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A Comparative Study Of Statistical Methods And Machine Learning Approaches For Stock Price Prediction

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Abstract— **The stock market contains numerous challenges to investors, ranging from volatility and excessive workload of information to behavioral factors and market manipulation. Stock market forecasting is crucial in addressing these challenges since it provides investors with valuable insights that aid in decision-making, risk management, and long-term investment planning. Investors can improve their understanding of market dynamics and their chances of achieving positive investment outcomes by leveraging predictive models and advanced analytics. There are various approaches for forecasting stock prices, both conventional statistics-based approaches and machine learning based advance and automated algorithms. Machine learning (ML) based algorithms are categorized as four different approaches, namely, Traditional ML approaches, deep learning & neural networks, time series analysis and graph-based approaches. While no single method can guarantee accuracy, combining multiple techniques or to use ensemble methods to improve forecasting performance is frequently advantageous. During the research of various algorithms for stock market prediction, it was discovered that moving averages work well with small datasets of historical data for descriptive analysis. According to the research works cited in this review paper, traditional statistical methods are incapable of taking into account many extra factors such as semantic factors, making them less accurate than machine learning approaches. Whereas, among machine learning approaches, Deep learning and neural networks have been identified as the best options for developing automated models and, Graph-based methods used in conjunction with these approaches can help the system connect the features.**

Keywords—stock market prediction, comparative study of conventional methods and machine learning methods, machine learning, graph, neural networks, deep learning, semantics, traditional machine learning, moving averages, ARIMA, statistical methods, stock market analysis.

I. Introduction

The stock market is a complex and nuanced system that is influenced by numerous factors such as economic data, corporate earnings, geopolitical events, and investor emotions. Accurately forecasting stock prices is a popular goal among investors, traders, and financial institutions. Stock market forecasting accuracy can influence project quality and have a substantial impact on the global economy.

Formerly, stock market forecasting depended on statistical analysis and time-series modelling approaches. These strategies are based on the notion that stock prices follow a random walk pattern and are impacted by previous prices and other economic factors. While these methodologies have had some success, they have limitations, particularly when it comes to predicting complicated and changing market situations.

In past years, there has been a surge of interest in the use of machine learning techniques to stock market forecasting. Machine learning algorithms are designed to learn from data and predict patterns and relationships in that data. These algorithms are highly adaptive and may discover complicated patterns that older approaches may lack.

Machine learning techniques for stock market prediction have exhibited significant promise in terms of boosting prediction accuracy and efficacy. Machine learning algorithms can adapt to shifting market conditions and generate real-time predictions. They can also detect complicated patterns and correlations in data that traditional approaches may miss. Machine learning approaches have been used to anticipate stock prices, predict stock trends, and uncover market abnormalities.

We will compare and contrast the performance of traditional methods and machine learning approaches on stock market prediction in this review paper. The effectiveness of these methods will be assessed utilising real-world data and metrics such as mean absolute error, mean squared error, and root mean squared error. We hope to provide insights into the most effective stock market prediction techniques by examining the strengths and weaknesses of each approach.

Moving averages, autoregressive integrated moving averages (ARIMA), and exponential smoothing are examples of traditional stock market prediction methods. Moving averages are based on the idea that a stock's average price over a given period is the best predictor of its future price. ARIMA models estimate future prices using historical data and are particularly useful for identifying trends in the data. Exponential smoothing is a time-series forecasting technique that forecasts future values using a weighted moving average.

Artificial neural networks (ANNs), decision trees, support vector machines (SVMs), and random forests are all machine learning techniques for stock market prediction. ANNs are artificial neural networks (ANNs) that are inspired by the structure and function of the human brain. They are especially useful for capturing complex data relationships. Decision trees are tree-like structures used to represent decisions and their potential outcomes. SVMs are supervised learning algorithms that are generally used for classification and regression analysis. Random forests are an ensemble learning algorithm that combines multiple decision trees to improve prediction accuracy.

The effectiveness of these methods for stock market prediction depends on several factors, such as the quality of the data, the accuracy of the model, and the complexity of the market conditions. Conventional methods are generally easier to understand and implement, but they may not be suitable for complex and dynamic market conditions. Machine learning techniques, on the other hand, are highly adaptable and can capture complex patterns in the data, but they may require significant computational resources and expertise.

II. Literature Review

A. *Conventional Statistical Methods*

Moving Averages: Moving averages are among the most popular traditional methods for forecasting stock market prices. Moving average performance is evaluated in paper[1] using three basic rules of trading with a moving average: first, the direction of the moving average, second, price & moving average crossover, and third, a crossover of two moving averages with different periods. In terms of profitability, the simple moving average (SMA) outperforms all other types of moving averages in all three rules tested, generating profits of 10367, 8747, and 8709 points for trading rules 1, 2, and 3 respectively.

Paper [2] proposes using machine learning on technical indicators to overcome the drawbacks of indicator-based trading strategies. This method identifies moving average latency as a disadvantage and proposes an algorithm to overcome it. The proposed model had an accuracy of 79.7 percent on the IBM stock, 80.4 percent on the GOOGL stock, and 80.5 percent on the AAPL stock.

ARIMA: In a section of book [3], Authors have stated that Autoregressive integral moving average (ARIMA) model is a kind of linear model that can represent stationary and non-stationary time series. ARIMA model depends on autocorrelation mode to a large extent. In ARIMA, authors of paper [4] defined the model parameters (p, d, q) as follows, the Auto Regression (AR) term (p), Moving Average (MA) term (q), ARIMA models are built up by integrating these two parts of the models using differencing term (d or I). The AR term refers to the regression of a specific variable against itself in order to forecast the variable of interest. The MA term, on the other hand, is based on the error terms of the previous time-step forecast to forecast a variable at a later time-step.

In paper [5], Authors have found that ARIMA-GARCH can further improve the accuracy of the ARIMA model by improving the white noise sequence.

B. *Machine Learning Approaches*

Traditional Machine Learning Methods: Supervised machine learning algorithms SVM, Random Forest, KNN, Naive Bayes Algorithm, and SoftMax Algorithm were used to predict stock prices in paper [6]. The results show that for large datasets, the Random Forest Algorithm outperforms all other algorithms in terms of accuracy, while when the size of the dataset is reduced to nearly half of its original size, the Nave Bayes Algorithm outperforms all other algorithms in terms of accuracy. Furthermore, reducing the number of technical indicators lowers the accuracy of each algorithm in predicting stock market trends.

As previously demonstrated, machine learning is a very powerful tool with numerous applications. So far, we've seen that machine learning is heavily reliant on data. Thus, it is critical to understand that data is extremely valuable, and that, as simple as it may sound, data analysis is a difficult task. Machine learning has found widespread application and has progressed into deep learning and neural networks, but the basic idea remains the same for all of them. This paper [7] provides a clear understanding of how to implement machine learning. There are numerous methods, methods, and techniques available to handle and solve various problems in various situations.

Authors of [8] concluded that different algorithms are appropriate for different types of data provided. For linear data, the most relevant components are identified using the Linear Regression model and PCA (Principal Component Analysis). SVM (Support Vector Machine) proved to be the best machine learning approach for non-linear data. For binary data, Random Forest and Multilayer Perceptron (MLP) have been found to be the most appropriate methods.

DEEP LEARNING AND NEURAL NETWORKS: Deep learning models, which have shown superior to prior machine learning methods as far as predictive accuracy and speed are concerned, are being used with the growing data and wish for forecasts. In research [9], a common deeper study model for stock market prediction, the Long-Short Memory (LSTM) recurring neural network has been utilized. In this task, Python modules are used to automatically download historical market data to forecast future stock prices by fitting an LSTM model to data.

In paper [10], The authors created three stock price prediction models using various input features with distinct characteristics. They hypothesized that using implicit meaning data for effective stock price prediction via artificial neural networks would be beneficial. They investigate which features would be useful for stock price prediction.

In paper [11], To forecast the stock's closing price, the Multi-Layer Perceptron model, Sequential Minimal Optimization model, and Partial Least Square Classifier were used. The experimental results show that sequential minimal optimization is the best algorithm for predicting the closing price of a stock among the three algorithms tested.

In Paper [12], Price prediction based on historical and real-time data is combined with news analysis in the system. For prediction, LSTM (Long Short-Term Memory) is used. It uses the most recent trading data and analysis indicators as input. Only relevant and live news from a large set of business news is collected for news analysis. The filtered news is analyzed to forecast company sentiment. The results of both analyses are combined to produce a response that includes a recommendation for future increases.

In this paper [13], ten years of Amazon historical data were used to train the LSTM model, and then different model architecture candidates were tested and evaluated to determine the best one for predicting Amazon's stock close price. It was discovered that the model with more neurons in each hidden layer and fewer LSTM layers and Dense layers produced a more accurate and stable forecast. On the other hand, the amount of historical information remembered did matter. The fewer memory days, the lower the mean absolute percentage error.

Due to the complexity and ambiguity of natural language used in the news, traditional machine learning models frequently fail to interpret the content of financial news. The success of recurrent neural networks (RNNs) in sequential data processing inspired the authors of paper [14]. As a result, they introduced an ensemble RNN approach (long short-term memory, gated recurrent unit, and Simple RNN) to forecast stock market movements. They applied sentiment analysis and the sliding window method to extract only the most representative features rather than extracting tens of thousands of features using traditional natural language processing methods. Their experimental results validate the efficacy of these two methods for feature extraction and demonstrate that the proposed ensemble approach outperforms other models in comparison

TIME SERIES ANALYSIS: In paper [15], The authors represented stock prices as time series and used normalized data in conjunction with a recurrent neural network model. The predicted values were found to be very close to the actual values.

Authors of [16] noticed the influence of the daily sentiment scores of various social media platforms such as twitter can influence the investors to buy/sell the stocks of company which can ultimately affect the stock value. In this paper, Authors have employed sentimental analysis as one of the indicators and gathered data from various platforms like Yahoo Finance, considering tweets (positive, negative or neutral) as features for prediction. They used opening and closing prices of stock for respective companies.

In order to extrapolate predictions, the data must be pre-processed. In paper [17], The authors attempted to predict the historical prices of TCS- Tata Consultancy Services and measured their accuracy for different epochs and batch sizes while avoiding the effects of data pre-processing. The model is then applied to the tweets associated with it. This work aimed to provide a comprehensive view of various data changes and the fidelity obtained.

GRAPH BASED APPROACHES: There has recently been a surge in interest in using graph-structured data in computer science research communities. Paper [18] proposed a hierarchical attention network for stock prediction (HATS) that predicts the stock market using relational data. Our HATS method selectively aggregates information on various relation types and adds it to the representations of each company. The experimental results show that performance can vary depending on the relational data used. HATS, which can automatically select information, outperformed all existing methods.

In paper [19], To simulate stock momentum spill over in the real market, authors developed a novel bi-typed and hybrid market knowledge graph. Then, to learn the stock momentum spill over features on the newly constructed MKG, they proposed a novel Dual Attention Networks equipped with both inter-class attention module and intra-class attention module. To test their method, they created two new datasets, CSI100E and CSI300E. The empirical experiments on the constructed datasets demonstrated that their method can successfully improve stock prediction with bi-typed and hybrid relational MKG via the proposed DANSMP.

III. Evaluation Of Both Methods

The various methods used to predict share market prices are broadly classified into two categories:

A. *Conventional Methods*

Moving Averages – This method forecasts future prices by taking the average of a stock's closing prices over a given time period. This method is simple and straightforward, but it may not produce accurate results.

ARIMA – The Auto Regressive Integrated Moving Average (ARIMA) method forecasts the next value in a series based on the previous values. It requires stationary data, and selecting parameters can be difficult.

Both of the conventional methods' performance is summarized in the table below. It represents the variance in performance of same algorithm on changing datasets and complexity of algorithm:

TABLE I: PERFORMANCE OF CONVENTIONAL METHODS

Category	**Evaluation**		
	Algorithm	***Metrics Used***	
Conventional statistical methods	Moving Averages [2]	Dataset: IBM	Accuracy = 79.7%
		Dataset: GOOGL	Accuracy = 80.4%
		Dataset: AAPL	Accuracy = 80.5%
	ARIMA [20]	For 3-time steps ahead:	RMSE ~15% MAPE = 20-25% MAE <= 15%
		For 9-time steps ahead:	RMSE = 15-20% MAPE = 20-25% MAE <=15%

B. *Machine Learning Methods*

Traditional Machine Learning Methods: There are traditional approaches such as linear regression analysis and logistic regression analysis.

Deep Learning and Neural Networks: Deep learning methods are a subset of machine learning techniques that leverage artificial neural networks with multiple layers to learn hierarchical representations of data. These methods have achieved remarkable success in various domains, including computer vision, natural language processing, and speech recognition. Many of these techniques make use of RNNs and LSTMs, which are subsets of RNNs.

Time Series Analysis Methods: This strategy employs forecasts and projections of discrete time data. Time series analysis is a statistical technique used to analyze and make predictions based on data collected at regular intervals over time. It is widely used in various fields, including finance, economics, weather forecasting, and stock market analysis.

Graph-Based Approaches: The stock market is frequently compared to a network of interconnected nodes where a change in one component affects the pricing of other components.

The following table demonstrates the performance of machine learning modern methods used in the references using various models:

TABLE II: PERFORMANCE OF MACHINE LEARNING METHODS

Category	Sub-Category	Algorithm	Metrics Used	
Machine Learning Approaches	Traditional Machine Learning Methods	Random Forest	Accuracy/F-measure = 0.9126732	
		PLS Classifier[21]	Average Error Value = 0.81225	
	Deep learning & neural networks	ANN Model (using open price, close price, low price, high price and volume data) on Samsung Electronics data	Model 1: Advanced existing features	MSE = 0.1105 MAE = 0.2447
			Model 2: Binary Mixed Input features	MSE = 0.0795 MAE = 0.2162
			Model 3: Technical Analysis Indicator	MSE = 0.1171 MAE = 0.2498
		SMO (Sequential Minimal Optimization)	Average Error Value = 0.81225	
	Time Series Analysis methods	Generalized Additive Model (GAM)[22]	Accuracy ~ 17% MAPE = 1-5%	
	Graph-based approaches	HATS (Hierarchical Graph Attention Network)[18]	Average Accuracy = 0.3948 > Average accuracy (CNN, MLP, GCN)	
			Average F1 score = 0.3389	

IV. ANALYSIS OF MAJOR CONTRIBUTIONS

After the evaluation of both conventional methods and machine learning methods, it has been identified that no single algorithm can be referred as best algorithm. Each of the algorithms have their advantages and disadvantages. The pros and cons of the all the stock market prediction techniques are described in table formats category wise.

A. Conventional Methods

The conventional methods include moving averages and ARIMA, which are broadly used for prediction purpose by statisticians and stock market predictors. It has been observed that the conventional methods work better for short-term forecasting than long-term predictions. Stock market depends on basic variables and many extra factors like sentiments and economic conditions, whereas Conventional methods assume that there is a linear relationship between variables. This is one of the reasons which limits the performance of conventional statistics-based methods.

TABLE III: MERITS AND DEMERITS OF CONVENTIONAL METHODS

Category	Merits	De-Merits
Moving Averages	Moving averages provide a clearer picture of the overall trend and can help filter out short-term market volatility by averaging out data over a specified time window.	Unusual market events, extreme price movements, or data irregularities can all distort the moving average calculation and reduce prediction accuracy.
	Traders and analysts can change the length of the moving average (for example, 10-day, 50-day, or 200-day) to meet their specific needs and investment horizons.	Moving averages do not account for external factors that can have a significant impact on stock prices, such as news events, company announcements, or economic indicators.
ARIMA (Autoregressive Integrated Moving Average)	ARIMA models are computationally efficient and can be used to analyze large datasets. Predictions can be generated quickly and easily once the model parameters have been estimated.	ARIMA models assume a linear relationship between variables. Stock prices, on the other hand, are influenced by a variety of complex factors, such as market sentiment, investor behavior, and economic conditions, which can exhibit non-linear patterns.
	ARIMA models are founded on sound statistical principles, providing a rigorous framework for analyzing and forecasting stock prices.	ARIMA models are usually better suited for short-term forecasting than long-term predictions.

B. Machine Learning Methods

The machine learning approaches for stock market prediction can be broadly categorised as Traditional machine learning algorithms, deep learning & neural networks, time series analysis methods and graph-based approaches.

Traditional machine learning algorithms, such as linear regression, decision trees, or support vector machines, provide clear rules or coefficients, making it easier to decipher the factors driving stock market predictions.

The stock market generates a massive amount of data, which includes historical price data, trade volumes, news mood, and macroeconomic factors. Deep learning models can process and learn from this massive amount of data, perhaps leading to increased forecast accuracy.

Time series analysis methods are created primarily for capturing and analysing temporal patterns and dependencies in data. These methods, in the context of stock market prediction, can discover trends, seasonality, and other recurring patterns in historical stock price data. Time series research provides insights into probable future price changes by capturing these trends.

Graph-based approaches use network analysis tools to glean significant insights from market structure. Degree centrality, betweenness centrality, and eigenvector centrality are all centrality measures that can be used to identify influential stocks, sectors, or market indices. By focusing on key entities and their relationships within the market network, these measurements can help to construct more accurate prediction models.

TABLE IV: MERITS AND DEMERITS OF MACHINE LEARNING METHODS

Category	Merits	Demerits
Traditional machine learning algorithms	Allow the use of interpretable features like technical indicators, fundamental financial ratios, and economic indicators.	They frequently treat each data point separately, failing to recognize the sequential dependencies and temporal dynamics inherent in stock market data. This can make it difficult for them to detect trends, seasonality, or long-term patterns.
	In the area of stock market prediction, where obtaining huge volumes of labelled data might be difficult, these algorithms can produce useful forecasts with smaller sample sizes.	These algorithms are susceptible to extreme values and can be influenced by market anomalies or data errors, potentially affecting the model's performance and reliability.
Deep Learning & neural networks	These algorithms are sensitive to extreme values and can be influenced by market anomalies or data errors, potentially affecting the model's performance and reliability.	To train the model effectively, these typically require a large and comprehensive dataset (especially for historical data with a long-time horizon), which is a difficult task in stock market prediction. Inadequate model performance can result from a lack of data.
	When recurrent neural networks (RNNs) and natural language processing (NLP) techniques are combined, they can effectively process and analyze textual data (from news articles, social media sentiment, or analyst reports), improving prediction accuracy.	Deep learning models are prone to overfitting due to their large number of parameters, especially when the dataset is limited or noisy.
Time series analysis methods	These methods account for market fluctuations by incorporating seasonality components such as daily, weekly, or yearly patterns. Time series analysis models can also detect and estimate trends, such as upward or downward movement.	These methods frequently rely on historical patterns and may take time to adapt to sudden changes in market behavior, potentially resulting in delayed or inaccurate predictions. As a result, they may struggle to detect and manage abrupt changes, anomalies, or outlier events that can have a significant impact on stock prices.
Graph-based approaches	These approaches can capture diverse market signals and provide a more holistic view of the market by incorporating multiple modalities into the graph structure.	Some stocks may have limited or missing data, and the available information may not capture and the entire market network. Incomplete or sparse graphs can affect the quality and reliability of predictions.
	Graph-based models often provide interpretable measures, such as importance scores for nodes or edges, which can assist in identifying key factors driving predictions.	Graph-based approaches may face challenges in capturing rapid changes in relationships, especially during changes in relationships, especially during major events. The static nature of the graph representation may limit the model's ability to adapt to rapidly changing market conditions.

V. CONCLUSION AND FUTURE SCOPE

It is worth noting that predicting stock prices is challenging due to the market's inherent randomness and the numerous external factors that influence it. While no single method can guarantee accurate forecasting, combining multiple techniques or employing ensemble methods to improve forecasting performance is frequently advantageous. Whereas, during the study of various algorithms for stock market prediction, it has been found that moving averages work well with small datasets of historical data for descriptive analysis. And, among those of the machine learning algorithms, Artificial Neural Networks have shown the highest average accuracy in many research papers. With respect to the comparison of conventional methods and machine learning approaches, research works cited in this review paper have shown that the conventional statistical methods are not able to consider semantic factors which makes them less accurate as compared to machine learning approaches. Machine learning approaches have been studied as four different categories in this review paper. Among these categories, deep learning and neural networks are found as most appropriate choice for making automated models for continuous predicting stock market systems. Whereas, Random Forest, a traditional machine learning approach, can be the optimum choice for small datasets using binary mixed inputs. Graph based methods used along with these approaches can facilitate the system in connecting the features.

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