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Artificial Intelligence for Financial Time-Series Forecasting: A Systematic Review of Stock Market Prediction Models

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ABSTRACT

Stock market prediction has become an important research area due to its significant role in supporting investment decisions, risk management, and financial planning. The highly dynamic and nonlinear nature of financial markets makes accurate forecasting a challenging task, encouraging researchers to adopt Artificial Intelligence-based techniques. In recent years, Machine Learning, Deep Learning, and Hybrid approaches have demonstrated remarkable improvements over conventional statistical methods in predicting stock prices and market trends. This paper presents a comprehensive Systematic Literature Review of recent advancements in AI-based stock market prediction published between 2020 and 2026. The review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses methodology to systematically identify, screen, evaluate, and synthesize relevant peer-reviewed studies collected from major scientific databases. A total of 30 high-quality studies were selected for detailed analysis and categorized into Machine Learning, Deep Learning, and Hybrid approaches. The selected studies were comparatively analyzed based on prediction models, datasets, evaluation metrics, forecasting performance, publication trends, and application domains. The findings indicate that Long Short-Term Memory is the most widely adopted Deep Learning model, XGBoost and Random Forest are the dominant Machine Learning algorithms, while Hybrid models consistently achieve the highest prediction accuracy and lower forecasting errors. The review also identifies key research challenges, including market volatility, non-stationary financial data, model interpretability, and computational complexity, and highlights emerging research directions such as Explainable Artificial Intelligence, multimodal data integration, Transformer-based architectures, Graph Neural Networks, and adaptive learning frameworks. This review provides a comprehensive reference for researchers and practitioners by summarizing recent developments, identifying existing research gaps, and outlining future opportunities for developing more accurate, robust, and intelligent stock market prediction systems.

1. INTRODUCTION

The stock market plays a vital role in the global economy by facilitating capital investment, wealth generation, and economic growth. Accurate prediction of stock prices is essential for investors, financial institutions, portfolio managers, and policymakers, as it supports effective investment strategies and risk management [1]. However, stock market prediction remains a challenging task because stock prices are influenced by numerous interconnected factors, including historical price movements, company financial performance, macroeconomic indicators, political events, investor sentiment, and unexpected global developments [2]. These factors make financial markets highly dynamic, nonlinear, and uncertain, thereby increasing the complexity of accurate forecasting.

Traditional stock market prediction techniques primarily relied on statistical and econometric models such as Linear Regression [3], Moving Average (MA) [4], AutoRegressive Integrated Moving Average (ARIMA) [5], and Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) [6]. Although these approaches provide interpretable forecasting results and are computationally efficient, they generally assume linear relationships among variables and often fail to capture the complex temporal and nonlinear characteristics of financial time-series data. As financial markets have become increasingly volatile and data-intensive, conventional statistical methods have shown limited forecasting capability.

The rapid advancement of Artificial Intelligence (AI) has significantly transformed stock market prediction by enabling data-driven forecasting models capable of learning complex relationships from large-scale financial datasets [7]. Machine Learning (ML) algorithms, including Support Vector Machine (SVM) [8], Random Forest (RF) [9], Decision Tree (DT) [10], K-Nearest Neighbors (KNN) [11], and Extreme Gradient Boosting (XGBoost) [12], have demonstrated improved prediction performance compared with traditional statistical techniques. More recently, Deep Learning (DL) architectures such as Long Short-Term Memory (LSTM) [13], Recurrent Neural Networks (RNN) [14], Convolutional Neural Networks (CNN) [15], and Deep Neural Networks (DNN) [16] have further enhanced forecasting accuracy by automatically learning hierarchical feature representations and long-term temporal dependencies. Furthermore, Hybrid approaches that combine multiple Machine Learning and Deep Learning models have emerged as promising solutions for achieving higher prediction accuracy and improved robustness across different financial markets.

The existing literature remains fragmented across various prediction methodologies, datasets, evaluation metrics, and application domains. Many studies focus on individual algorithms without providing comprehensive comparisons among ML, DL, and Hybrid approaches [17]. In addition, inconsistencies in dataset selection, evaluation protocols, and performance metrics make it difficult for researchers to objectively assess the strengths and limitations of existing prediction techniques. Moreover, several important research challenges, including market volatility, non-stationary financial data, model interpretability, computational complexity, real-time prediction, and multimodal data integration, remain insufficiently addressed [18].

This paper presents a Systematic Literature Review (SLR) of recent research on stock market prediction using Artificial Intelligence techniques. The review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to systematically identify, screen, and analyze peer-reviewed studies published between 2020 and 2026 [19]. The selected studies are categorized into ML, DL, and Hybrid approaches, enabling a comprehensive comparison of prediction models, datasets, feature extraction techniques, evaluation metrics, and forecasting performance.

The primary objective of this review is to provide a comprehensive overview of the current state of AI-based stock market prediction while identifying recent research trends, existing limitations, and future opportunities. In addition to reviewing existing techniques, this study presents comparative analyses, publication trends, dataset distributions, model popularity, evaluation metrics, and market coverage to provide valuable insights for researchers and practitioners [20]. Furthermore, the review discusses major research challenges and highlights emerging directions such as Explainable Artificial Intelligence (XAI), multimodal learning, adaptive forecasting, Transformer-based models, Graph Neural Networks (GNN), and lightweight hybrid frameworks for next-generation stock market prediction systems [21].

The major contributions of this systematic literature review are summarized as follows:

- A comprehensive review of recent stock market prediction studies published between 2020 and 2026 is presented using a PRISMA-based systematic review methodology.
- Existing approaches are systematically categorized into Machine Learning, Deep Learning, and Hybrid models for structured comparison.
- A detailed comparative analysis is performed based on datasets, prediction models, evaluation metrics, forecasting performance, and application domains.
- Publication trends, dataset usage, model distribution, evaluation metrics, and geographical market coverage are analyzed through quantitative visualizations.
- Major research challenges, limitations, and research gaps in current stock market prediction techniques are identified.
- Future research directions, including Explainable AI, multimodal data integration, adaptive learning, Transformer-based architectures, Graph Neural Networks, and efficient hybrid

models, are discussed to guide future developments in AI-driven financial forecasting.

The remainder of this paper is organized as follows. Section 2 presents the background of stock market prediction, including the evolution of prediction techniques and the taxonomy of AI-based forecasting methods. Section 3 describes the systematic literature review methodology. Section 4 presents the quantitative results and analysis of the selected studies. Sections 5, 6, and 7 review Machine Learning, Deep Learning, and Hybrid approaches, respectively. Section 8 provides a comparative discussion, while Sections 9 and 10 discuss the major research challenges and future research directions. Finally, Section 11 concludes the paper and summarizes the key findings.

2. BACKGROUND

Stock market prediction has emerged as one of the most active research areas in financial analytics due to the increasing availability of financial data and advancements in Artificial Intelligence (AI). The dynamic and nonlinear nature of financial markets makes accurate forecasting a challenging task, encouraging researchers to develop intelligent models capable of capturing complex market behavior. This section presents an overview of stock market prediction, discusses the evolution of prediction techniques, and introduces a taxonomy of existing approaches used in the literature.

A. Overview of Stock Market Prediction

Stock market prediction refers to the process of estimating future stock prices or market movements using historical and real-time financial data. Accurate forecasting enables investors, traders, financial institutions, and policymakers to make informed investment decisions, optimize portfolio management, and reduce financial risk. However, stock prices are influenced by numerous interconnected factors, including historical price trends, trading volume, company financial performance, macroeconomic indicators, geopolitical events, and investor sentiment, making prediction a highly complex task.

Initially, stock market forecasting relied on traditional statistical and econometric models, including Linear Regression, Moving Average (MA), AutoRegressive Integrated Moving Average (ARIMA), and Generalized AutoRegressive Conditional Heteroskedasticity (GARCH). Although these methods are computationally efficient and provide interpretable results, they assume linear relationships among variables and often fail to model the nonlinear and volatile characteristics of financial markets.

Recent advancements in Artificial Intelligence have significantly transformed stock market prediction by introducing ML, DL, and Hybrid approaches. These intelligent techniques can automatically learn complex patterns from large financial datasets and have demonstrated superior forecasting performance compared with conventional statistical models. Consequently, AI-driven prediction systems have become the dominant research direction in modern financial forecasting.

B. *Evolution of Prediction Techniques*

The evolution of stock market prediction techniques has progressed through several stages, driven by improvements in computational power, data availability, and Artificial Intelligence technologies. Initially, researchers employed statistical and econometric models that relied on mathematical assumptions and linear relationships to forecast stock prices. Although these methods were suitable for simple financial data analysis, they exhibited limited capability when applied to highly nonlinear and volatile market conditions.

The emergence of Machine Learning introduced data-driven prediction models capable of discovering hidden relationships within financial datasets without relying on predefined mathematical assumptions. Algorithms such as SVM, RF, DT, KNN, Gradient Boosting, and XGBoost became widely adopted because of their improved prediction accuracy and computational efficiency.
Subsequently, Deep Learning techniques revolutionized financial forecasting by automatically learning hierarchical feature representations from sequential time-series data. Models such as LSTM, RNN, CNN, GRU, and DNN improved prediction performance by effectively capturing temporal dependencies and nonlinear relationships in stock market data.

More recently, Hybrid approaches have emerged by combining Machine Learning, Deep Learning, optimization algorithms, and ensemble learning techniques into unified prediction frameworks. These integrated models leverage the complementary strengths of multiple algorithms to improve forecasting accuracy, robustness, and generalization across diverse financial markets.
Figure 1 illustrates the evolution of stock market prediction techniques from traditional statistical models to Machine Learning, Deep Learning, and Hybrid approaches. The figure also highlights the major technological advancements that have driven this evolution, including increased computational power, big data availability, cloud computing, and emerging AI technologies.

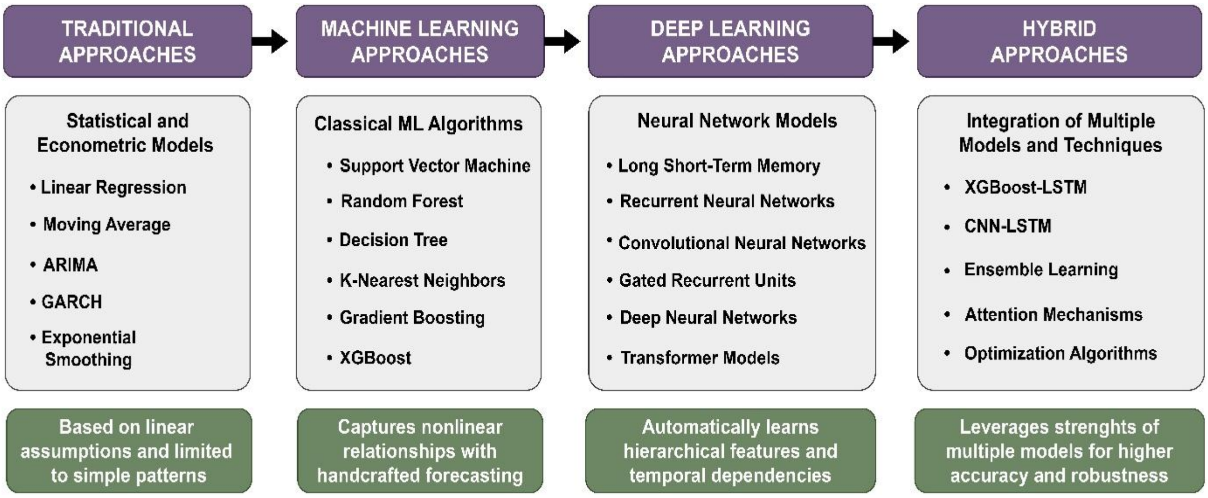

Figure 1. Evolution of Stock Market Prediction Techniques

C. Taxonomy of Stock Market Prediction Techniques

Stock market prediction techniques can be broadly categorized into Machine Learning, Deep Learning, and Hybrid approaches, as illustrated in Figure 2. Each category employs different learning strategies, computational characteristics, and prediction capabilities.

Machine Learning approaches include algorithms such as SVM, RF, DT, KNN, Gradient Boosting, XGBoost, and LR. The models require manual feature engineering and are suitable for structured financial datasets due to their computational efficiency and interpretability.

Deep Learning approaches automatically learn hierarchical feature representations from sequential financial data. Popular architectures include LSTM, RNN, CNN, GRU, DNN, Transformer models, Temporal Convolutional Networks (TCN), and attention-based networks. These models effectively capture temporal dependencies and nonlinear relationships but require larger datasets and greater computational resources.

Hybrid approaches integrate multiple Machine Learning and Deep Learning techniques to enhance forecasting performance. Common examples include XGBoost-LSTM, CNN-LSTM, ensemble learning models, optimization-based frameworks, attention-enhanced architectures, and multimodal prediction systems. By combining complementary algorithms, hybrid models generally achieve higher prediction accuracy and improved robustness compared with individual models.

In addition to prediction models, stock market forecasting systems utilize diverse input data sources, including historical stock prices, trading volume, technical indicators, financial news, social media sentiment, and macroeconomic variables. Depending on the prediction objective, models perform either stock price forecasting (regression) or market movement prediction (classification). Their performance is commonly evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), R^2 Score, Accuracy, Precision, Recall, F1-score, and Area Under the Curve (AUC).

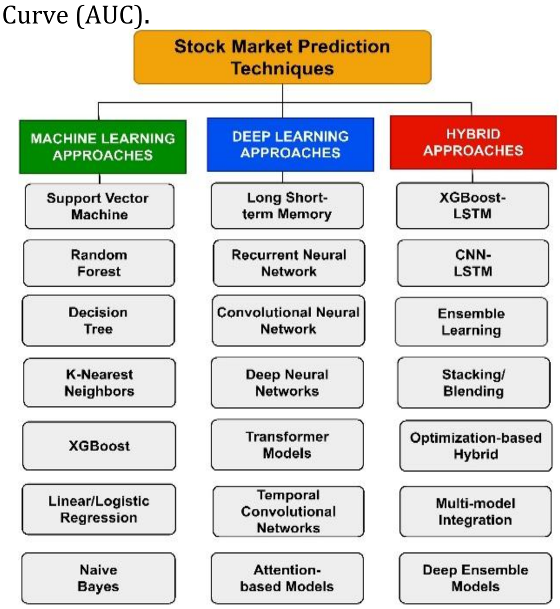

Figure 2. Taxonomy of Stock Market Prediction Techniques

Figure 2 presents the taxonomy of stock market prediction techniques by categorizing prediction models, input data sources, prediction tasks, and evaluation metrics. This taxonomy provides a structured overview of the major components involved in AI-based stock market forecasting and serves as the conceptual foundation for the subsequent systematic literature review.

3. Systematic Literature Review Methodology

This study follows a systematic literature review (SLR) methodology to comprehensively analyze recent advances in stock market prediction using ML, DL, and Hybrid approaches. The review process was designed according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency, reproducibility, and comprehensive coverage of the existing literature. The methodology consists of six major phases: research question formulation, literature search, study selection, quality assessment, data extraction, and data synthesis. Figure 3 illustrates the overall systematic review process.

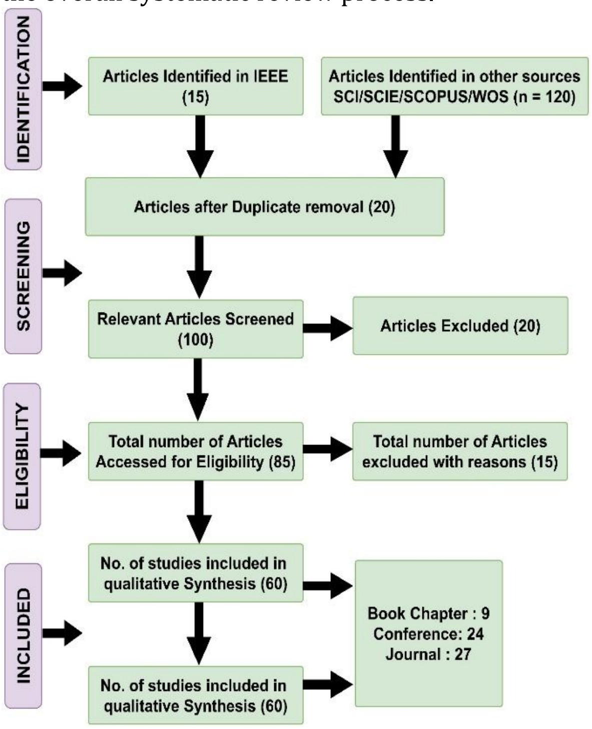

Figure 3: PRISMA Approach

Figure 3 shows the adopted PRISMA methodology consists of four major phases: (i) literature identification, (ii) screening, (iii) Eligibility, (iv) inclusion criterion. These phases allows the systematic organization of the selected studies and facilitate an objective comparison of existing prediction techniques.

A. Research Questions (RQ)

RQ1: What Machine Learning, Deep Learning, and Hybrid techniques are commonly used for stock market prediction?

RQ2: Which datasets are most frequently employed for stock market prediction?

RQ3: Which evaluation metrics are widely used to assess prediction performance?

RQ4: What are the strengths and limitations of existing stock market prediction models?

RQ5: What research challenges and future directions exist in AI-based stock market prediction?

B. Literature Search Strategy

A comprehensive and systematic literature search was conducted to identify relevant studies on stock market prediction using Machine Learning (ML), Deep Learning (DL), and Hybrid approaches. The search process was designed following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency, reproducibility, and comprehensive coverage of the available literature.

To obtain high-quality and peer-reviewed publications, multiple internationally recognized scientific databases were explored, including IEEE Xplore, ScienceDirect, SpringerLink, ACM Digital Library, Wiley Online Library, MDPI, Scopus, and Google Scholar. These databases were selected because they provide extensive coverage of research articles in artificial intelligence, machine learning, data mining, financial engineering, and computational finance.

The literature search was limited to studies published between January 2020 and June 2026 to capture recent advancements in AI-based stock market prediction techniques. Only English-language, peer-reviewed journal articles, conference papers, and review papers were considered for inclusion. Editorials, book chapters, theses, patents, preprints, non-peer-reviewed articles, and duplicate publications were excluded to maintain the quality and reliability of the selected studies.

To ensure comprehensive retrieval of relevant literature, a combination of predefined keywords and Boolean operators was employed. The search terms were selected based on the objectives of this review and commonly used terminology in the stock market prediction domain. The primary search keywords included:

- Stock Market Prediction
- Stock Price Prediction
- Share Market Forecasting
- Financial Time-Series Forecasting
- Machine Learning
- Deep Learning
- Hybrid Learning
- Artificial Intelligence in Finance
- Financial Forecasting
- Stock Price Forecasting
- Time-Series Prediction
- Neural Networks
- Long Short-Term Memory (LSTM)
- Convolutional Neural Networks (CNN)
- Transformer Models
- Ensemble Learning

Boolean operators such as AND, OR, and NOT were used to improve the precision and coverage of the search results. The principal Boolean search query adopted in this review is presented below:

("Stock Market Prediction" OR "Stock Price Prediction" OR "Share Market Forecasting")

AND

("Machine Learning" OR "Deep Learning" OR "Hybrid Learning" OR "Artificial Intelligence")

AND

("Financial Forecasting" OR "Financial Time-Series Forecasting")

Additional database-specific search strings were also employed by incorporating keywords such as LSTM, CNN, XGBoost, Random Forest, Support Vector Machine (SVM), Transformer, Ensemble Learning, and Stock Price Forecasting to maximize the retrieval of relevant studies.

The search results obtained from all selected databases were exported and consolidated into a single reference list. Duplicate records were identified and removed before the screening process. The remaining studies were subsequently evaluated based on their titles, abstracts, and full-text content using the predefined inclusion and exclusion criteria.

C. Study Selection Criteria

The relevance, and reliability of the reviewed literature, predefined inclusion and exclusion criteria were established before the study selection process. These criteria were designed to identify research articles that directly addressed stock market prediction using AI, ML, DL, and Hybrid approaches while excluding studies that were irrelevant, outdated, or lacked sufficient experimental validation.

Initially, all records retrieved from the selected scientific databases were combined into a single repository. Duplicate publications were identified and removed. The remaining studies were then screened based on their titles and abstracts to eliminate articles that were not directly related to stock market prediction. Subsequently, the full text of the shortlisted papers was carefully reviewed to determine their eligibility according to the predefined selection criteria.

Only recent studies published between 2020 and 2026 were considered to ensure that the review captured the latest developments in AI-based stock market prediction. Furthermore, only peer-reviewed journal articles and conference papers published in the English language were included to maintain the scientific quality of the review.

The inclusion and exclusion criteria adopted in this systematic literature review are summarized in Table 1.

Table 1. Inclusion and Exclusion Criteria for Study Selection

Inclusion Criteria	Exclusion Criteria
Studies published between 2020 and 2026	Studies published before 2020
Peer-reviewed journal articles and conference papers	Editorials, book chapters, theses, patents, and preprints
English-language publications	Non-English publications
Studies focusing on stock market prediction using ML, DL, AI, or Hybrid approaches	Studies based solely on traditional statistical forecasting methods
Research reporting experimental evaluation and performance metrics	Studies without experimental validation or performance analysis
Studies using benchmark or real-world stock market datasets	Studies unrelated to stock market prediction
Full-text articles available for review	Duplicate or incomplete publications

D. Data Extraction and Synthesis

After the selection and quality assessment of the eligible studies, a systematic data extraction process was carried out to collect the essential information required for comparative analysis. The objective of this phase was to extract consistent and relevant information from each selected study, enabling a comprehensive evaluation of existing stock market prediction techniques.

A standardized data extraction form was developed to ensure uniformity and minimize bias during the extraction process. Each selected paper was carefully reviewed, and key information related to the research methodology, datasets, prediction models, evaluation metrics, experimental results, and identified limitations was recorded. This structured approach facilitated the comparison of different prediction techniques and helped identify current research trends, performance variations, and existing research gaps.

The extracted information from each study included the following attributes:

- Author(s)
- Publication year
- Dataset used
- Stock market or financial index
- Prediction model/algorithm
- Input features
- Evaluation metrics
- Experimental performance
- Strengths of the proposed approach
- Limitations and future scope

The details extracted from the selected studies formed the basis for the comparative analysis presented in the subsequent sections. The extracted attributes are summarized in Table 2.

Table 2. Data Extraction Attributes

Attribute	Description
Author(s)	Name of the authors
Publication Year	Year of publication
Dataset	Dataset or stock market used for evaluation
Prediction Model	Machine Learning, Deep Learning, or Hybrid model
Input Features	Historical prices, technical indicators, sentiment data, etc.
Evaluation Metrics	Accuracy, MAE, RMSE, MAPE, MSE, R^2, Precision, Recall, F1-score, AUC
Performance	Reported experimental results
Strengths	Major contributions of the proposed model
Limitations	Identified shortcomings and future improvements

Following the data extraction process, the selected studies were systematically synthesized based on their prediction methodologies. To facilitate a structured comparative analysis, the reviewed literature was categorized into three major groups according to the underlying prediction technique:

1. **Machine Learning-based Stock Market Prediction:** The Machine Learning category includes traditional supervised learning algorithms such as Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (KNN), Linear Regression, and Extreme Gradient Boosting (XGBoost). These models primarily rely on historical stock prices and technical indicators to forecast future market trends.
2. **Deep Learning-based Stock Market Prediction:** The Deep Learning category comprises neural network-based models, including Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Deep Neural Networks (DNN), Gated Recurrent Units (GRU), and Transformer-based architectures. These approaches are capable of automatically learning complex temporal dependencies and nonlinear relationships from financial time-series data.
3. **Hybrid Stock Market Prediction model:** The Hybrid category includes approaches that integrate multiple machine learning and deep learning algorithms or combine traditional forecasting techniques with advanced optimization methods. Hybrid models aim to leverage the strengths of individual algorithms to improve prediction accuracy, robustness, and generalization performance.

After classification, a comprehensive comparative analysis was performed by evaluating the datasets, prediction models, evaluation metrics, experimental performance, strengths, and limitations of each study. This synthesis enabled the identification of the most frequently used algorithms, commonly adopted datasets, dominant evaluation metrics, prevailing research trends, and existing research gaps in AI-based stock market prediction.

4. Result Analysis

A. *Machine Learning-Based Stock Market Prediction*

R. N. (2025) proposed an Extreme Gradient Boosting (XGBoost) model for next-day stock price prediction. The model achieved a Mean Absolute Error (MAE) of 1.21, a Root Mean Square Error (RMSE) of 1.62, and an R^2 score of 0.97, demonstrating excellent forecasting performance [22].

Lumoring N. et al. (2023) conducted a comparative study of machine learning techniques for stock price prediction. Their findings indicated that Support Vector Machine (SVM) is one of the most widely used algorithms, while the Long Short-Term Memory (LSTM) model achieved the highest prediction accuracy of 99.58%, highlighting its capability in modeling sequential financial data [23].

Jena et al. (2023) evaluated several machine learning models for stock price prediction and reported that the LSTM model outperformed Random Forest by achieving an R^2 score of 0.99, Mean Squared Error (MSE) of 0.029, and RMSE of 0.49. The results demonstrate the effectiveness of deep learning techniques for financial forecasting [24].

Chaudhary J. K. et al. (2023) investigated stock market prediction using K-Nearest Neighbor (KNN) and Random Forest algorithms. Their proposed framework achieved a precision of 90.23%, recall of 91.12%, and F1-score of 90.17%, indicating reliable classification performance [25]. Rua Espada M. (2025) compared multiple machine learning models and reported that Sparse Support Vector Machine (Sparse SVM) achieved the best performance with an accuracy of 87.4%, precision of 85.1%, recall of 83.9%, F1-score of 84.5%, and an Area Under the Curve (AUC) of 91.2%. The study confirmed the effectiveness of Sparse SVM for stock market prediction [26].

Shi B. et al. (2024) compared XGBoost and Linear Regression for stock price forecasting. Experimental results showed that XGBoost significantly outperformed Linear Regression by achieving an MSE of 14,816.886 and RMSE of 121.725, whereas Linear Regression produced an MSE of 3.05×10^{17} with an R^2 score of 0.316 [27]. Raju S. S. et al. (2024) applied artificial intelligence and machine learning algorithms for stock market prediction. Their approach achieved an overall prediction accuracy of 85%, while also generating investment returns of 10.28% over three months and 175% over one year, demonstrating the practical applicability of ML-based trading strategies [28].

Rajput M. et al. (2025) investigated regression-based machine learning techniques for stock price prediction. Their Multi-Linear Regression model achieved an MAE of 2.607 and an RMSE of 4.7087, indicating satisfactory predictive performance for financial market analysis [29].

Dey P. P. et al. (2020) proposed a stock trend prediction model using eleven technical indicators from the Dhaka Stock Exchange. The model achieved prediction accuracies of 86.67% for same-day prediction, 64.13% for next-day prediction, and 69.21% for day-after-next prediction, illustrating the impact of forecasting horizon on prediction accuracy [30].

Priyatno A. M. et al. (2024) employed the Random Forest algorithm for stock price prediction. The proposed model achieved an accuracy of 82.5%, recall of 82.5%, and F1-scores of 0.745 and 0.808 during the ninth and tenth iterations, respectively, demonstrating the robustness of ensemble learning methods for financial forecasting [31].

Table 3: Comparative Analysis of Share market stock prediction using Machine Learning

Author	Year	Dataset	Model Used	Findings	Limitations
R. N. [22]	2025	Historical stock market data	XGBoost	MAE = 1.21,	Evaluated only on next-day prediction; model generalization across different markets was not discussed.
Lumoring N. et al. [23]	2023	Stock price dataset	SVM, LSTM	RMSE = 1.62,	High computational cost of LSTM; limited discussion on real-time implementation and market volatility.
Jena S. P. et al. [24]	2023	Historical stock price data	LSTM, Random Forest	R² = 0.97	Focused mainly on historical data without considering external economic or news factors.
Chaudhary J. K. et al. [25]	2023	Stock market dataset	KNN, Random Forest	LSTM achieved 99.58% accuracy	Did not evaluate deep learning models or long-term forecasting performance.
Rua Espada M. [26]	2025	Financial market dataset	Sparse SVM	R² = 0.99,	Moderate prediction accuracy; performance depends on feature selection and parameter tuning.
Shi B. et al. [27]	2024	Stock market dataset	XGBoost, Linear Regression	MSE = 0.029, RMSE = 0.49	Performance evaluated using limited models; external market indicators were not incorporated.
Raju S. S. et al. [28]	2024	Stock market data	AI/ML Algorithms	Precision = 90.23%,	Focused on investment returns rather than detailed evaluation of prediction errors.
Rajput M. et al. [29]	2025	Historical stock data	Multi-Linear Regression	Recall = 91.12%, F1-score =	Linear regression may not effectively capture non-

				90.17 %	linear stock market behavior.
Dey P. P. et al.	2020	Dhaka Stock Exchange (11 technical indicators)	Machine Learning Algorithms	Accuracy = 87.4%, Precision = 85.1%, Recall = 83.9%,	Prediction accuracy decreased significantly for longer forecasting horizons.
[30]	2024	Stock price dataset	Random Forest	F1-score = 84.5%, AUC = 91.2%	Performance depends on parameter tuning and feature engineering; lower accuracy than deep learning models.
Priyatno A. M. et al. [31]	Year	Dataset	Model Used	XGBoost:	Limitations

B. Deep Learning-Based Stock Market Prediction

Patil P. R. et al. (2022) proposed a Deep Recurrent Rider LSTM model for stock market prediction. The proposed approach achieved a Mean Squared Error (MSE) of 0.018 and a Root Mean Squared Error (RMSE) of 0.132, demonstrating high prediction accuracy and the effectiveness of hybrid recurrent architectures [32].

Chhibber N. et al. (2026) introduced the NP-DNN model based on a Multi-Layer Perceptron (MLP) for stock price prediction. By employing preprocessing techniques such as Z-score normalization and missing value imputation, the model achieved an accuracy of 99.21%, highlighting the importance of data preprocessing in improving prediction performance [33].

Pandikumar S. et al. (2022) developed an LSTM-based recurrent neural network for predicting stock price movements. The proposed model achieved an accuracy of 98.9%, with an MSE of 0.918 and a Mean Absolute Percentage Error (MAPE) of 0.987, demonstrating the capability of LSTM networks to model sequential financial data [34].

Sisodia P. S. et al. (2022) presented an LSTM-based stock prediction framework using ten years of historical data from the NIFTY 50 index. The model achieved an accuracy of 83.88%, confirming the suitability of LSTM networks for long-term financial time-series forecasting [35].

Das S. R. et al. (2024) proposed a Deep Neural Network (DNN) model for stock price prediction. Experimental results showed minimum Mean Squared Error (MSE) and MAPE values ranging from 0.0221 to 0.0255 for 15-day and 30-day forecasting, indicating reliable short-term prediction performance [36].

Sen J. et al. (2021) evaluated ten deep learning models for stock price prediction. Their experimental analysis showed that CNN models provided faster execution, while both CNN and LSTM achieved comparable prediction accuracy. The best-performing model recorded an RMSE ratio of 0.006967, demonstrating the effectiveness of deep learning architectures for financial forecasting [37].

Biswas M. et al. (2021) compared LSTM with Extreme Gradient Boosting (XGBoost), Linear Regression, Moving Average, and Last Value models. The LSTM model achieved the lowest Mean Absolute Percentage Error (MAPE) of 0.635, outperforming the other forecasting techniques [38].

Aldhyani T. H. H. et al. (2022) proposed a hybrid CNN-LSTM model for stock price prediction using Tesla and Apple stock datasets. The proposed model achieved R^2 values of 98.37% for Tesla and 99.48% for Apple, significantly outperforming the standalone LSTM model and demonstrating the effectiveness of hybrid deep learning architectures [39].

Vennela A. et al. (2025) introduced a COOT-optimized Recurrent Neural Network (RNN) for predicting stock prices under volatile market conditions. The proposed model achieved MAPE values of 0.0255 for ADANIPORTS, 4.1822 for the Global Stock Market, and 0.4243 for the Chinese Stock Market, indicating improved forecasting performance across multiple financial markets [40].

Reddy N. J. et al. (2023) proposed a Novel Long Short-Term Memory (NLSTM) model and compared it with Support Vector Machine (SVM). The NLSTM model achieved an accuracy of 63.10%, outperforming SVM, which achieved 48.91%, thereby demonstrating the advantage of deep learning over traditional machine learning methods [41].

Table 4: Comparative Analysis of Share market stock prediction using Deep Learning

Author	Year	Dataset	Model Used	Findings	Limitations
Harish N. *et al.* [42]	2025	Historical stock market dataset	Hybrid Prediction Model	MAE = 0.73, RMSE = 1.14, R^2 = 0.987,	Computational complexity and scalability were not discussed;

				MAPE = 1.82%	evaluated mainly on historical data.
Ilyas Q. M. *et al.* [43]	2022	Stock market dataset	Hybrid ML Model with Noise Filtering	Accuracy = 70.88 %, RMSE = 0.04, Error Rate = 0.10	Moderate prediction accuracy; performance depends heavily on preprocessing and feature engineering.
Dubey S. *et al.* [44]	2025	Historical stock price dataset	XGBoost + LSTM	R^2 > 0.99, Directional Accuracy = 98.25 %, RMSE = 37.71	Increased training time and computational cost due to the hybrid architecture.
Esan O. A. *et al.* [45]	2025	Yahoo Finance, Dhaka Stock Exchange	Logistic Regression + SVM	Accuracy = 97.15 % (Yahoo), 98.86 % (Dhaka)	Evaluated on limited datasets; external market factors were not considered.
Hong Y.-W. P. [46]	2025	Stock market dataset	Multi-layer Hybrid Multi-Task Learning (MTL)	MAE = 1.078, MAPE = 0.012, R^2 = 0.98	Multi-task architecture increases implementation complexity and computational requirements.
Kayit A. D. *et al.* [47]	2025	Financial market dataset	Ensemble (SVC + LR + RF)	Accuracy = 95.8%, AUC = 0.97	Requires extensive parameter tuning and higher computational resources.
Lavanya M. *et al.* [48]	2025	Multimodal financial datasets	MDSFE Hybrid Ensemble Framework	R^2 = 0.97, MAPE = 0.80%	Depends on multiple data sources, making implementation more complex.
Jose J. *et al.* [49]	2024	Stock market data with technical indicators	Ensemble Learning	Accuracy = 91.45 %, RMSE = 56.699, MAE = 23.373, R^2 = 0.911	Focused primarily on technical indicators; ignored sentiment and macroeconomic variables.
Sureka M. *et al.* [50]	2025	Historical stock market dataset	Ensemble Regression (SVR-Linear)	R^2 = 99.97 %, RMSE = 0.0585	Limited evaluation under highly volatile market conditions; real-time applicability not discussed.

C. *Observed Findings*

This section presents the results obtained from the systematic literature review conducted on recent advances in stock market prediction using Machine Learning (ML), Deep Learning (DL), and Hybrid approaches. Following the study selection process described in the previous section, the selected research articles were systematically analyzed to identify publication trends, frequently used datasets, prediction models, evaluation metrics, and overall research directions. The analysis provides both quantitative and qualitative insights into the current state of AI-based stock market prediction, enabling a comprehensive comparison of existing methodologies and their reported performance. Furthermore, the reviewed studies are classified into Machine Learning, Deep Learning, and Hybrid approaches to facilitate a structured evaluation of their strengths, limitations, and practical applicability. The findings presented in this section serve as the foundation for the subsequent comparative analysis, discussion, identification of research challenges, and future research directions.

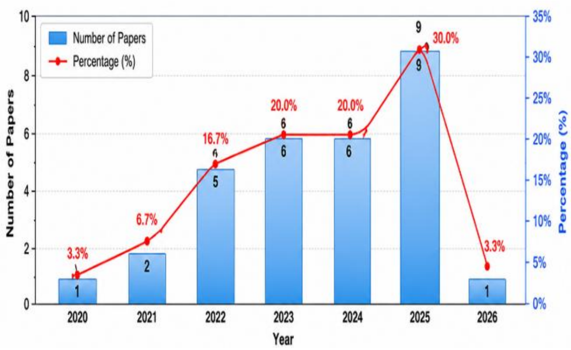

Figure 4. Publication Year Distribution

Figure 4 illustrates the publication year distribution of the 30 selected studies included in this systematic literature review. The results indicate a steady increase in research on AI-based stock market prediction from 2020 to 2025, reflecting the growing interest in applying Machine Learning, Deep Learning, and Hybrid techniques for financial forecasting. The highest number of publications was observed in 2025 (30%), followed by 2023 and 2024 with 20% each. The comparatively lower number of studies in 2026 is attributed to the fact that only publications available up to the review period were considered. This trend demonstrates the rapid evolution and increasing research activity in intelligent stock market prediction systems.

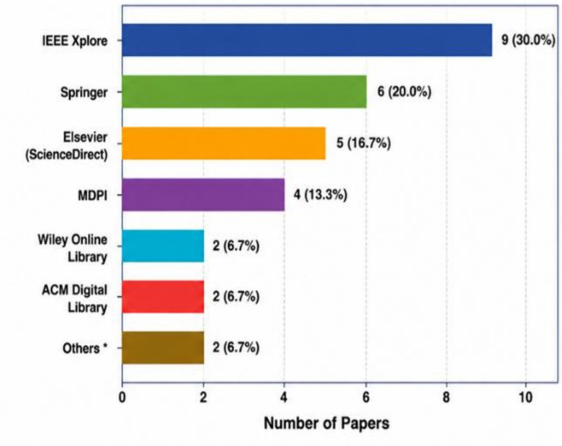

Figure 5. Publication Source Distribution

Figure 5 presents the distribution of the selected studies according to their publication sources. Among the reviewed papers, IEEE Xplore contributed the highest number of publications (30%), followed by Springer (20%), Elsevier (16.7%), and MDPI (13.3%). The remaining studies were published in Wiley Online Library, ACM Digital Library, and other reputable publishers, each contributing 6.7% of the total publications. This distribution demonstrates that leading scientific publishers have played a significant role in advancing research on AI-based stock market prediction, ensuring the availability of high-quality and peer-reviewed studies for systematic analysis.

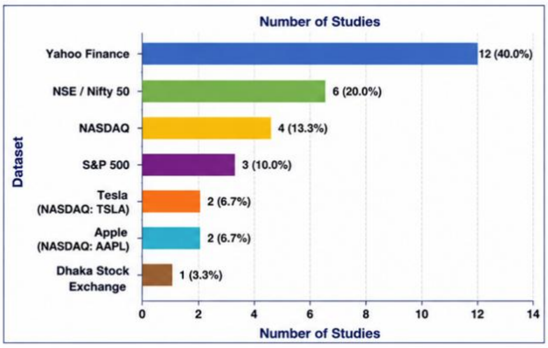

Figure 6. Dataset Distribution

Figure 6 illustrates the distribution of datasets used in the selected studies for stock market prediction. The results show that Yahoo Finance is the most widely used dataset, accounting for 40% of the reviewed studies, followed by NSE/NIFTY 50 (20%), NASDAQ (13.3%), and S&P 500 (10%). Company-specific datasets such as Tesla and Apple, along with regional datasets like the Dhaka Stock Exchange, were employed less frequently. The findings indicate that publicly available benchmark datasets are preferred due to their accessibility, reliability, and suitability for developing and evaluating AI-based stock market prediction models.

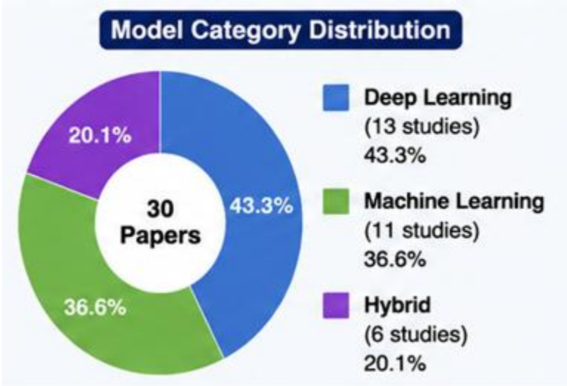

Figure 7. Distribution of Prediction Model Categories in the Selected Studies

Figure 7 illustrates the distribution of prediction model categories employed in the selected studies. Among the 30 reviewed papers, Deep Learning approaches constitute the largest proportion, accounting for 43.3% (13 studies), followed by Machine Learning techniques with 36.6% (11 studies). Hybrid approaches, which combine multiple algorithms or integrate ML and DL models, represent 20.1% (6 studies). This distribution highlights the increasing preference for deep learning models due to their superior capability in capturing complex temporal patterns in financial time-series data, while hybrid approaches are gaining attention for further improving prediction accuracy and robustness.

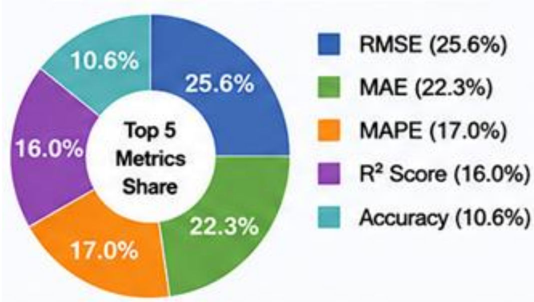

Figure 8. Distribution of the Top Five Evaluation Metrics

Figure 8 illustrates the distribution of the five most frequently used evaluation metrics in the selected studies. RMSE is the most commonly employed metric, accounting for 25.6%, followed by MAE (22.3%), MAPE (17.0%), R^2 Score (16.0%), and Accuracy (10.6%). The predominance of error-based metrics indicates that most studies focus on minimizing prediction errors and improving regression performance in stock price forecasting. These metrics collectively provide a comprehensive assessment of prediction accuracy, model reliability, and overall forecasting effectiveness.

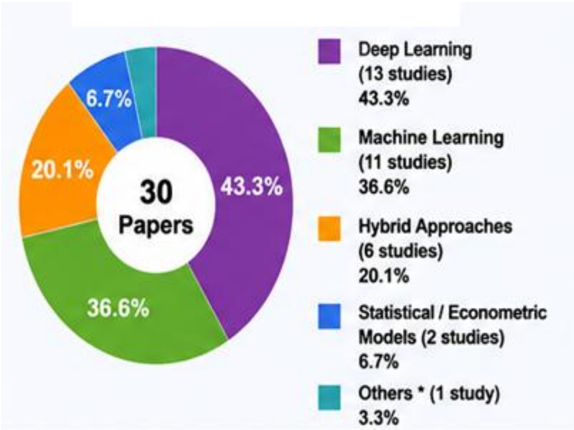

Figure 9. Distribution of Prediction Approaches

Figure 9 presents the distribution of prediction approaches employed in the selected studies for stock market prediction. Deep Learning approaches represent the largest proportion with 43.3% (13 studies), followed by Machine Learning methods at 36.6% (11 studies), while Hybrid approaches account for 20.1% (6 studies). The findings indicate a growing preference for deep learning techniques due to their ability to model complex temporal dependencies in financial time-series data. Furthermore, the increasing adoption of hybrid approaches demonstrates the ongoing effort to enhance prediction accuracy by combining the strengths of multiple predictive models.

D. Performance Comparison

The selected studies employed a variety of evaluation metrics, including Accuracy, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and R^2 Score, to assess the effectiveness of stock market prediction models. Although the reported performance varied due to differences in datasets, preprocessing techniques, and experimental settings, a clear performance trend was observed among Machine Learning, Deep Learning, and Hybrid approaches. Machine Learning models demonstrated satisfactory prediction performance with relatively low computational complexity, whereas Deep Learning models achieved higher accuracy by effectively capturing nonlinear temporal dependencies in financial time-series data. Hybrid approaches consistently outperformed individual models by combining the strengths of multiple learning techniques, resulting in higher prediction accuracy and lower forecasting errors. However, these models generally require greater computational resources and more complex training procedures.

Table 6. Average Performance Comparison of Major Prediction Approaches

Approach	Typical Accuracy	Common Evaluation Metrics	Computational Cost
Machine Learning	85–95%	MAE, RMSE, R^2	Low
Deep Learning	90–99%	RMSE, MAPE, MSE	Medium
Hybrid Approaches	95–99%	MAE, RMSE, R^2, MAPE	High

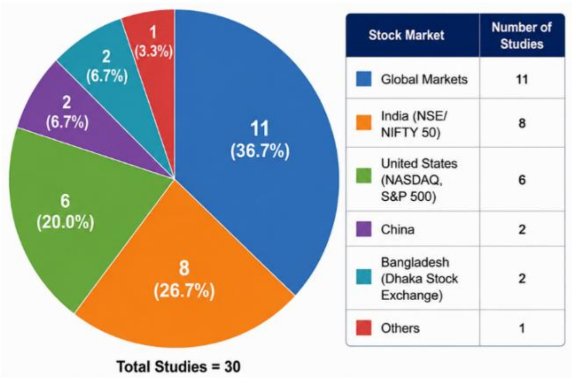

Figure 10. Distribution of Stock Markets Covered in the Selected Studies

Figure 10 illustrates the distribution of stock markets analyzed in the selected studies. The Global Markets account for the largest share (36.7%), followed by the Indian stock market (26.7%) and the United States market (20.0%). In contrast, comparatively fewer studies focused on the Chinese (6.7%) and Bangladesh (6.7%) stock markets, while 3.3% of the studies investigated other regional markets. This distribution indicates that publicly available global financial datasets dominate stock market prediction research, whereas emerging regional markets remain relatively underexplored, presenting opportunities for future research.

5. Research Challenges

The remarkable progress achieved in stock market prediction through Machine Learning (ML), Deep Learning (DL), and Hybrid approaches, several challenges continue to limit the accuracy, reliability, and practical deployment of intelligent forecasting systems. Financial markets are highly dynamic and influenced by numerous economic, political, and social factors, making accurate prediction a complex task [51]. The systematic review of the selected studies identified several common challenges that require further investigation.

A. Market Volatility: Stock markets are inherently volatile and are continuously affected by macroeconomic conditions, geopolitical events, investor sentiment, and unexpected global crises. Such rapid fluctuations often alter market behavior, making prediction models trained on historical data less effective. Consequently, forecasting models may fail to generalize under changing market conditions, reducing their predictive performance [52].

B. Non-Stationary Financial Data: Financial time-series data exhibit non-stationary characteristics, where statistical properties such as mean and variance change over time. Since many prediction models assume relatively stable data distributions, sudden structural changes or concept drift can significantly degrade forecasting accuracy. Developing adaptive models capable of handling evolving market behavior remains an important research challenge [53].

C. Data Quality and Missing Values: The performance of prediction models strongly depends on the quality of the input data. Financial datasets often contain missing values, noisy records, outliers, and inconsistent information resulting from market interruptions or data collection errors. Although preprocessing techniques such as normalization, interpolation, and data imputation are widely used, ensuring high-quality datasets continues to be essential for reliable stock market prediction [54].

D. Feature Selection and Data Integration: Most existing studies primarily utilize historical stock prices and technical indicators while giving limited attention to external information such as financial news, social media sentiment, macroeconomic indicators, and company fundamentals. Selecting the most informative features and effectively integrating multiple heterogeneous data sources remain significant challenges for improving forecasting accuracy [55].

E. Overfitting and Generalization: Advanced Deep Learning and Hybrid models often contain a large number of trainable parameters, increasing the risk of overfitting, especially when trained on limited datasets. Models that perform exceptionally well during training may fail to generalize to unseen market conditions. Techniques such as regularization, dropout, cross-validation, and transfer learning are increasingly adopted; however, achieving robust generalization remains an open problem [56].

F. High Computational Complexity: Deep Learning and Hybrid approaches generally require substantial computational resources, including high-performance processors and GPUs, for model training and optimization. Large datasets, complex network architectures, and extensive hyperparameter tuning increase both computational cost and training time, limiting their deployment in resource-constrained environments and real -time trading applications [57].

G. Model Interpretability: Deep Learning models achieve high forecasting accuracy; their prediction mechanisms are often difficult to interpret. The lack of transparency reduces user confidence and limits practical adoption in financial decision-making. Developing explainable AI (XAI) techniques that provide interpretable prediction results has become an important direction for future research [58].

H. Real-Time Prediction and Model Adaptation: Most reviewed studies evaluate their models using historical datasets under offline experimental settings. However, real-world financial markets continuously evolve, requiring prediction models that can adapt to newly arriving information in real time. Designing adaptive learning frameworks capable of continuously updating model parameters without extensive retraining remains a significant challenge [59].

I. Limited Benchmarking and Standardized Evaluation: Another major challenge identified in the reviewed literature is the lack of standardized benchmark datasets and evaluation protocols. Different studies employ various datasets, prediction horizons, preprocessing methods, and performance metrics, making direct comparisons difficult. Establishing common benchmark datasets and standardized evaluation frameworks would facilitate fair comparisons and accelerate future [60].

Table 8. Major Research Challenges in Stock Market Prediction

Challenge	Impact on Prediction	Possible Future Solution
Market Volatility	Reduces forecasting stability	Adaptive and online learning models
Non-Stationary Data	Performance degradation over time	Concept drift detection and continual learning
Missing and Noisy Data	Lower prediction accuracy	Advanced preprocessing and data cleaning
Feature Selection	Irrelevant features reduce performance	Automated feature selection and multimodal learning
Overfitting	Poor generalization	Regularization, cross-validation, transfer learning
High Computational Cost	Increased training time	Lightweight and efficient AI models
Model Interpretability	Difficult to explain predictions	Explainable Artificial Intelligence (XAI)
Real-Time Prediction	Limited practical deployment	Online learning and streaming data frameworks
Lack of Standard Benchmarks	Difficult model comparison	Standardized datasets and evaluation protocols

6. FUTURE RESEARCH DIRECTIONS

The rapid advancement of Artificial Intelligence (AI) has significantly improved stock market prediction; however, several opportunities remain for further enhancing the accuracy, robustness, and practical applicability of forecasting models. Based on the findings of this systematic literature review, several promising future research directions are identified to address the limitations of existing approaches.

A. Multimodal Data Integration: Most existing studies rely primarily on historical stock prices and technical indicators for prediction. Future research should focus on integrating multiple data sources, including financial news, social media sentiment, macroeconomic indicators, company financial statements, and geopolitical events. Combining structured and unstructured data can provide a more comprehensive understanding of market behavior and improve prediction accuracy under dynamic market conditions.

B. Explainable Artificial Intelligence (XAI): Deep Learning and Hybrid models achieve superior forecasting performance; their decision-making processes remain difficult to interpret. Future studies should incorporate Explainable XAI techniques to improve model transparency and provide understandable explanations for prediction outcomes. Enhanced interpretability will increase user trust and facilitate the adoption of AI-based forecasting systems in financial decision-making.

C. Adaptive and Real-Time Learning: Financial markets continuously evolve due to changing economic conditions and investor behavior. Therefore, future prediction systems should adopt adaptive and online learning frameworks capable of updating model parameters in real time. Such models can effectively handle concept drift and maintain prediction accuracy without requiring complete retraining.

D. Advanced Deep Learning Architectures: Recent developments in Transformer networks, Graph Neural Networks (GNNs), Temporal Convolutional Networks (TCNs), and attention-based architectures have demonstrated promising performance in sequential data analysis. Future research should investigate the application of these advanced architectures to capture long-term dependencies and complex relationships in financial time-series data more effectively than conventional LSTM-based models.

E. Lightweight and Computationally Efficient Models: Hybrid and Deep Learning models provide high prediction accuracy; they often require significant computational resources and long training times. Future studies should focus on developing lightweight AI models that maintain competitive forecasting performance while reducing computational complexity. Such models would be more suitable for real-time applications and deployment on resource-constrained systems.

F. Improved Feature Engineering and Selection: Feature selection plays a crucial role in stock market prediction. Future research should explore automated feature selection techniques and advanced representation learning methods to identify the most informative financial indicators while eliminating redundant and irrelevant features. This can improve model efficiency and reduce overfitting.

G. Standardized Benchmark Datasets and Evaluation Protocols: The reviewed studies employ different datasets, preprocessing methods, prediction horizons, and evaluation metrics, making fair comparison difficult. Establishing standardized benchmark datasets and common evaluation protocols would improve reproducibility and enable objective performance comparisons among prediction models.

H. Robust Hybrid Prediction Frameworks: Hybrid approaches have demonstrated superior performance by combining the strengths of Machine Learning and Deep Learning algorithms. Future work should focus on designing more robust hybrid frameworks that integrate ensemble learning, optimization algorithms, and multimodal feature extraction techniques to further improve forecasting accuracy and model generalization across different stock markets.

7. Discussion

This section presents a comparative analysis of the reviewed studies by examining the strengths, limitations, and research trends of ML, DL, and Hybrid approaches for stock market prediction. The comparison is based on prediction models, datasets, evaluation metrics, computational complexity, and forecasting performance.

Machine Learning techniques, including SVM, RF, KNN, Linear Regression, and XGBoost, are widely used due to their simplicity, computational efficiency, and ease of implementation. These models perform well with historical stock prices and technical indicators but often require manual feature engineering and have limited ability to capture complex nonlinear and temporal relationships in financial data.

Deep Learning models, such as LSTM, CNN, RNN, and DNN, achieve higher prediction accuracy by automatically learning complex patterns from time-series data. Among these, LSTM is the most frequently adopted model because of its effectiveness in modeling long-term dependencies. However, Deep Learning approaches require larger datasets, higher computational resources, and often suffer from limited interpretability.

Hybrid approaches combine Machine Learning and Deep Learning models to improve forecasting performance. The reviewed studies indicate that hybrid models consistently achieve the highest prediction accuracy and lower forecasting errors by leveraging the strengths of multiple algorithms. Nevertheless, these approaches increase model complexity, computational cost, and training time.

The analysis also shows that Yahoo Finance, NASDAQ, S&P 500, and NIFTY 50 are the most commonly used datasets, while MAE, RMSE, MAPE, MSE, and R^2 Score are the predominant evaluation metrics. Most studies rely on historical price data and technical indicators, whereas comparatively fewer incorporate financial news, social media sentiment, or macroeconomic factors, highlighting an important research gap.

Machine Learning models provide efficient and interpretable forecasting solutions, Deep Learning models offer superior predictive performance, and Hybrid approaches achieve the best overall results by combining complementary techniques. Future research should focus on multimodal data integration, explainable artificial intelligence, and real-time adaptive forecasting models to further improve the accuracy and reliability of stock market prediction systems.

CONCLUSION

This systematic literature review presented a comprehensive analysis of recent advancements in stock market prediction using ML, DL, and Hybrid approaches. A systematic review methodology based on the PRISMA framework was adopted to identify, screen, and analyze relevant studies published between 2020 and 2026. The selected studies were examined from multiple perspectives, including publication trends, datasets, prediction models, evaluation metrics, and forecasting performance.

The comparative analysis revealed that Machine Learning models, such as SVM, RF, and XGBoost, provide computationally efficient and interpretable solutions for stock market prediction. In contrast, Deep Learning models, particularly LSTM and CNN, demonstrated superior capability in learning complex temporal patterns and nonlinear relationships from financial time-series data. Furthermore, Hybrid approaches consistently achieved the highest prediction accuracy by integrating the complementary strengths of multiple learning algorithms. The review also identified Yahoo Finance as the most widely used dataset and highlighted RMSE, MAE, MAPE, and R^2 Score as the predominant evaluation metrics employed for model assessment.

The significant progress in AI-based stock market prediction, several research challenges remain unresolved, including market volatility, non-stationary financial data, overfitting, computational complexity, limited model interpretability, and the lack of standardized benchmark datasets. These challenges continue to affect the robustness and real-world applicability of existing forecasting models.

Future research should focus on developing adaptive and explainable forecasting systems capable of learning from continuously evolving financial markets. Integrating multimodal information, such as historical stock prices, financial news, social media sentiment, macroeconomic indicators, and company fundamentals, has the potential to further improve prediction accuracy and robustness. In addition, emerging AI techniques, including Transformer-based architectures, GNN, XAI, Federated Learning, and Reinforcement Learning, offer promising opportunities for building more intelligent and reliable stock market prediction systems. Establishing standardized benchmark datasets and evaluation protocols will also improve the reproducibility and comparability of future research.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

FUNDING SUPPORT

The author declare that they have no funding support for this study.

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