OPEN ACCESS JOURNALS
Indiana Journal of Multidisciplinary Research
Abbriviate Tittle- Ind J Multi Res
ISSN *(Online)*- 2583-3820
Journal Homepage Link- https://indianapublications.com/Journals/IJMR
DOI: https://doi.org/10.5281/zenodo.12685839

INDIANA PUBLICATIONS
PRODUCTIVE AND QUALITY RESEARCH

Research Article

Volume-04|Issue-03|2024

Stock Market Prediction with Machine Learning: A Comprehensive Review

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Article History
Received: 20.05.2024
Accepted: 05.06.2024
Published: 30.06.2024

Citation
Swamy, S. R., Rajgoli, S. R., & Hegde, T. (2024) Stock Market Prediction with Machine Learning: A Comprehensive Review. *Indiana Journal of Multidisciplinary Research, 4*(3), 265-271.

Abstract: The incorporation of artificial intelligence (AI) methods, especially those in machine learning (ML) and deep learning (DL), has transformed stock market prediction. This review delves into contemporary trends, algorithms, and challenges in AI-driven stock market forecasting. It examines the deployment of machine learning (ML) and deep learning (DL) techniques such as Support Vector Machines (SVM), Random Forests, and K-nearest neighbors (KNN), demonstrating how they effectively identify complex patterns and trends in stock data. This paper also discusses the role of feature engineering and selection in crafting robust predictive models, along with common datasets and preprocessing methods used in stock prediction studies. While AI has achieved remarkable advancements, challenges like overfitting, hyperparameter tuning, and data quality persist, indicating a need for ongoing research to build more precise and dependable prediction models for financial markets. This paper offers a thorough assessment of the state of the art in AI-driven stock market prediction, outlining possible directions for further investigation and going over the issues that still need to be resolved in the field.

Keywords: K-nearest neighbors, Artificial Intelligence, Random Forests, Support Vector Machines, Machine Learning, Stock Market Prediction.

INTRODUCTION

Forecasting the stock market with precision is inherently difficult due to its complex and ever-changing characteristics, driven by a wide range of factors. Fraz *et al.* [6] suggest that traditional methods of forecasting frequently fall short, given the unpredictable and volatile nature of financial markets. Accurate stock market predictions hold significant importance for investors, financial institutions, and policymakers because they enable better decision-making, reduce risks, and optimize returns on investments [19][10][4]. There has been a noticeable increase in interest in using machine learning (ML) techniques to improve the precision and dependability of stock market forecasting [20]. By developing more accurate and reliable predictive models, the use of ML to stock market forecasts has the potential to completely alter the industry [5][14][21]. Machine learning (ML) is becoming more and more popular in the financial markets because it can analyze massive datasets and find complex patterns that traditional statistical models cannot. Machine learning algorithms have proven to have improved predictive performance, frequently outperforming conventional forecasting techniques in terms of accuracy and reliability. Furthermore, ML techniques such as ensemble learning, deep learning, and recurrent neural networks have demonstrated exceptional performance in deciphering the intricate dynamics of stock market data [18].

LITERATURE SURVEY

Many comprehensive literature studies have shed a great deal of light on the application of AI methods in stock market forecasting. With an emphasis on machine learning (ML) and deep learning (DL) models, datasets, performance indicators, and problems, these studies provide a complete analysis of the most recent developments in AI. For example, [6] carried out a systematic review that assessed machine learning methods for stock market prediction. They looked at algorithms like K-Nearest Neighbours, Random Forest, and Support Vector Machines and discussed the advantages and disadvantages of each. Soni *et al.* [14] conducted a thorough analysis of the latest developments in AI-based stock market prediction, highlighting noteworthy breakthroughs and suggesting directions for future research, especially in light of the expanding application of ML and DL techniques. Zhang and Lei [21] conducted a comparative study of various deep learning models (DL) for stock market forecasting. Specifically, they examined CNNs and RNNs, contrasting their efficacy with conventional statistical models and emphasizing their capacity to capture intricate market patterns. Additionally, Yao *et al.*[19] performed a systematic literature review on AI techniques in financial trading and stock market prediction, providing insights into a range of AI applications, including ML, DL, and natural language processing (NLP), for predicting stock prices and guiding financial trading strategies. Collectively, these reviews deepen our understanding of AI applications in

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stock market forecasting, presenting valuable insights into current best practices, emerging trends, and potential directions for future research.

MATERIALS AND METHODS

Support Vector Machines (SVM)

In machine learning, support vector machines(SVMs) have received a lot of attention, particularly for their ability to anticipate stock market movements. The 1995 publication "The Nature of Statistical Learning Theory" by Vladimir Vapnik contained the initial explanations of the fundamental ideas and mathematical principles of SVMs. Vapnik described in this work how to locate the best separation hyperplane in feature space with higher dimensions. Additionally, he developed the "kernel trick," which made it possible to compute dot products in high-dimensional spaces effectively. This groundbreaking work played a key role in popularising SVMs and laying the groundwork for their continued advancement and broad use in a variety of industries, including stock market prediction. A novel method for automating the optimization of Support Vector Machine(SVM) learning parameters is presented in the paper "Efficient optimization of support vector machine learning parameters for unbalanced datasets". It suggests a method for optimizing SVM parameters that makes use of a derivative-free numerical optimizer and is especially helpful when handling unbalanced datasets. By doing away with the requirement for intricate derivative-based optimization procedures, this technique improves efficiency. Additionally, a modified Quadratic Programming(QP) solver with a decomposition technique that takes into account various class weights is presented in the research, which enhances SVM's capacity to handle imbalanced data more successfully. This method significantly improves the performance and adaptability of SVM, particularly when dealing with unevenly distributed data classes. According to recent research, Support Vector Machines (SVMs) are highly accurate in predicting the stock market. The work "Efficient Stock-Market Prediction Using Ensemble Support Vector Machine," which presented a Genetic Algorithm-optimised SVM (GASVM) model, is one noteworthy example. This model outperformed other traditional machine learning models, with an accuracy of 93.7% in predicting 10-day fluctuations in stock prices on the Ghana Stock Exchange. Even with these encouraging outcomes, there are still issues to be resolved, such as overfitting, choosing the right hyperparameters, and the requirement for more efficient feature selection techniques. To further improve the resilience and dependability of SVM-based stock market prediction models, these issues must be resolved. The main benefits of using Support Vector Machines (SVMs) for stock market prediction are:

- ***High Prediction Accuracy:*** SVM algorithms frequently beat conventional machine learning models in predicting stock price movements, with astonishing accuracy rates of up to 93.7%.
- ***Effective for High-Dimensional and Nonlinear Problems***: SVMs excel in dealing with high-dimensional datasets and complex, nonlinear patterns commonly found in stock market data.
- ***Robustness and Fast Convergence:*** Support Vector machines (SVMs) are well-known for their robustness and fast convergence. They are useful for real-world financial applications because they produce accurate and efficient outcomes in stock price prediction tasks.
- ***Versatility and Adaptability***: SVMs' predictive power and versatility for stock market forecasting can be further increased by combining them with other optimization methods like swarm intelligence and genetic algorithms.

Although Support Vector Machines (SVMs) offer many benefits for stock market prediction, they also face several limitations:

- ***Overfitting***: SVMs can become overly complex if not properly managed, leading to overfitting, where the model performs well on training data but poorly on unseen data.
- ***Difficulties in Hyperparameter Tuning***: Selecting the optimal hyperparameters for SVMs can be challenging, requiring careful adjustments to ensure the model's stability and performance.
- ***Ineffective Feature Selection***: The effectiveness of SVMs depends heavily on selecting the right features, and an improper feature selection process can impact the model's accuracy.
- ***Sensitivity to Noisy, High-Dimensional Data***: SVMs can be sensitive to noisy data and may struggle with very high-dimensional datasets without appropriate preprocessing or dimensionality reduction techniques.

Addressing these limitations is essential for enhancing the effectiveness and reliability of SVM-based models in real-world stock market prediction tasks.

Random Forest

As an algorithm for predicting stock market movements, Random Forest has gained popularity and reliability. Leo Breiman's groundbreaking work on random forests offers key ideas and lays out the method's theoretical underpinnings. The fundamental ideas of Random Forests are explained in Breiman's paper, with particular attention to important elements like the "out-of-bag" estimates used for internal model validation and the random selection of characteristics at each node. The research also provides actual evidence

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demonstrating the accuracy and robustness advantages of Random Forests over other machine learning models. Random Forests is now a commonly used technique in many different applications, including stock market prediction, thanks to this ground-breaking research. Leo Breiman highlights in his study the higher performance of Random Forests over other methods and their noise immunity, making it an extremely effective algorithm for classification applications. The method adds random feature selection, which makes the algorithm more resilient and lowers the chance of overfitting by having each node take into account a random subset of features. Further enhancing the model's dependability and effectiveness is the idea of "out-of-bag" estimations, in which a subset of the data is used for validation rather than training. Because of these advancements, Random Forests offer a good combination of accuracy, robustness, and efficiency in challenging classification tasks, making them a great option for stock market prediction. According to recent research, Random Forest models predict the stock market with great accuracy rates. A number of studies have revealed prediction accuracy rates for stock prices that surpass 90%, even at times of extreme market volatility, such as the COVID-19 pandemic. Furthermore, Random Forest models have shown strong performance throughout a variety of forecasting horizons, performing exceptionally well in both short- and long-term stock market predictions. Their superior performance over conventional time-series models, such as ARIMA, highlights their adaptability and versatility across a variety of market scenarios. Because of its consistent performance, Random Forest is a recommended option for stock market prediction assignments since it provides accuracy and dependability in a variety of settings. The main benefits of using Random Forest for stock price prediction are:

- ***High Accuracy***: Random Forest models consistently achieve accuracy rates exceeding 90% when predicting stock price movements, demonstrating reliability in various contexts.
- ***Ability to Handle Complex Non-Linear Relationships***: Random Forests are ideal for modelling the complex, non-linear patterns that are often present in stock market data, providing a flexible approach to prediction.
- ***Robustness to Overfitting and Noise***: As an ensemble method, Random Forest is less prone to overfitting and is more tolerant of noisy data compared to individual decision trees, resulting in a more stable model.
- ***Suitability for Long-Term and Short-Term Forecasting:*** Random Forest models are adaptable to a variety of stock price prediction tasks due to their outstanding performance over both short- and long-term forecasting horizons.
- ***Outperformance During Volatile Market Conditions:*** In times of extreme market volatility, Random Forest models have been shown to perform better than conventional time-series models like ARIMA, giving them an advantage.

When used for stock market prediction, Random Forest models have a few drawbacks despite their advantages:

- ***Inability to Extrapolate Beyond Training Data***: The range of the training data typically constrains Random Forest models, making it challenging for them to extrapolate into uncharted territory or make predictions outside of it.
- ***Sensitivity to Covariate Shift***: If market conditions change, Random Forest models may become less accurate in predicting future outcomes due to their sensitivity to shifts in the covariate distribution of input data.
- ***Difficulty Capturing Long-Term Trends***: Due to their inherent structure, Random Forest models can struggle to capture long-term trends or continuous changes, focusing more on the current dataset's patterns.
- ***Potential for Overfitting***: Even while Random Forests are more resistant to overfitting than individual decision trees, improper tuning can still cause them to overfit, particularly when dealing with high-dimensional data.
- ***Interpretability Challenges***: The ensemble nature of Random Forests makes it difficult to interpret their decision-making process, which can be a challenge in financial applications where transparency is crucial.

Improving Random Forest models' applicability and dependability for stock market prediction would require addressing these drawbacks, particularly in real-world financial applications where precision and flexibility are crucial.

k-Nearest Neighbors (kNN)

One well-known algorithm used for stock market prediction is K-Nearest Neighbours (KNN). Evelyn Fix and Joseph Lawson Hodges Jr. presented the basic idea of the KNN algorithm in a technical report that was never published in 1951. The non-parametric classification strategy described in this article served as the foundation for the KNN algorithm's development. Thomas Cover and Peter Hart's landmark 1967 article "Nearest Neighbour Pattern Classification" contained the crucial advancement and popularisation of KNN. The KNN algorithm's formal structure and technique were created in this study, which also showed the algorithm's effectiveness in pattern recognition and classification tasks. Since then, KNN has been widely used in a variety of domains, such as stock market prediction, where its adaptability and simplicity make it a desirable alternative for modelling and predicting financial trends. The Graph Sparse KNN (GS-KNN) methodology is presented in the publication "Efficient

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kNN Algorithm Based on Graph Sparse Reconstruction" and is more efficient than conventional KNN techniques. This novel method finds the ideal value of k (the number of nearest neighbors) for every test sample by using a sparse reconstruction procedure. The KNN technique is more accurate and efficient when k is dynamically adjusted, which makes it especially helpful when handling unbalanced datasets. The versatility and effectiveness of the GS-KNN algorithm add to its appeal in several applications, such as stock market prediction, where it can enhance performance in situations with inconsistent patterns or unevenly dispersed data. Research studies on the accuracy of K-Nearest Neighbors (KNN) models in stock market prediction have reported varying results. For example, some papers have indicated accuracy rates ranging from 80.53% to as high as 97.27%, depending on the dataset, the specific application, and the methodology used in each study. These variations highlight the importance of careful model tuning and selection of the right features for stock market prediction tasks. The diversity in reported accuracy rates also suggests that KNN's effectiveness can vary based on factors like data quality, preprocessing, the chosen value of k, and the type of stock market movement being predicted. Despite these variations, KNN remains a popular choice for stock market prediction due to its simplicity and versatility. Here are the key advantages of using K-Nearest Neighbors (KNN) for stock market prediction:

- ***High Accuracy***: KNN models have achieved accuracy rates as high as 97.27% in predicting stock performance, indicating their capability to provide reliable predictions.
- ***Ability to Capture Complex Patterns***: KNN is effective at capturing intricate patterns and trends in stock market data, making it suitable for modelling complex relationships.
- ***Ease of Implementation***: KNN is relatively straightforward to implement, requiring minimal parameter tuning, which makes it accessible to a wider range of practitioners.
- ***Versatility***: KNN can be applied to both classification and regression tasks, allowing it to be used in various aspects of stock market prediction.

These attributes make KNN a popular choice for stock market prediction tasks, offering a combination of accuracy, simplicity, and flexibility.

K-Nearest Neighbors (KNN) models, despite their popularity, face several limitations in stock market prediction. Here are some of the primary challenges:

- ***Inability to Predict Dramatic Events***: KNN models rely heavily on historical data and may struggle to predict sudden, unforeseen events or dramatic market shifts.
- ***Reliance on Historical Patterns***: KNN's performance is based on identifying patterns from historical data, which might not always accurately reflect future market movements.
- ***Assumptions About Probability Distributions***: KNN generally assumes that similar data points will have similar outcomes, which might not hold in stock market scenarios influenced by complex factors.
- ***Difficulty in Determining Optimal Number of Neighbors (k)***: Finding the ideal value of k can be difficult without a lot of trial and error, but choosing the right number of neighbors for a KNN is essential.
- ***Potential for Overfitting***: If k is too small, KNN can overfit the training data, leading to poor generalization on unseen data.

To address these limitations, additional research is required to refine KNN models and improve their effectiveness for real-world financial applications. In summary, Support Vector Machines (SVMs), Random Forests, and K-Nearest Neighbors (KNN) are potent machine learning algorithms that have demonstrated promise in stock market prediction. Each has distinct strengths and drawbacks, highlighting the need for ongoing research and innovation to create more robust, accurate, and adaptable stock market prediction models for practical financial applications.

RESULT AND DISCUSSION

Here is an overview of commonly used datasets in stock prediction research:

- ❖ ***StockNet Dataset***: This dataset focuses on stock movement prediction using tweets and historical stock prices. It spans two-year price movements for 88 stocks across various sectors, providing ample data for predicting stock trends[11].
- ❖ ***Uniqlo Stock Price Prediction Dataset***: This dataset, which focuses on Uniqlo as a single entity, provides comprehensive stock data and company-specific variations to facilitate the creation of customized predictive models[21].
- ❖ ***Historical Stock Market Dataset***: This dataset comprises daily prices and volume information for US stocks and ETFs from the NYSE and NYSE markets, offering a rich source of historical financial data for analysis and prediction [13].
- ❖ ***News and Stock Data Dataset***: Designed for a binary classification task, this dataset combines information from Reddit's r/worldnews and the Dow Jones Industrial Average, providing a mix of news and stock data for prediction tasks[13].
- ❖ ***Stock Market Turnover Ratio Dataset***: This dataset covers the total value of shares traded within specific periods, cross-referenced with average market capitalization, helping to understand stock market dynamics [13].

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Because these datasets have a variety of data sources, such as news articles, historical stock data, and company-specific information, which helps to create precise predictive models, they are frequently utilized in stock prediction research. Research articles indicate that the most often utilized characteristics for stock prediction are:

- The open, close, high, low, and volume of historical stock prices are essential for assessing previous market behavior and spotting possible trends. Models for prediction and analysis of the stock market are built using this data [6].
- Technical indicators are used to identify patterns in stock prices and their strength. They are developed from past price and volume data. Bollinger Bands, the Relative Strength Index (RSI), the Moving Average Convergence Divergence (MACD), and moving averages like the Simple Moving Average (SMA) and Exponential Moving Average (EMA) are common examples. According to Fraz *et al.* [6], these indications assist traders in making well-informed judgments when buying and selling.
- With an emphasis on macroeconomic variables and financial measurements unique to individual companies, fundamental indicators are crucial for stock market analysis. Stock prices can be greatly impacted by macroeconomic variables such as interest rates, inflation, GDP growth rates, and geopolitical events. A company's financial performance and health can be inferred from company-specific indicators such as debt-to-equity ratio, price-to-earnings (P/E) ratio, and earnings per share (EPS) [6].
- Research indicates that the accuracy and dependability of stock prediction models are improved by mixing different feature kinds, such as fundamental, technical, and basic indicators. To choose the most pertinent features for precise stock market predictions, Fraz *et al.* [6] emphasize the significance of feature selection and extraction methodologies. To find significant features, methods such as principal component analysis, random forest, autoencoders, and correlation criteria are used. By combining text data from news sources, natural language processing (NLP) approaches also contribute to stock market prediction. Stock market trends can be influenced by the insights that are extracted from news stories and social media posts using techniques like topic modelling and news sentiment analysis [19]. Combining advanced feature engineering and selection techniques with a diverse range of input features helps create robust and accurate stock prediction models. Data preparation strategies are crucial for preparing stock market datasets for machine learning models, which in turn improves prediction models' performance. They ensure that the information is organized, standardized, and clean.
- Preprocessing techniques that are commonly used in research on stock market prediction include the following:
- Managing missing values and guaranteeing consistency across several sources are two aspects of data cleaning. Imputation using mean or median values or deleting incomplete records are standard methods for addressing missing values because untreated missing values can negatively impact model performance. Maintaining a consistent dataset devoid of errors is essential for building more dependable prediction models. Robust models and accurate stock market forecasts depend on well-cleansed data.
- By scaling characteristics to a common range, a technique called normalization stops any one feature from significantly affecting model training because of its larger magnitude. By ensuring that every feature contributes equally to model learning, normalization enhances the performance and stability of the model. You can attain balanced training and possibly improve prediction accuracy by scaling data.

To capture pertinent stock market patterns, feature engineering entails building new features from raw data. Typical feature engineering methods include the following:

- ***Moving Averages:*** These are used to find trends and smooth stock price data. While the Exponential Moving Average (EMA) lends greater weight to current prices and responds to changes more quickly than the Simple Moving Average (SMA), it also computes the average stock price over a specified time.
- ***Technical Indicators:*** Used to assess market trends and signals, these indicators are derived from past stock price and volume data. Bollinger Bands for price volatility, Moving Average Convergence Divergence (MACD) for trend direction and strength, and Relative Strength Index (RSI) for momentum are popular indicators.
- ***Fundamental Indicators:*** To evaluate the intrinsic stock value and larger economic trends, take into account macroeconomic and company-specific elements. Interest rates are among the examples. In stock market prediction involving time series forecasting, sequence-based representation involves splitting historical price data into overlapping sequences of a fixed length. This technique enables deep learning models to detect temporal patterns and dependencies within the data. By representing the data in this manner, the models can more effectively learn underlying trends and fluctuations over time, improving stock market prediction accuracy. When working with stock market data,

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exploratory data analysis (EDA) is a crucial step that focuses on gaining insights, comprehending the properties of the data, and identifying patterns that direct preprocessing and modelling. Statistical analysis, correlation analysis, and data visualization are common EDA techniques that assist researchers in finding important aspects and correlations within the data. Researchers can train machine learning models on stock market datasets in an acceptable manner by employing EDA approaches, which will produce forecasts that are more dependable and accurate.

CONCLUSION

Stock market prediction has advanced dramatically as a result of artificial intelligence (AI) approaches, particularly deep learning and machine learning. Our thorough analysis of the literature sought to investigate the most recent developments, approaches, and difficulties in using AI for stock market trend forecasting. Our research showed that using AI approaches to increase the precision and dependability of stock market forecasts is becoming more and more common. In the context of stock market forecasting, we looked at several Machine Learning (ML) and Deep Learning (DL) techniques, including Support Vector Machines (SVM), Random Forests, and K-Nearest Neighbours (KNN). The techniques have exhibited encouraging outcomes in identifying complex patterns and behaviors within stock market data, resulting in enhanced prediction precision and resilience. The importance of feature engineering and selection methods for creating trustworthy prediction models was also covered. Through the integration of diverse aspects such as fundamental, technical, and basic indicators, researchers can enhance the efficacy of stock prediction models and more effectively discern pertinent market trends. Additionally, we underlined the significance of data preprocessing approaches in creating datasets for ML and DL models and highlighted popular datasets used in stock prediction studies. Techniques like feature engineering, data cleaning, normalization, and exploratory data analysis are essential for guaranteeing that stock market datasets are prepared for model training, which produces forecasts that are more reliable and accurate.

In conclusion, even though AI-driven stock market prediction has advanced significantly, several problems still need to be solved, such as overfitting, improper hyperparameter adjustment, and poor data quality. To solve these issues and provide more accurate and reliable prediction models for practical financial applications, more investigation and creativity are needed. To improve stock market prediction models' efficacy and dependability, AI approaches must be further refined, and rich and diverse datasets must be used. This helps progress AI in financial environments and benefits investors, financial institutions, and policymakers alike. We hope that this literature review will shed light on the most recent advancements in AI-based stock market prediction, as well as address the difficulties and potential avenues for future study in this area.

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