional neural networks (CNN) and LSTM were combined.

Research comparing the effects of binary data translation on model performance across various machine learning and deep learning models is still lacking, despite the progress made in predictive models. By assessing how much binary data conversion can improve the predictive accuracy of both ML and DL models, this work seeks to close this gap.

III. METHODOLOGY OF THE STUDY

3.1 Data Collection and Preprocessing

The Tehran Stock Exchange was used to gather historical data from four stock market groups—diversified financials, petroleum, basic metals, and non-metallic minerals—spanning ten years, from November 2009 to November 2019. The open, close, high, and low prices in the dataset were utilized to compute ten technical indicators, including the Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), and Simple Moving Average (SMA).

3.2 Data Conversion Approaches

Continuous Data: Normalized technical indicators were fed into prediction algorithms.

Binary Data: Continuous data was transformed into binary values, which show upward (+1) and downward (-1) trends, using an extra preprocessing layer.

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IV. PREDICTION MODELS AND EVALUATION METRICS

4.1 Machine Learning Models

Decision Tree (DT): Decision rules serve as the foundation for this straightforward classification approach.
Random Forest (RF): A collection of decision trees that compiles findings.
AdaBoost: A boosting method that creates a strong model by combining weak classifiers.
XGBoost: An enhanced gradient boosting method for increased precision and speed.
An approach for classification that finds the best decision boundary is the Support Vector Classifier (SVC).
Naïve Bayes (NB): Bayes' Theorem-based probabilistic classifier.
K-Nearest Neighbors (KNN): This non-parametric classifier uses k-nearest neighbors to determine a class.
A statistical model for binary classification is called logistic regression (LR).
Artificial Neural Network (ANN): A neural network for pattern recognition that has several hidden layers.

4.2 Deep Learning Models

Sequential dependencies are captured by recurrent neural networks (RNNs) using hidden layers.
An improved RNN that avoids the vanishing gradient issue by retaining information across longer sequences is called Long Short-Term Memory (LSTM).

4.3 Assessment Criteria

Three performance metrics were employed in the evaluation of the models:
F1-Score: For overall performance, it strikes a balance between recall and precision.
Accuracy: Indicates the percentage of right guesses.
The area under the curve is used to assess classification performance using ROC-AUC.

V. DATA ANALYSIS

5.1 Continuous Data Approach Results

Models were first evaluated using continuous data, with RNN and LSTM outperforming other models.

Model	F1-Score (%)	Accuracy (%)	ROC-AUC (%)
Decision Tree	68.12	69.45	66.78
Random Forest	75.34	76.89	74.45
AdaBoost	78.21	79.67	76.89
XGBoost	80.67	82.1	81.35
Support Vector Classifier	73.85	74.65	72.58
Naïve Bayes	67.29	68.12	65.43
K-Nearest Neighbors	72.54	73.12	71.67
Logistic Regression	70.49	71.38	69.84
Artificial Neural Network	82.43	83.92	81.76
Recurrent Neural Network	85.78	87.45	86.21
Long Short-Term Memory	86.25	88.12	87.14

5.2 Binary Data Approach Results

When binary data was used, model performance improved significantly, with RNN and LSTM maintaining top positions while the gap between other models narrowed.

Model	F1-Score (%)	Accuracy (%)	ROC-AUC (%)
Decision Tree	84.67	85.45	83.92
Random Forest	88.34	89.12	87.45
AdaBoost	89.21	90.1	88.76
XGBoost	90.45	91.2	89.87
Support Vector Classifier	86.87	87.45	85.91
Naïve Bayes	83.89	84.76	82.54
K-Nearest Neighbors	85.78	86.12	84.43
Logistic Regression	84.45	85.23	83.78
Artificial Neural Network	91.67	92.45	90.45
Recurrent Neural Network	90.89	92.12	91.43
Long Short-Term Memory	91.45	93.1	92.34

5.3 Performance Improvement with Binary Data

Binary data preprocessing led to significant performance improvement across all models, especially for traditional ML models such as Decision Tree and Naïve Bayes.

Model	F1-Score Gain (%)	Accuracy Gain (%)	ROC-AUC Gain (%)
Decision Tree	16.55	16	17.14
Random Forest	13	12.23	13
AdaBoost	11	10.43	11.87
XGBoost	9.78	9.1	8.52
Support Vector Classifier	13.02	12.8	13.33
Naïve Bayes	16.6	16.64	17.11
K-Nearest Neighbors	13.24	13	12.76
Logistic Regression	13.96	13.85	13.94
Artificial Neural Network	9.24	8.53	8.69
Recurrent Neural Network	5.11	4.67	5.22
Long Short-Term Memory	5.2	4.98	5.2

VI. DISCUSSION

- **Top Performing Models:** LSTM and RNN consistently demonstrated superior performance in both continuous and binary data approaches.
- **Impact of Binary Conversion:** Binary data conversion significantly improved the performance of traditional ML models, reducing the gap between ML and DL approaches.
- **Computational Cost:** Deep learning models required longer training times due to their complex architectures, but the increase in accuracy justified the computational cost.
- **Model Suitability:** While DL models performed best, XGBoost and AdaBoost emerged as strong alternatives when computational resources are limited..

VII. CONCLUSION

This research demonstrated how well ML and DL models can forecast stock market trends, with deep learning models like RNN and LSTM outperforming more conventional models. Across all models, predicted accuracy was greatly increased by converting continuous data to binary data. Future studies can apply these methods to different stock markets and concentrate on hybrid models that combine the advantages of ML and DL approaches.

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