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MACHINE LEARNING MODELS FOR STOCK PRICE PREDICTION: A COMPREHENSIVE REVIEW OF DSE APPLICATIONS

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ABSTRACT

The prediction of stock prices remains a complex challenge due to the non-linear and volatile nature of financial markets. Traditional methods, such as fundamental and technical analyses, struggle to capture these complexities, limiting their effectiveness. This study examines the application of machine learning (ML) techniques to improve stock price forecasting, focusing on the Dhaka Stock Exchange (DSE). The research aims to explore how ML models, including supervised learning, deep learning, and hybrid approaches, can enhance prediction accuracy by identifying complex patterns in large datasets. The study reviews various methodologies, including Long Short-Term Memory (LSTM) networks, Support Vector Machines (SVM), and ensemble models, alongside hybrid models that combine artificial neural networks (ANN) with technical indicators like Moving Average Convergence Divergence (MACD) and Relative Strength Index (RSI). Time series data from the DSE is used in these studies to evaluate prediction performance. The results show that ML techniques significantly outperform traditional methods in forecasting short-term stock price trends. Hybrid models, particularly those integrating ANN with technical indicators, offer higher precision. The incorporation of sentiment analysis and big data analytics further improves model adaptability to dynamic market conditions. The major findings indicate that while ML models enhance prediction accuracy, challenges such as the limited availability of high-quality datasets, the lack of integration of macroeconomic factors, and difficulties in real-time validation remain. The DSE's high volatility and sectoral variability further complicate accurate predictions.

INTRODUCTION

The stock market is a complex and ever-evolving financial system, making precise stock price forecasting a challenging task. Accurate predictions are valuable for investors, analysts, risk managers, and policymakers, enabling data-driven decision-making. Traditional approaches, including fundamental and technical analyses, rely on financial data, market trends, and historical patterns but often fail to capture the non-linear and chaotic nature of stock market behavior (Abu-Mostafa & Atiya, 1996).

Traditional methods have long been used for stock price prediction, with fundamental analysis being a prominent approach since the early 20th century. This method evaluates a company's intrinsic value by analyzing financial health, macroeconomic indicators, and industry trends. Key factors include earnings growth, revenue trends, and financial ratios like the price-to-earnings (P/E) ratio and debt-to-equity (D/E) ratio, offering insights into valuation and risk profile (Damodaran, 2012).Macroeconomic variables, including GDP growth, inflation, exchange rate movements, and monetary policies, significantly impact corporate performance and broader stock market trends (Bodie, Kane, & Marcus, 2014).

Technical analysis is a data-driven approach to predicting stock prices. The history of technical analysis can be traced to the Amsterdam market of the 17th century and Japanese rice trading in the early 18th century (Abu-Mostafa & Atiya, 1996).This method uses tools such as chart patterns—candlesticks, support, and resistance levels—and technical indicators like moving averages (MA), relative strength index (RSI), moving average convergence divergence (MACD), and Bollinger Bands to assess trends, momentum, and volatility (Murphy, 1999). Volume analysis is critical for validating price movements, providing confirmation of trend strength or potential reversals (Pring, 2021).

Machine learning (ML) has emerged as a powerful tool, replacing traditional fundamental analysis (FA) and technical analysis (TA) in stock price prediction by automating data processing and identifying complex patterns. Unlike

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FA, which relies on manual interpretation of financial reports and macroeconomic trends, ML algorithms can process vast datasets, including financial metrics, market sentiment, and economic indicators, to detect subtle relationships affecting stock performance (Krauss, Do, & Huck, 2017). Similarly, ML goes beyond TA by dynamically analyzing historical price data, volume, and technical indicators using methods such as time-series models (e.g., Long Short-Term Memory networks) and clustering algorithms, thus avoiding the limitations of fixed rules and human biases (Fischer & Krauss, 2018). By integrating FA and TA data into hybrid ML systems, such as ensemble learning models or deep neural networks, ML provides more accurate and adaptable predictions, offering significant advantages over traditional methods (Chen, Yun Dai, & Zhou, 2013).

The structure of this review article is designed to provide a comprehensive understanding of machine learning (ML) applications in stock price prediction, particularly in the context of the Dhaka Stock Exchange (DSE). The article begins with a brief overview of key ML methods used in stock price prediction, exploring techniques such as supervised learning, deep learning, reinforcement learning, and ensemble methods, and their relevance to financial forecasting. Next, the analysis of ML applications in the DSE context will examine how these methods have been specifically implemented for predicting stock prices in the DSE, taking into account the unique characteristics of the market. The article will then present a comparison of accuracy across various models, evaluating the effectiveness of different approaches in achieving reliable predictions, and addressing challenges such as data limitations, volatility issues. Finally, the discussion of challenges, future research directions and recommendations will highlight emerging trends in ML research and suggest strategies to improve prediction accuracy, considering advancements in data availability, model complexity, and computational power.

LITERATURE REVIEW

Machine learning (ML) approaches have gained popularity in stock price prediction due to their ability to process large datasets and uncover complex patterns beyond traditional methods. Supervised models like linear regression and support vector machines (SVMs) are widely used for predicting stock prices using historical data and financial indicators. Deep learning techniques, such as long short-term memory (LSTM) networks, effectively capture temporal dependencies in time-series data, making them suitable for stock market prediction (Fischer & Krauss, 2018). Ensemble methods like random forests and gradient boosting enhance accuracy and reduce overfitting by combining multiple models (Krauss et al., 2017). Unsupervised methods like k-means clustering help identify market regimes or group similar stocks. ML models offer higher accuracy and adaptability compared to traditional analysis, particularly in volatile, data-scarce markets (Chen, Yun Dai, & Zhou, 2013).

The Dhaka Stock Exchange (DSE), Bangladesh's primary stock exchange, exhibits high volatility driven by economic, political, and global factors, creating non-linear trends ideal for ML techniques like neural networks and SVMs (Fischer & Krauss, 2018). DSE inefficiencies, including low liquidity, wide bid-ask spreads, and irregular trading, make it suitable for adaptive methods like reinforcement learning (Pring, 2021). Challenges like limited high-quality data and trading noise are addressed using data augmentation and preprocessing (Fischer & Krauss, 2018). Retail investor dominance drives sentiment-based trading, positioning NLP-based sentiment analysis as a promising approach (Pring, 2021). Sectoral variability across industries such as financial services and textiles has been analyzed using clustering and classification techniques. LSTM models explore interactions between global and local indicators, given the DSE's partial exposure to global trends (Fischer & Krauss, 2018). Recent regulatory reforms and automation have spurred the use of causal inference models to study their impact on efficiency and investor behavior (Pring, 2021). These unique features make the DSE a valuable focus for ML research to improve market predictions and trading strategies.

Stock market forecasting has consistently been a key topic of study in financial research. With the rise of machine learning (ML), there have been notable improvements in both prediction accuracy and market insights. This review takes a closer look at the various ML techniques that have been applied to the Dhaka Stock Exchange (DSE), summarizing their key findings and highlighting the existing research gaps. By exploring these studies, we gain a better understanding of how ML has advanced stock forecasting and where further work is needed to address its limitations.

Machine learning techniques, including LSTM (Long Short-Term Memory), Support Vector Machines (SVM), and hybrid models, have shown promise in predicting stock prices. For instance, several studies highlight that LSTM excels in handling sequential data, achieving high accuracy in both short- and long-term predictions. A study using LSTM models reported RMSE of 0.95 and MAPE of 0.50%, showing superior alignment with actual stock prices over a 15-day horizon. However, limited exploration of unpredictable market dynamics remains a concern. SVM models have also demonstrated reliable performance, particularly for DSE data, with an R-squared value of 97.04%. Kernel parameter optimization further improved SVM's prediction accuracy, although the study was restricted to selected companies. Hybrid models that integrate multiple ML approaches have outperformed individual algorithms. A study combining rough sets (RS) and artificial neural networks (ANN) achieved prediction accuracy of 97.68% for falling stock prices and 96.33% for rising prices. Such models have demonstrated their strength in capturing market patterns, though external factors like global trends remain unexplored. The integration of technical indicators, such as Moving Average Convergence Divergence (MACD) and Relative Strength Index (RSI), alongside ensemble methods, has improved prediction accuracy significantly. However, minimal use of advanced ML techniques and limited datasets restrict these methods' broader applicability. Deep Learning and Big Data Analytics Deep learning models like LSTM and Artificial Neural Networks (ANN) consistently outperform traditional methods such as ARIMA (Auto-Regressive Integrated Moving Average) in financial forecasting. LSTM models were pivotal in studies leveraging multivariate data, incorporating sentiment analysis and external factors, which improved prediction accuracy by incorporating public sentiment and macroeconomic trends. However, real-time validation and anomaly considerations are lacking. Big data techniques enhanced predictions with 87% accuracy, emphasizing the integration of sentiment analysis and technical indicators. Despite this, the challenges of implementing big data in real-time financial systems remain unaddressed. Several studies have tailored their models to the DSE, providing unique insights: Logistic regression and Partial Least Squares Discriminant Analysis (PLS-DA) were effective for handling multicollinearity in simpler models, yet no exploration of non-linear classification was attempted. Studies on windowing operators and normalization techniques revealed their ability to enhance pattern discovery in DSE data but lacked comparative analysis with other ML models. Hybrid models integrating ANN and technical indicators demonstrated reduced error rates and superior short-term prediction performance. However, their focus on short-term movements overlooked long-term prediction capabilities. The studies collectively reveal several limitations: 1) Data Diversity: Many models relied exclusively on DSE datasets, limiting the generalizability of results to other emerging markets or international datasets. 2) External Factors: Minimal incorporation of macroeconomic indicators, global market trends, and sentiment data restricts the contextual applicability of models. 3) Real-Time Predictions: While some studies proposed live forecasting platforms, validation of these systems in real-time scenarios remains insufficient. 4) Model Comparisons: Few studies provided comparative analyses of different ML algorithms, especially hybrid models versus single techniques. 5) Long-Term Forecasting: Most research focused on short-term predictions, leaving long-term stock trend analysis under-explored.

Future research should address these gaps by: 1) Exploring hybrid models combining deep learning and reinforcement learning for real-time forecasting. 2) Integrating external economic indicators and sentiment data from social media for enhanced prediction accuracy. 3) Expanding datasets to include diverse and global markets for better validation. 4) Comparing ML techniques comprehensively to identify optimal approaches for specific market conditions. 5) Developing robust systems for anomaly detection and handling unpredictable market dynamics.

MATERIALS AND METHODS

This study adopts a comprehensive approach to examine the application of machine learning (ML) techniques for predicting stock prices on the Dhaka Stock Exchange (DSE). The methodology is divided into three primary stages: data collection, model development, and evaluation.

Data Collection

The research uses historical stock price data from the DSE, which includes daily closing prices, trading volumes, and other relevant market indicators over a specified period (e.g., 5 to 10 years). Additional features such as technical indicators (e.g., Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), Bollinger Bands) are also incorporated to enhance the prediction model. Sentiment data from financial news articles, social media, and other sources is collected using natural language processing (NLP) techniques to supplement the stock price data.

Model Development

Several machine learning models are developed to predict stock prices, including:

- **Supervised Learning Models:** Support Vector Machines (SVM), Decision Trees, and Random Forests are trained on historical stock data. These models are chosen for their ability to handle non-linear data relationships.
- **Deep Learning Models:** Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), are utilized for their capacity to learn temporal dependencies in time series data.
- **Hybrid Models:** A combination of Artificial Neural Networks (ANN) with technical indicators such as MACD and RSI is employed. This hybrid approach aims to improve prediction accuracy by integrating various sources of information.
- **Sentiment Analysis Models:** Sentiment analysis is performed on financial news and social media content, which is processed using NLP techniques (e.g., VADER, BERT) to extract sentiment scores and included as features in the prediction models.

Data Preprocessing

Data preprocessing involves several steps, including:

- **Normalization**: Rescaling data to standardize the range of input features, making it suitable for ML algorithms.
- **Handling Missing Data**: Imputation techniques or removal of missing values are applied to ensure data completeness.
- **Feature Engineering**: Technical indicators and sentiment scores are generated as additional features to improve model performance.
- **Data Splitting**: The dataset is divided into training and testing sets, typically with an 80-20% or 70-30% ratio, to ensure proper model evaluation.

Model Evaluation

The performance of each model is evaluated based on accuracy, precision, recall, F1-score, and root mean squared error (RMSE). Cross-validation is performed to assess the generalization capability of the models, and hyperparameter tuning is carried out using grid search or random search techniques. The models' ability to predict short-term stock price movements is specifically tested.

Performance Comparison

The results of ML models are compared against traditional prediction methods, such as technical analysis and statistical models, to assess improvements in prediction accuracy and robustness. Additionally, the impact of incorporating sentiment analysis and hybrid model approaches is analyzed in terms of forecasting performance. This methodology provides a systematic framework for assessing the effectiveness of machine learning techniques in forecasting stock prices, with a focus on the Dhaka Stock Exchange.

DISCUSSIONS

While there are relatively few articles focusing on machine learning (ML) and stock prediction for the Dhaka Stock Exchange (DSE), the existing research does offer significant contributions. Researchers have explored a variety of machine learning and statistical models, applying them to DSE datasets to improve prediction accuracy and reliability. These studies have gone beyond traditional methods such as ARIMA and logistic regression, incorporating advanced models like Long Short-Term Memory (LSTM), Support Vector Regression (SVR), and hybrid techniques that combine multiple algorithms. The results highlight both the strengths and limitations of these predictive approaches, shedding light on their potential for further advancements. The sections that follow provide a detailed overview of these findings, examining the methodologies, results, and implications of the studies in a chronological manner.

Algorithms to Predict Opening Price Trading Decisions

Alam et al. (2011) used bin-partitioning and normalization to improve short-term predictions on the DSE by reducing outliers and identifying data patterns. However, comparisons with other models and long-term forecasts were lacking, suggesting future work validate these methods on broader datasets and explore advanced ML models.

Predicting Stock Prices Using Support Vector Regression (SVR)

Meesad and Rasel (2013) enhanced SVR performance using windowing operators, achieving a 0.04% 1-day-ahead error rate. They recommended extending the approach to larger datasets and incorporating advanced techniques like ensemble learning to address market complexities.

Market Timing Decisions by Hybrid Models

Khan et al. (2013) demonstrated that hybrid models improve buy/sell decision accuracy by reducing misclassifications. However, they highlighted gaps in analyzing external factors and recommended integrating genetic algorithms and dimensionality reduction to refine model performance.

Hybrid Machine Learning Technique

Banik et al. (2014) achieved over 96% accuracy using Rough Sets (RS) and Artificial Neural Networks (ANN) for DSE predictions. The study lacked consideration of external factors like macroeconomic trends, recommending future work enhance robustness and adapt to market volatility.

Improved Stock Prediction with Ensemble Methods

Hasan et al. (2017) showed that combining ensemble methods with technical indicators like MACD and RSI reduced errors. However, reliance on small datasets limited applicability, suggesting broader data sources and advanced algorithms for improved performance.

Indices Prediction of Bangladesh Stocks

Hossain et al. (2020) found Feedforward Neural Networks (FFNN) outperformed ARIMA with 90% accuracy. They emphasized the need for hybrid models, deeper exploration of deep learning, and inclusion of macroeconomic and sentiment data.

Performance Analysis of Recurrent Models

Bhowmick et al. (2019) demonstrated LSTM's superiority over ARIMA in capturing temporal patterns with lower RMSE. They recommended future research explore advanced neural networks and portfolio optimization for better prediction accuracy.

Predicting Daily Closing Prices Using SVM

Hossain et al. (2020) achieved high prediction accuracy using SVM but noted a need for regularization to improve generalization and comparisons with advanced models like neural networks for adaptability across markets.

Forecasting Trends Using ML and Technical Indicators

Dey et al. (2020) combined technical indicators with ML, achieving 86.67% accuracy. They proposed integrating macroeconomic data and real-time validation but highlighted a gap in long-term trend forecasting.

An Intelligent Technique for Stock Prediction

Banik et al. (2014) achieved 96.39% accuracy using linear regression but noted limitations in analyzing external factors like global market influences. They recommended developing hybrid models incorporating sentiment data for enhanced robustness.

SVR vs KNN for Stock Prediction
Islam et al. (2021) showed SVR outperformed KNN with 97.04% accuracy. They recommended exploring non-linear SVR and larger datasets to improve adaptability and scalability.

Predicting Stock Prices Using Logistic Regression
Karimuzzaman et al. (2021) highlighted logistic regression's reliability in reducing errors but suggested exploring hybrid models and non-linear methods while incorporating external economic factors for enhanced accuracy.

Stock Prediction Web Service Using LSTM
Hasan et al. (2021) developed a livestock prediction service using LSTM with 70% accuracy. They emphasized refining the architecture and improving data cleaning to enhance real-time predictions.

Logical Strategy for Stock Prediction
Biswas et al. (2021) found LSTM outperformed traditional methods, achieving a MAPE of 0.635. They recommended incorporating sentiment analysis and addressing missing data for improved model resilience.

Multi-Layer ANN Models for Forecasting
Rubi et al. (2022) showed ANN outperformed ARIMA in short-term predictions. They suggested exploring hybrid techniques like ANFIS and focusing on long-term trends to enhance robustness.

Sentiment-Driven Deep Learning
Islam et al. (2023) integrated sentiment analysis into LSTM models for improved prediction but highlighted the need for real-time validation and leveraging social media data for market insights.

Impact of Big Data Analytics
Islam et al. (2023) achieved 87% accuracy using big data techniques combining technical and sentiment analysis. They recommended including macroeconomic indicators and addressing computational challenges for practical implementation.

LSTM for Stock Price Prediction
Jabed (2024) achieved high accuracy with LSTM (RMSE of 0.95, MAPE of 0.50%) but identified challenges in long-term forecasting and accounting for external factors. Refining techniques and integrating diverse data sources were suggested to improve accuracy.

Comparative Overview of Key Findings in Stock Price Prediction Studies on DSE
Table 1. Provides a chronological overview of the applied techniques, findings, challenges, and recommendations for future work.

Study	Key Techniques	Findings	Limitations	Future Directions
Alam et al. (2011)	Bin-partitioning, normalization	Improved short-term prediction accuracy.	Lacked long-term prediction capability.	Validate on diverse datasets, integrate advanced ML models, explore long-term forecasting.
Meesad & Rasel (2013)	Support Vector Regression (SVR), windowing operators	Achieved 0.04% error rate in 1-day-ahead predictions.	Limited use of advanced data-mining techniques.	Incorporate feature selection, ensemble learning, and hybrid models for better accuracy.
Khan et al. (2013)	Hybrid machine learning models	Improved decision accuracy for buy/sell decisions using a confusion matrix.	Lacked analysis on psychological and macroeconomic factors.	Incorporate genetic algorithms, dimensionality reduction techniques, and optimize models.
Banik et al. (2014)	Rough Sets (RS), Artificial Neural Networks (ANN)	Achieved 97.68% accuracy for falling prices and 96.33% for rising prices.	Did not explore external factors such as macroeconomic influences or geopolitical disruptions.	Integrate external elements into models, focus on scalability, robustness, and volatility adaptation.
Hasan et al. (2017)	Ensemble methods, technical indicators (MACD, RSI)	Reduced mean squared error (MSE) for improved prediction accuracy.	Reliance on small datasets, limiting generalizability.	Expand datasets, incorporate advanced algorithms for improved performance.
Hossain et al. (2020)	ARIMA, Feedforward Neural Networks (FFNN)	FFNN outperformed ARIMA with 90% accuracy for ABBANK stock.	Limited exploration of deep learning architectures and external indicators.	Develop hybrid models, explore deep learning, and integrate macroeconomic/sentiment analysis.
Bhowmick et al. (2019)	Long Short-Term Memory (LSTM) models, ARIMA	LSTM outperformed ARIMA with lower RMSE for stock price predictions.	Limitations with MACD indicator due to data volatility.	Explore advanced neural networks and portfolio optimization strategies.
Hossain et al. (2020)	Support Vector Machines (SVM)	SVM achieved high accuracy in predicting stock prices with closely matching actual prices.	Lacked cross-model comparisons with other advanced algorithms.	Explore regularization constraints, test adaptability to different markets.
Dey et al. (2020)	Technical indicators, machine learning methods	Achieved 86.67% accuracy by combining	Did not address long-term trend analysis.	Incorporate long-term forecasting, include fundamental factors like company financials.

		technical indicators with ML methods.		
Banik et al. (2014)	Linear regression	Achieved 96.39% accuracy in predicting stock prices on DSE.	Lacked analysis on external factors like global economic influences.	Develop hybrid models, integrate sentiment data, improve preprocessing techniques.
Islam et al. (2021)	Support Vector Regression (SVR), K-Nearest Neighbors (KNN)	SVR outperformed KNN with 97.04% accuracy for stock prediction.	Lack of diversity in the dataset and limited exploration of non-linear SVR models.	Use larger, varied datasets, explore non-linear SVR configurations.
Karimuzzaman et al. (2021)	Logistic regression, Partial Least Squares Discriminant Analysis (PLS-DA)	Logistic regression reduced misclassification errors in stock prediction.	Did not investigate non-linear classification methods.	Explore hybrid models, integrate external economic factors, and analyze non-linear methods.
Hasan et al. (2021)	Long Short-Term Memory (LSTM) models	Created a web service for live stock price predictions with 70% accuracy.	Challenges with data cleaning and accurately capturing market trends.	Enhance model robustness, incorporate additional parameters, refine trend analysis.
Biswas et al. (2021)	LSTM models	Achieved a MAPE of 0.635, outperforming traditional methods.	Lack of sentiment analysis integration, limited missing data handling.	Explore sentiment analysis, improve missing data handling, and refine robustness.
Rubi et al. (2022)	Artificial Neural Networks (ANN), ARIMA	ANN models outperformed ARIMA in stock price forecasting with short-term accuracy.	Focused on short-term forecasting, lacked exploration of long-term trends.	Explore hybrid models like ANFIS, focus on long-term forecasting and real-world applicability.
Islam et al. (2023)	Multivariate LSTM, sentiment analysis	Integrated sentiment analysis into LSTM models, improving prediction accuracy.	Lack of real-time validation in dynamic market conditions.	Further explore sentiment-driven approaches and real-time testing, especially on social media data.
Islam et al. (2023)	Big data analytics, technical and sentiment analysis	Achieved 87% accuracy by integrating technical and sentiment analysis for stock prediction.	Challenges in implementing big data methods, managing data volume, and computational complexities.	Incorporate macroeconomic indicators, refine sentiment analysis, and address data management issues.
Jabed (2024)	Long Short-Term Memory (LSTM) models	Achieved RMSE of 0.95 and MAPE of 0.50%, effective in capturing stock market trends.	Challenges in long-term predictions, difficulty accounting for external market factors.	Integrate additional data sources, improve model tuning, and refine predictive techniques.

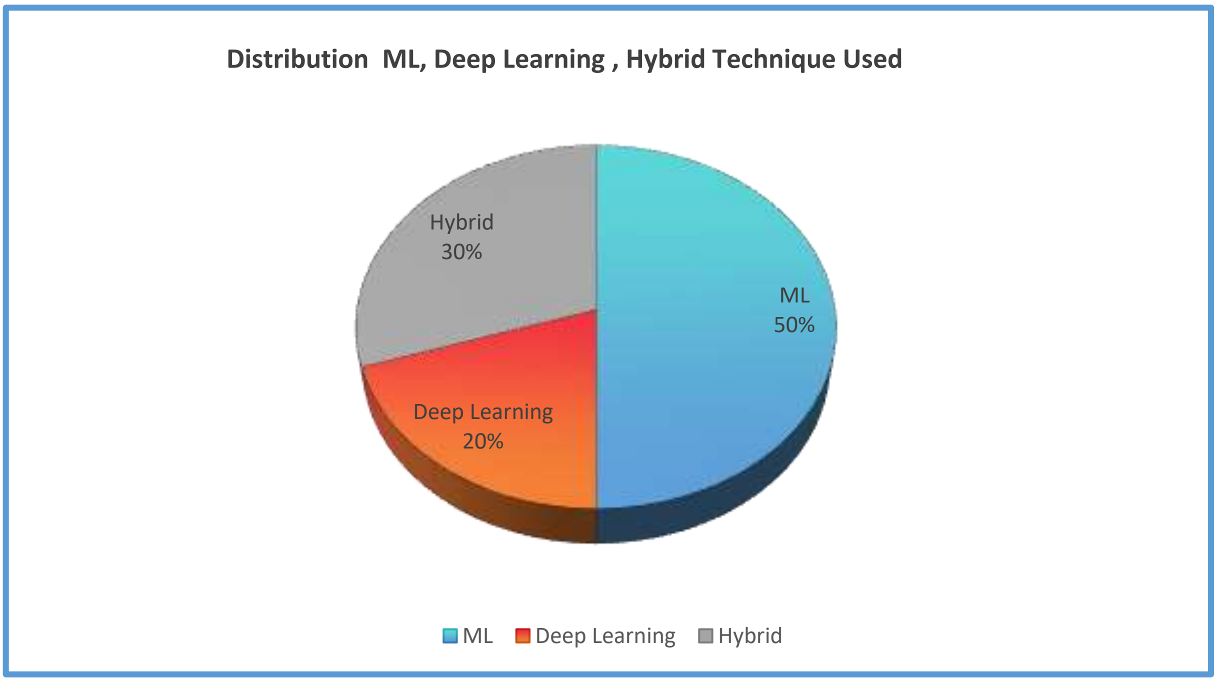

Figure 1. Shows Techniques used in the study are analyzed in terms of their distribution

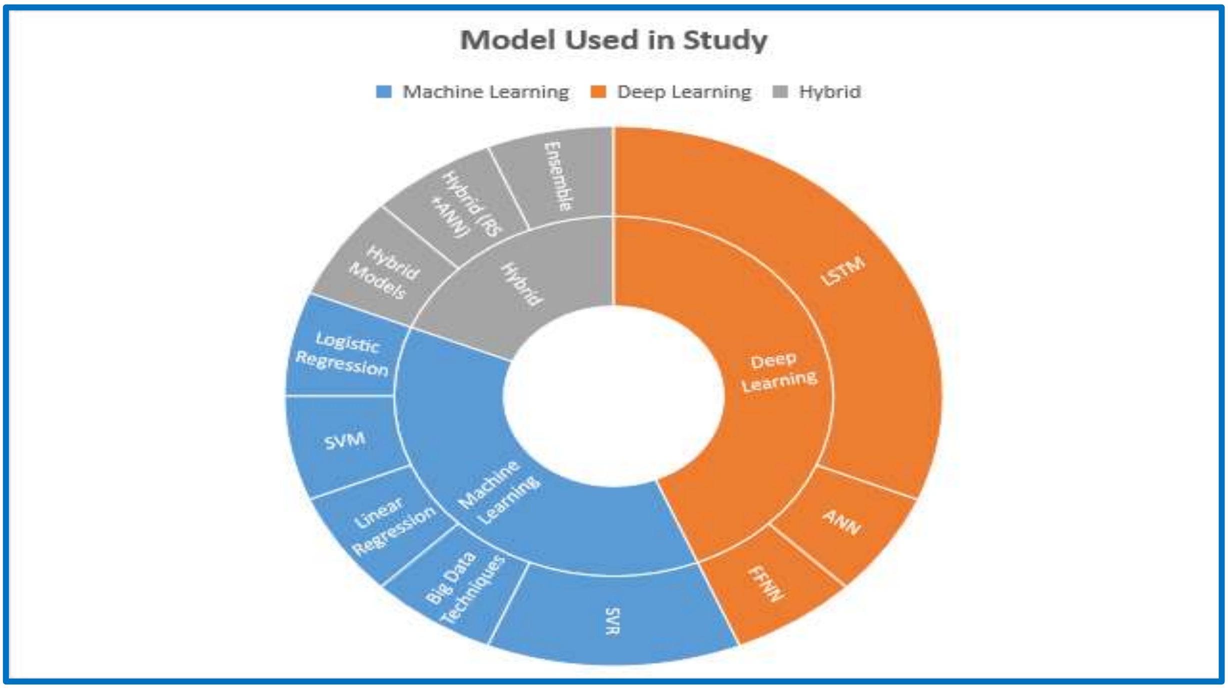

Figure 2. Application of various models in machine learning, deep learning, and hybrid methods in the study

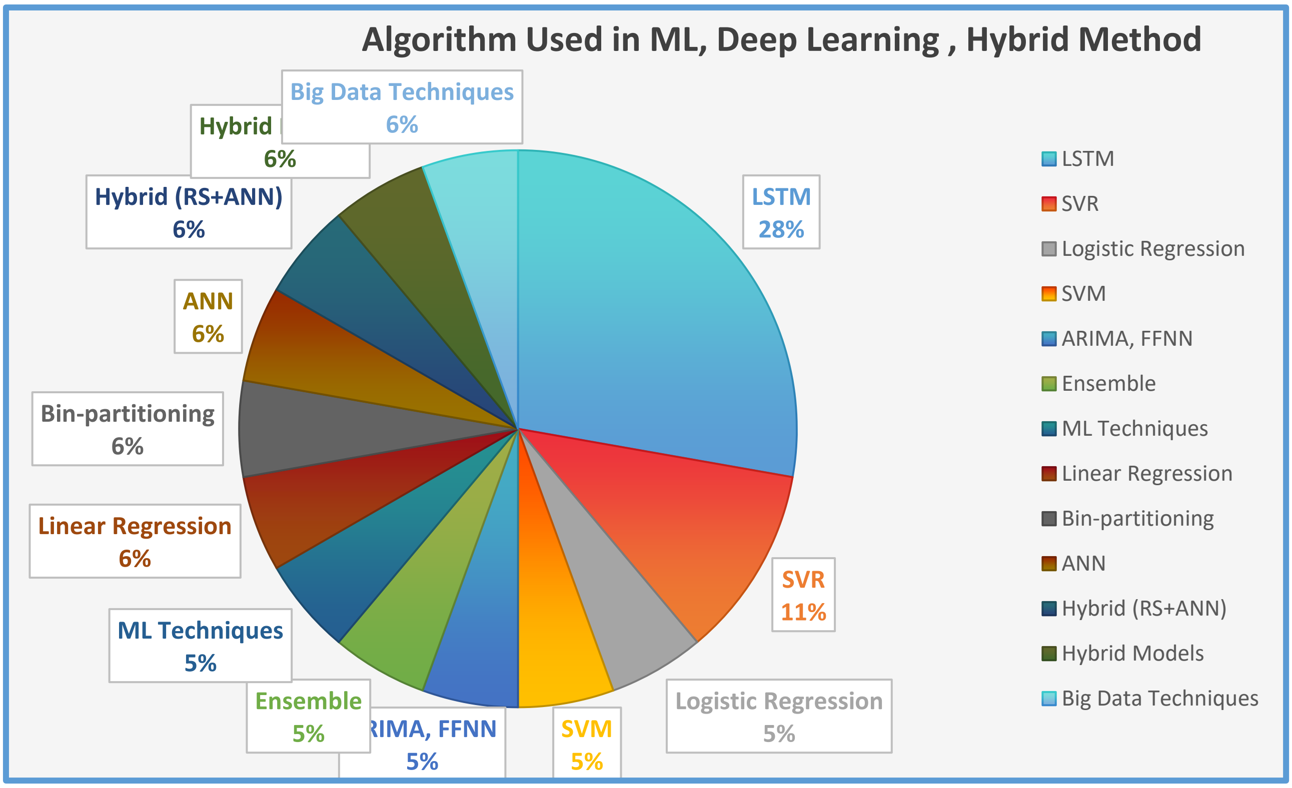

Figure 3. Explores the percentage utilization of algorithms in the domains of machine learning, deep learning, and hybrid approaches

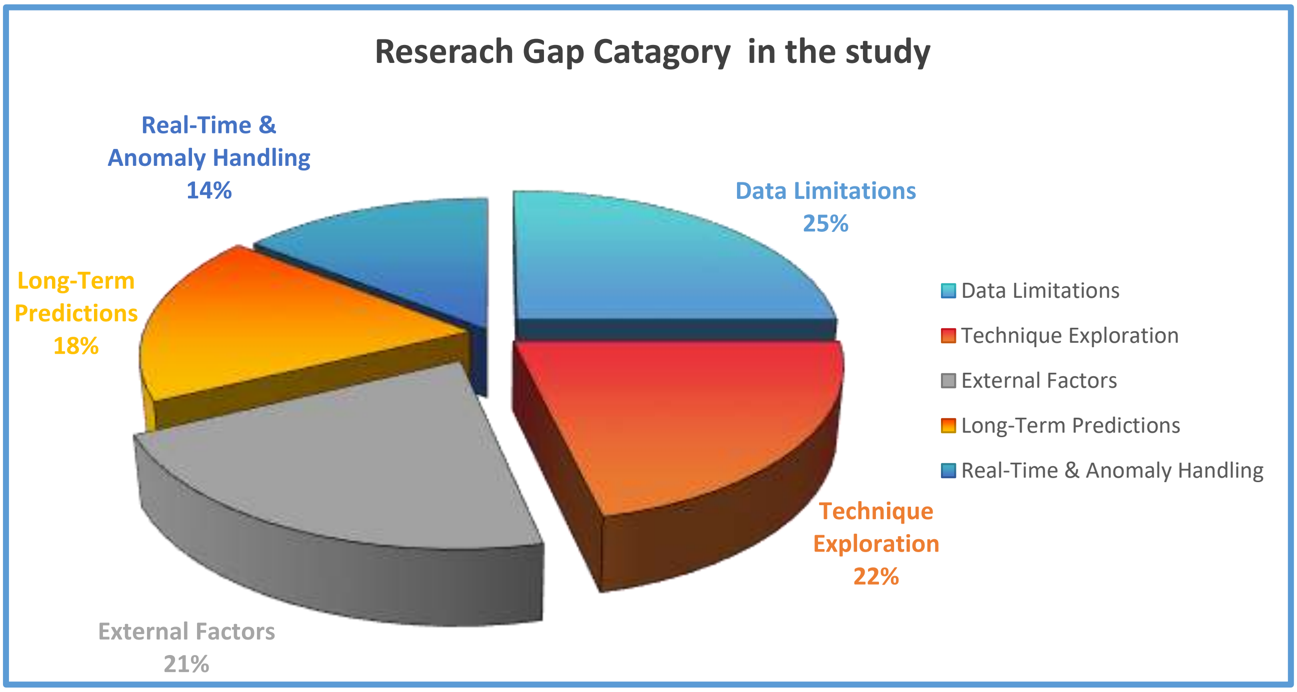

Figure 4. Identifies Research gap segmentation in the study

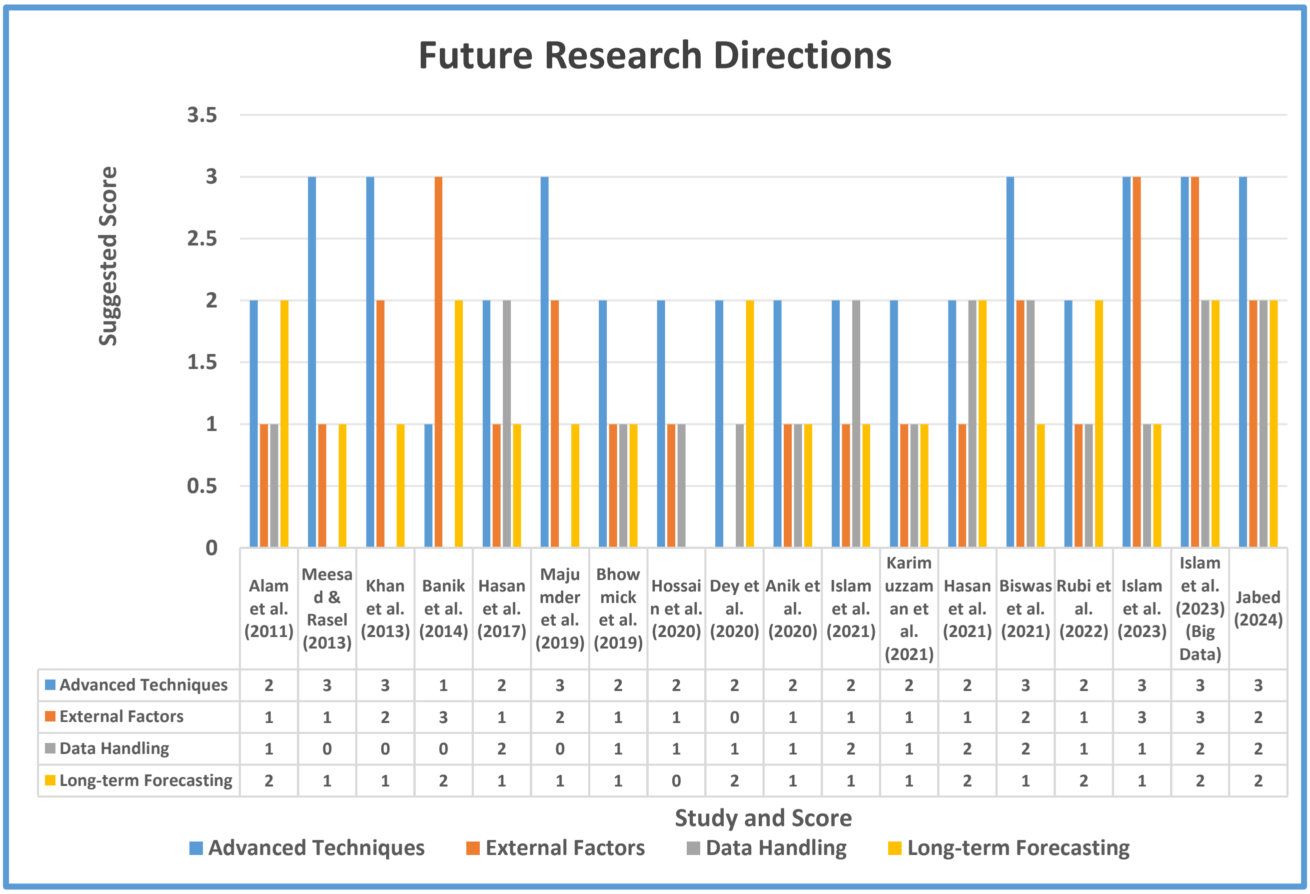

Figure 5. Represents Future Research Directions suggested in the study

The reviewed studies underscore the substantial progress made in stock price prediction, particularly with the adoption of machine learning and hybrid models. Early research primarily focused on simpler techniques like linear regression and ARIMA, which were effective for basic time-series data and short-term forecasting. However, as the field evolved, there was a noticeable shift toward more complex methods, such as neural networks and hybrid models, which demonstrated superior accuracy and adaptability. This transition highlights the increasing sophistication of stock market prediction research, though challenges like dataset-diversity and the lack of integration of external factors persist.

Hybrid models have emerged as a dominant approach in stock market prediction, consistently outperforming standalone methods. By combining techniques such as artificial neural networks with indicators like MACD and RSI, these models leverage the strengths of different algorithms to achieve superior predictive accuracy. However, while these advancements are promising, gaps such as limited exploration of long-term forecasting and challenges with real-time scalability remain. Addressing these gaps in future research could lead to more comprehensive, scalable and adaptable models, advancing the practical and academic utility of stock price prediction systems.

In recent years, there has been a growing emphasis on using big data techniques and real-time prediction tools to enhance model performance. Studies have increasingly incorporated sentiment analysis and macroeconomic indicators, acknowledging the critical role of external factors in market movements. This marks a significant advancement from earlier research that relied predominantly on localized datasets, such as those from the Dhaka Stock Exchange. The integration of these external elements, combined with real-time validation, has the potential to improve the applicability and robustness of predictive models, catering to more dynamic and volatile market conditions.

Based on the findings and analysis presented in this article, several key recommendations are proposed to improve the accuracy, robustness, and practical applicability of machine learning (ML) techniques in predicting stock prices on the Dhaka Stock Exchange (DSE). Future studies should prioritize the development of hybrid models that integrate advanced techniques such as Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and reinforcement learning. Combining these methods with traditional technical indicators like RSI and MACD, as well as macroeconomic variables, can leverage the strengths of multiple approaches to enhance prediction accuracy. Additionally, the incorporation of external factors, including macroeconomic indicators, global market trends, and sentiment analysis from social media platforms, is critical to improving the contextual accuracy of predictions, particularly given the influence of retail investor behavior on the DSE.

To enhance model generalizability and reliability, expanding data diversity by including international market indices, sectoral data, and larger datasets is essential. Addressing issues such as data noise, missing values, and inconsistencies through advanced preprocessing techniques will further improve prediction outcomes. Developing real-time forecasting systems that utilize live data streams is also recommended to ensure the practical usability of ML models for active trading and timely decision-making. While most current research focuses on short-term predictions, greater attention should be given to long-term forecasting models, which are valuable for strategic investors. Techniques like multivariate LSTMs and RNNs can be explored to capture complex temporal relationships in stock market data.

Furthermore, improved feature engineering techniques, such as dimensionality reduction and genetic algorithms, should be employed to optimize input variables and enhance computational efficiency. Comparative analyses between different ML models, including traditional, hybrid, and deep learning approaches, are also necessary to identify the most effective techniques under varying market conditions. Finally, integrating ML-based predictive models with portfolio optimization tools will allow investors to make data-driven decisions while managing risk more effectively. By implementing these recommendations, future research can address existing challenges, advance model performance, and ensure broader practical applicability in both the DSE and other emerging markets.

CONCLUSIONS

The reviewed studies highlight significant advancements in stock market prediction through machine learning, deep learning, and hybrid techniques. Models like LSTM and RS-ANN demonstrate high accuracy in short-term predictions by capturing temporal patterns and managing data complexity, while sentiment analysis and big data analytics enhance robustness. However, small datasets and limited integration of external factors constrain model generalizability. Future research should focus on expanding datasets with diverse markets and real-time data, incorporating macroeconomic indicators, and improving feature engineering. Developing hybrid models that combine technical, fundamental, and sentiment inputs, along with real-time validation and long-term forecasting, will enhance practical applicability. Advancing portfolio optimization tools and benchmarking models will further strengthen decision-making in dynamic markets, paving the way for more effective financial forecasting and investment strategies.

Future research in stock market prediction should prioritize the development of advanced machine learning and deep learning models, including RNN, CNN, and multivariate LSTM, while also exploring hybrid techniques such as ANFIS or genetic algorithms. These sophisticated approaches can address current gaps in scalability and accuracy by enabling longer forecast horizons and improving predictive robustness. Additionally, hybrid models that integrate technical indicators (e.g., RSI, MACD), sentiment analysis, and external economic factors offer a promising avenue for creating comprehensive systems. Ensemble techniques and innovative methods like genetic algorithms can further enhance accuracy and adaptability, making these models more practical for real-world applications.

Another critical focus should be on expanding data diversity and incorporating external factors, such as macroeconomic indicators and social media sentiment, to understand broader market dynamics. Extending research beyond localized datasets, such as Dhaka Stock Exchange data, to include international markets and diverse indices will enhance generalizability. Real-time prediction tools that leverage live datasets and dynamic data streams can significantly improve decision-making for investors. Moreover, advancements in feature engineering and preprocessing techniques will play a key role in handling high-dimensional, incomplete data, while also improving the quality of model inputs. Future studies should also explore long-term forecasting and trend analysis, shifting beyond short-term predictions to multi-month or yearly horizons, thus catering to strategic investment decisions. Integrating these elements with decision-making tools and portfolio optimization systems will enable actionable, investor-friendly strategies, further bridging the gap between academic research and practical applications.

Predicting stock prices in the Dhaka Stock Exchange (DSE) faces challenges due to limited data diversity, small sector-specific datasets, and poor-quality data with missing or inconsistent entries, restricting model generalizability. High market volatility, driven by political and economic instability, makes models struggle to adapt to sudden changes. Over-reliance on technical indicators like RSI and MACD, without integrating macroeconomic trends or investor sentiment, limits prediction accuracy. Long-term forecasting and real-time predictions remain underexplored due to a lack of infrastructure for dynamic data integration. The underutilization of advanced ML techniques, such as CNNs, LSTMs, and hybrid models, highlights a technological gap. Regulatory constraints, limited transparency, and the absence of investor-centric tools further hinder practical implementation. Addressing these issues requires advanced algorithms, external factor integration, improved data quality, and real-time tools to bridge theory and practice.

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