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A SURVEY OF TIME SERIES-BASED AUTOMATED TRADING STRATEGIES IN STOCK MARKETS USING MACHINE LEARNING AND DEEP LEARNING

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Abstract: Predicting the stock market and automated trading are both very difficult practices because of the financial markets' nature, which is highly volatile, dynamic, and non-linear. Time Series-Based Automated Trading Strategies in Stock Markets are popular because they can help capture the intricate, changing patterns of the market and allow investments to be made based on data. The current study thoroughly reviews all the methods of classical and modern forecasting of financial time series, mainly from the perspective of their applications in stock trading. Traditional statistical models such as AR, MA, ARIMA, and ARCH/GARCH have provided foundational methods for modelling dependencies in stock prices, solving volatility problems, and determining when to apply the stationary process. However, as global financial markets have become increasingly complex, deep learning (DL) architectures, such as RNNs, LSTMs, CNNs, and hybrid CNN-LSTM models, have risen to the forefront as adept tools for managing sequential dependencies and deriving features for stock market prediction. In addition, machine learning (ML) methods such as supervised Linear Regression, KNN, SVM, and Naïve Bayes, as well as unsupervised K-Means, DBSCAN, Gaussian Mixture Models, and Mean Shift, have collectively provided robust solutions for market segmentation and pattern recognition. The study portrays the coming of age, the hurdles posed by non-stationarity, and the future of sophisticated learning frameworks for improving forecasting precision and automated trading in today's financial markets by combining these approaches.

Keywords: Stock market forecasting, Predictive accuracy, Trading strategy optimization, Predictive accuracy, Investor preferences, Ensemble learning, Model interpretability, Data stream mining.

1 INTRODUCTION

The digital era witnesses a massive transformation in the finance sector, which is basically the result of fast technology innovations, as well as the strong need to adapt to the changing social and economic conditions[1]. One of the main aspects of this transition is sustainable finance, which is the backbone of the green economy. Financial innovations, for instance, improving climate change mitigation, energy efficiency, and the circular economy, are some of the long-term initiatives that are steadily drawing attention through the provision of funds by the financial tools introduced in sustainable finance.

The rapid advent of deep learning (DL) and machine learning (ML) technologies in the past few years has significantly increased interest in stock market prediction [2]. To put it another way, forecasting has undergone a revolution by the introduction of these methodologies, which not only provided advanced but also data-driven strategies that were able to analyze huge amounts of financial data. Using historical data, economic indicators, sentiment analysis, and other factors, stock market prediction makes estimates about market trends, volatility, and stock prices[3][4]. Financial institutions, traders, and investors may all benefit greatly from accurate forecasts, which can have an impact on risk management, investment strategies, and decision-making procedures.

Thus, there is a direct connection between ML problems and investor goals in the automated stock trading system. The complexity and volatility of the stock market make it impossible to include all relevant factors in a model, making the development of a trustworthy automated stock trading system a challenge for financial engineers and authorities. In the stock market, a trading strategy is a plan that aims to achieve a good return by going long, purchasing, or short, or selling securities[5][6]. A buy signal or bullish crossover occurs when the smaller exponential moving average crosses to the upside of the bigger one. The models are highly effective at discovering intricate relationships and patterns in time-series data, which makes them ideal for applications like stock price prediction[7]. However, access to huge datasets and significant computational resources is frequently necessary for them to be effective.

Predicting financial markets has always been a tough challenge due to the noise, unpredictability, and volatility of the market. Nevertheless, the introduction of DL algorithms offers the first chance to increase prediction accuracy substantially by revealing, through simulations, the dynamic correlations that were previously hidden by conventional statistical methods. DL allows for a more comprehensive range of inputs, which includes not only the historical market data but also macroeconomic factors and textual data from news and social media, whereas traditional algorithmic trading techniques have generally relied on technical indicators only. This very transformation has allowed the algorithmic trading systems to initiate the execution of trades and make active adjustments and optimizations of the setups[8]. ML has become a powerful analysis tool for data and thus, it has been the main area of research in the finance sector lately. Simply put, ML is a technique that provides computer systems with the ability to learn from data and thus, improve over time, making them capable of performing specific tasks automatically without explicit. In the financial [9][10], ML is a powerful tool for evaluating large amounts of time series data, which may be used to make informed investment decisions. This data can include interest rates, stock prices, currency rates, and other financial indicators.

1.1 Structure of the paper

This review covers AI and ML applications in stock market forecasting. Section 2 introduces evolution of time series in stock markets. Section 3 discusses ML in stock market forecasting. Section 4 covers DL approaches for time series trading. Section 5 summarizes recent studies with key findings and challenges. Section 6 concludes with future research directions.

2 EVOLUTIONS OF TIME SERIES IN STOCK MARKETS

In the stock market, fundamental analysts utilize data on the company's profits, both past and present, to assess fairness and compare it to market value to decide whether to invest in or omit it [11]. The most important theory in modern finance states that "any asset value equals the present value of all expected future cash flows discounted at the required return." This formula takes into account both the certainty and uncertainty of a company's cash flow generation capabilities, which in turn determine the company's worth.

2.1 Time Series Analysis for The Stock Market

Time series analysis can be applied to any collection of variables that exhibit time-dependent changes. Time series are commonly utilized for stock or share prices to track the price of a security over time[12]. The opening to closing prices of securities on a daily basis, the closing prices of those same securities on a monthly basis over the past 15 to 20 years, or even the price of a security from the beginning of the business day to its finish are all examples of short-term tracking of this. The stock market's most notable features are seasonal trends and flows. Any number of related economic variables, such as a company's capital or security, may be monitored in this way. Yet another use case is examining the correlation between the chosen data point's change and the changes in other variables over the same time frame.

2.2 Classical Approaches of Financial Time Series

This section includes four primary time series models: autoregressive (AR), moving average (MA), autoregressive integrated moving average (ARIMA) and ARCH/GARCH.

- **AR:** The AR model analyzes past values derived from a time series. The financial industry. The previous stock's price determines future stock prices, and stock returns also exhibit autocorrelation [13]. The AR model is appropriate for this purpose because there is a linear relationship between an asset's present value and its prior value. The AR model is effective for short-term financial forecasting in stable markets.
- **Moving Average (MA):** The Moving Average (MA) Model uses the link between future values and past mistakes (or shocks) to forecast, making it a powerful tool. Because prior forecast mistakes can explain variance, the MA model works well with random shocks or short-term volatility.
- **ARIMA:** The predicted value in ARIMA is based on linear combinations of the individual's own prior observed values; this is one of the three components of auto-regressive integrated moving averages (ARIMA). The time series is differentiated to make it stationary after integration (I). A non-stationary time series may yield erroneous predictions due to the influence of trend and seasonality. That's why differencing—that is, the difference between the observations and the previous data—is used to initially make the time series stationary.
- **ARCH/GARCH:** The ARCH and GARCH models are the two time-varying volatility models. Predicting the conditional variance of return series is the goal of the ARCH model [14]. One of the most advanced statistical methods used in volatility is the GARCH model. The GARCH model makes better use of resources (fewer parameters) than the ARCH model.

2.3 Characteristics of Financial Time Series

The swift advancement of technology and transportation, along with the growing interconnectedness and integration of global financial markets. Financial markets are always changing and growing, from the conventional energy and equities markets to the newly formed cryptocurrency sector [15]. For financial markets to function and manage risk, forecasting financial time series changes is crucial. Some characteristics of financial time series are discussed below:

- **Non-Stationarity:** In short-term modeling, non-stationarity can result in misleading regressions because short-term variations are very unpredictable and random. Notably, non-stationary features affect the modeling of short-term and long-term dependence in different ways.
- **Volatility:** Volatility, which gauges how much prices fluctuate around their mean value, is a critical measure of asset price swings in financial markets. Volatility plays a decisive role in risk evaluation and in investors' decision-making. Because

increased volatility generally means heightened risk, which in turn might lead to market crashes and heavy portfolio losses, volatility has again become a focus of research since the 2008 global financial crisis [16]. Thus, precise volatility measurement and forecasting become indispensable for risk management and the stability of financial markets.

- **Signal-to-Noise Ratio:** A vital issue to be considered is the low signal-to-noise ratio (SNR) in financial data processing. A low SNR suggests that noise or random oscillations are overpowering the signal, which is the useful information. Noisy financial data can lead to misunderstandings and incorrect conclusions, which could result in large losses. Conversely, data noise can impair ML models' effectiveness, reduce the accuracy of their predictions, and increase the risk of poor decision outcomes.

3 MACHINE LEARNING IN STOCK MARKET FORECASTING

ML technology provides a data-driven method of making stock market predictions by looking at a lot of historical data to find trends and connections that the original model might have missed.

3.1 Supervised Learning Setting

The problem of one-step forecasting can be addressed as a supervised learning problem. In supervised learning, the relationship between a set of input variables and one or more output variables—which are thought to be partially reliant on the inputs—is modeled using a limited number of observations[17]. Certain supervised learning approaches are discussed below:

- **Linear Regression (LR):** Predicting stock or market prices using linear regression requires a model that takes into account at least one attribute, such as trading volume, closing price, or open price. Replicating the linear connection between the dependent and independent variables is the main objective of regression modeling. The linear regression model's best-fit line depicts the connection between the dependent variable and the independent components.
- **K-Nearest Neighbor (KNN):** In the realm of classification and regression, KNN is known as the "lazy learner" because of its relatively low learning threshold. KNN is one of the simplest ML algorithms, which is one of its benefits. For KNN, the only steps required are to compute the Euclidean distance and the value of K [18]. This method outperforms other algorithms due to its slow learning feature.
- **Support Vector Machine (SVM):** Support vector machines (SVMs) are a kind of classification and regression algorithm that have the potential to be the most useful tool for predicting stock prices and market trends. The comparison of SVM and its variations, including "Peeling + SVM" and "CC + SVM," demonstrates that more sophisticated SVM techniques can enhance its prediction. A support vector machine uses a separator and supervised learning to classify many attributes. The separator is located after the first data mapping to a high-dimensional feature space. By categorizing the data points that occur in an n-dimensional space, the optimal hyperplane may be discovered.
- **Naïve Bayes (NB):** Stock price predictions for various banking stock studies may be made using a supervised ML technique known as Naïve Bayes. Using a mixture of probability, Naïve Bayes is a classification technique that uses a dataset to aggregate values and frequencies. Whether the naïve Bayes qualities are independent or interdependent is assumed by the Bayes theorem using the class variable values[19]. In the existence of an output value, attribute values are independent, according to the fundamental idea of naïve Bayes.

3.2 Unsupervised Learning for Clustering

Unsupervised ML necessitates large data sets. In most cases, supervised learning functions similarly, with the model's accuracy increasing with the number of instances supplied. Data scientists start using datasets to train algorithms is an example of unsupervised learning. Some clustering algorithms are discussed below:

- **K-Means Clustering:** Clustering, often known as cluster analysis, is the act of arranging data points into sets. It is possible to differentiate between probabilistic, overlapping, hierarchical, and partitioning clustering. The term "exclusive pooling" might also describe it[20]. Partitioning is illustrated via K-means. Every data point is treated as a cluster in the hierarchical clustering approach. It is possible to allocate each point to two or more categories with differing degrees of association. The data paired with an appropriate membership value in this scenario, like K-Means clustering. Lastly, in probabilistic modeling, clusters are created using the probability distribution.

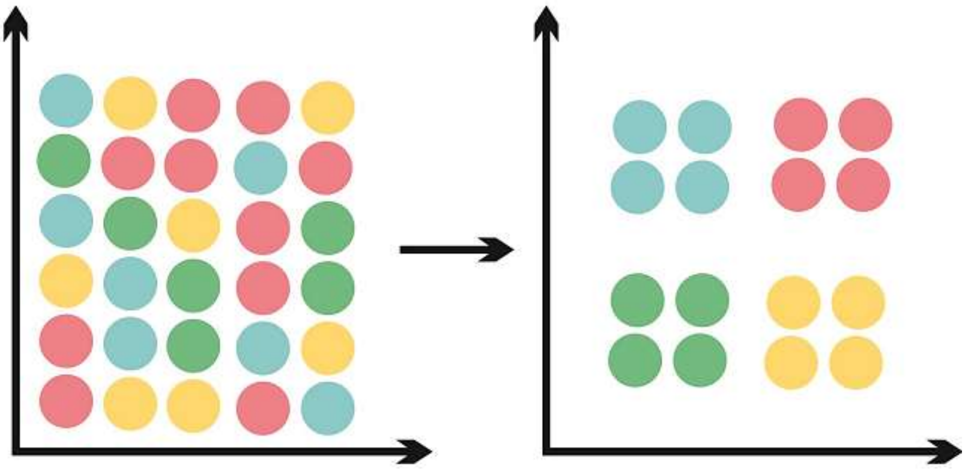

Figure 1: Example of Clustering

Figure 1 illustrates data clustering or classification. On the left, 24 colored data points (red, teal, green, yellow) appear scattered without clear boundaries. After transformation (indicated by the arrow), the right side shows the same points grouped into four distinct clusters teal (top-left), red (top-right), green (bottom-left), and yellow (bottom-right) demonstrating how an algorithm can separate data into meaningful categories.

- **DBSCAN Clustering:** It is common practice to employ k-means for initial point optimization in clustering algorithms due to its sensitivity to the starting point. Similarly, while using the DBSCAN clustering method, users often forget to optimize the starting point[21] compared to k-means. But according to [22], Improving the beginning point of the DBSCAN method can somewhat improve the clustering impact.
- **Gaussian Mixture Distribution:** The general deviation of individual stock return distributions from normal or t-distributions, with more complicated patterns like bimodality or skewness, is well documented [23]. Complex distributions of returns on financial assets can be effectively characterized by the Gaussian mixture distribution, a powerful statistical tool that combines multiple Gaussians to accurately capture and depict data distributions. They found that the mixed distribution may accurately simulate a variety of return distributions, supporting its efficacy.
- **Mean Shift Clustering:** As a nonparametric clustering technique, mean-shift clustering that may be used as an algorithm to find local maxima (modes) or to identify the modes of an underlying probability distribution from a collection of discrete samples. Using kernel density estimation to find areas of high data point density, Finding the largest value of a density function is the goal of the mode-seeking method known as mean-shift clustering.

4 DEEP LEARNING APPROACHES FOR TIME SERIES TRADING

DL is and addressed several particular DL designs that are frequently utilized in applications related to the stock market. It is important to remember that, notwithstanding references to particular applications of different network topologies in the stock market [24], all of the designs discussed are also often utilized for other purposes. However, when the stock market is the aim, several particular factors need to be considered [25]. These include the model's construction as well as the criteria and procedures for back testing and assessment.

- **Recurrent Neural Networks (RNNs) and LSTM for Sequential Data:** A unique kind of neural network known as a recurrent neural network (RNN) retains a representation of the input data that has been seen previously. Procedures that rely heavily on the input example's temporal or sequential sequence are good fits for these networks. Left Short-Term Memory (LSTM) is one type of RNN. Self-storing input memory is a remarkable feature of RNNs, making them a potent kind of artificial neural network. They are therefore especially well-suited to resolving issues with time series or other sequential data. The problem of vanishing gradient, which affects many RNNs, causes the model's learning to slow down or stop altogether[26]. The development of LSTMs in the 1990s was an attempt to solve this problem[27]. LSTMs allow them to learn from stimuli that are far apart in time.
- **Convolutional Neural Networks (CNNs) for Feature Extraction:** The effectiveness of CNNs in time series forecasting has been demonstrated, however, choosing an architecture is still a difficult problem. In order to predict future time series, a single multiplicative neuron model was used, this study proposes a CNN with the goal of removing the architectural complexity of conventional CNN while maintaining its computing efficiency [28]. Because local receptive fields exist, a CNN can extract local characteristics from data. Figure 1 shows the process of feature extraction from time-series data using CNN.

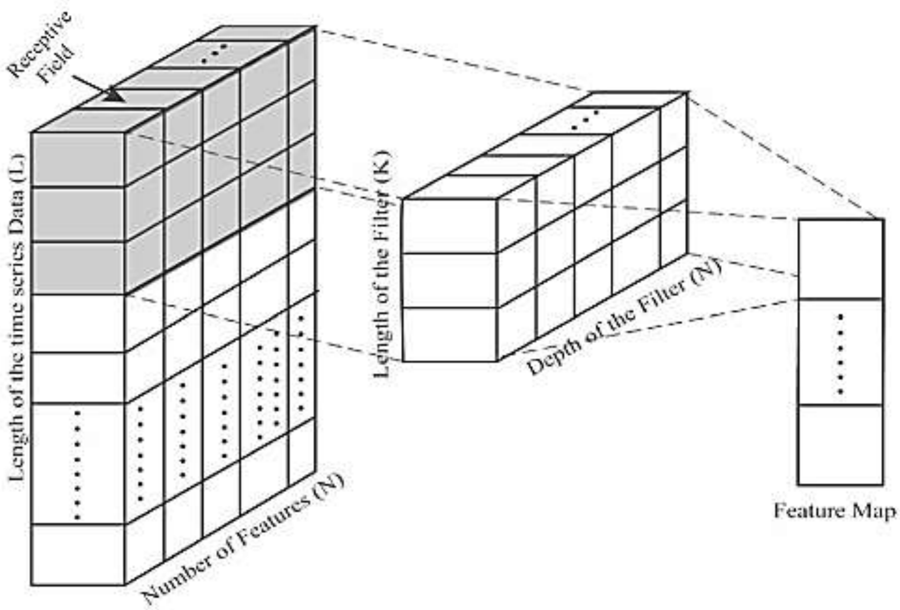

Figure 2: Feature Extraction in Time Series

Figure 2 illustrates the primary function of a time series processing layer of a 1D Convolutional Neural Network (CNN). The input is a 3D tensor that is determined by the number of features (N) and the length (L) of the time series. A filter (kernel), also a 3D tensor with length (K, where $K < L$) and depth (N), slides along the input length. At each position, the filter covers a receptive field (grey region), performs element-wise multiplication and summation with the corresponding input segment, and generates a single output value. The feature map (activation map) is the result of repeating this for all locations. The method is to get the spatially invariant patterns, so turning the original L × N input into the condensed sequence of learned features, which is the vital step in CNN-based time series analysis.

- **Hybrid CNN-LSTM for Time-Series Trading:** The CNN-LSTM is a sophisticated deep learning architecture that merges the strengths of LSTMs and CNNs. Although CNNs are very efficient in getting the spatial information out of the data, LSTMs have the upper hand in recognizing and understanding the long-term relations [29]. The combination of CNNs and LSTMs has led to the great effectiveness of the CNN-LSTM model across tasks such as natural language processing (NLP), speech recognition, and image classification.

5 LITERATURE REVIEW

The literature survey examines automated trading strategies based on time series, highlighting factors such as predictive accuracy, adaptability, and efficiency. The research is mainly concentrated on the application of deep learning in market dynamics' nonlinearity, feature engineering, and reinforcement learning for trading execution as well as the development of hybrid frameworks that combine technical, macroeconomic, and sentiment data for improving stock market prediction and decision-making.

Pattanayak, Sahoo and Swetapadma (2025). This research analyses the role of Deep Reinforcement Learning (DRL) techniques in predicting the financial market, namely the use of Deep Q-Network (DQN) and DQN with Long Short-Term Memory (LSTM) networks combination. Historical stock price data along with DQN models are to discover the optimal trading strategies first, then the market changes will be followed on the way and profits made. Experimental results demonstrate that DQN-based approaches outperform conventional ML models in terms of profitability and adaptability [30].

V, M and N (2025). The project describes algorithmic trading using ML with Arima, LSTM and Boost (ALX) for stock prediction and Alpaca API-based trading. It generates historical movements and creates technical indicators like moving average, RSI, MACD and executes the LSTM ML algorithms to predict market trends and generate sell or buy signals. The system applied is designed with a debugging module that is to enable debugging remotely and configuration files to keep API credentials safe. System deployment is defined and designed by establishing debugging modes [31].

Rajesh Dey (2025). In this research, we use ML and DL methods to predict how the Indian stock market will perform in the future. The primary goal is to help intraday and short-term traders make informed decisions by offering data-driven forecasts. This study included three powerful algorithms: LSTM, Boost and Random Forest (RF). To improve prediction accuracy, an ensemble learning technique lowers overfitting and boosts generalization in RF. Boost, which is renowned for its effectiveness and superior performance, uses gradient-boosting techniques to maximize predictions [32].

Al-Ali and Al-Alawi (2024). This study's primary goal is to analyse earlier studies that employed DL and ML algorithms to forecast stock market values and to emphasise the appropriate methods for doing so. In order to achieve this goal, eleven research articles were selected for review that examined the use of ML and DL algorithms in stock market prediction[33].

Ahmad *et al.* (2024) Stock market prediction using ML algorithms was the focus of this study. Now more than ever, the scientific community is enthralled with ML, or the capacity of computers to perform tasks often requiring human brains. According to their results, their LSTM model has produced more accurate price predictions than simpler models. The purpose of this article is to present a model for predicting stock market values using RNN, with a focus on the LSTM network in particular[34].

Kumar, Pal and Tripathi (2024). This research explores a method for predicting stock prices using ML, LSTM networks. These learning-based networks solve the problem by accurately identifying intricate patterns in historical stock data. Their aim in reviewing the literature and looking at real-world applications is to add to the conversation on using ML, and more especially LSTM networks, to make stock price predictions more accurate and reliable[35].

Ul-Haq, Purwandari and Mahatma (2023) this study, five supervised ML algorithms were evaluated, including Naive Bayes, Decision Tree, Support Vector Machine (SVM), RF, and Gradient Boosted Trees, to predict market manipulation based on the list of stocks marked by the Indonesian Stock Exchange as having Unusual Market Activity (UMA). SMOTE was used to address imbalanced data. The empirical findings of this research demonstrate that the developed model is highly accurate. RF has the highest accuracy, with a three-day historical price of 97% [36].

Al-Alawi and Alaali (2023) this paper, highlight the appropriate ML methods for stock price prediction are highlighted. A review of 12 research publications pertaining to the use of DL and ML algorithms to stock price prediction is the approach employed to accomplish this goal. In contrast to previous studies, Instead of selecting articles at random, our research centers on two main sectors: healthcare and banking[37].

Julian *et al.* (2023) explain the process of using ML to foretell the same. To achieve mostly reliable predictions, they suggested an ML algorithm trained on datasets from previously accessible companies. Share market forecasting is a method for predicting how much a financial asset, such as a company's shares, would be worth in the future when exchanged on a stock exchange. A quantifiable, significant gain is the sole objective of stock market forecasting, coupled with, of course, preventing significant losses[38].

Table 1 presents a compilation of contemporary investigations on the application of AI, ML, and DL techniques in stock market prediction and trading, emphasizing the methods adopted, significant results, constraints, and prospects for further research.

Table 1: Summary of Recent Studies on AI, ML and ML Applications in Stock Market Forecasting and Trading

Reference	**Study On**	**Approach**	**Key Findings**	**Challenges / Limitations**	**Future Directions**
Pattanayak, Sahoo & Swetapadma (2025)	Financial forecasting with Deep Reinforcement Learning	Deep Q-Network (DQN) and hybrid LSTM-DQN using historical stock data	DQN models learn optimal trading strategies, outperforming conventional ML in profitability and adaptability	Lack of explainability, no explicit risk management, assumes ideal market conditions	Develop hybrid LSTM-DQN models; integrate real-world trading constraints and risk controls
V, M & N (2025)	Algorithmic trading system	ALX model combining ARIMA, LSTM, XGBoost with Alpaca API; technical indicators (MA, RSI, MACD)	Generates market trend predictions and automated buy/sell signals; supports remote debugging and secure deployment	Requires continuous API reliability; sensitive to data quality	Enhance robustness for live trading; expand to multi-asset and high-frequency environments
Rajesh Dey (2025)	Stock value prediction for intraday/short-term trading	Ensemble of LSTM, Gradient Boost (Boost), and Random Forest	Improved prediction accuracy; ensemble lowers overfitting and increases generalization	May require extensive hyperparameter tuning; market volatility affects performance	Explore broader ensemble techniques and real-time adaptive learning
Al-Ali & Al-Alawi (2024)	Review of ML/DL for stock market prediction	Survey of 11 research papers on ML & DL	Identifies effective algorithms and their comparative performance	Limited to selected studies; lacks experimental validation	Provide standardized benchmarks; extend review to more recent datasets and techniques

Ahmad et al. (2024)	Stock market forecasting with deep learning	Recurrent Neural Networks, specifically LSTM	LSTM outperforms simpler models; highlights advantages of DL over linear models	Requires large training data; potential overfitting	Explore hybrid RNN architectures and transfer learning for varied markets
Kumar, Pal & Tripathi (2024)	Stock price prediction using LSTM	Deep learning with LSTM networks on historical stock data	Captures complex temporal patterns for precise forecasts	Sensitive to sudden market shocks; computational cost	Integrate external economic indicators; improve real-time adaptability
Ul-Haq, Purwandari & Mahatma (2023)	Detecting market manipulation	Gradient Boosted Trees, Random Forest, SVM, Decision Trees, Naive Bayes, and SMOTE for imbalance	Random Forest achieved 97% accuracy with 3-day historical price data	Model may not generalize across markets; relies on accurate UMA labels	Apply to other exchanges; incorporate additional fraud detection features
Al-Alawi & Alaali (2023)	Review of ML/DL techniques for banking & healthcare stock sectors	Literature review of 12 research papers	Highlights suitable ML/DL techniques for sector-specific stock prediction	Limited scope; no empirical testing	Sector-wise comparative analysis with larger datasets
Julian et al. (2023)	Stock market forecasting	Machine learning on multi-company historical datasets	Demonstrates potential for profit despite Efficient Market Hypothesis skepticism	Forecast accuracy limited by market randomness and data quality	Develop ensemble ML methods; integrate alternative data (social sentiment, news)

6 CONCLUSION AND FUTURE WORK

Automated trading strategies based on time-series in Stock Markets have come a long way, integrating classical statistical models, ML algorithms, and advanced DL architectures that have contributed to prediction accuracy and trading efficiency. The research is showing that old-fashioned models like AR, MA, ARIMA, and ARCH/GARCH have not lost their value since they are still good for the comprehension of short-term price movements, volatility, and market dynamics, while the modern ones, such as CNNs, RNNs, LSTMs, and hybrid CNN-LSTM models, have superior understanding for drawing up complex characteristics and getting long-term relationships with data coming from finance. In addition to machine learning techniques such as supervised SVM, Linear Regression, and KNN, and unsupervised clustering methods like K-Means, DBSCAN, Gaussian Mixtures, and Mean Shift, all are reliable for the backbone of pattern recognition, market segmentation, and risk assessment. In time-series analysis of the finance sector, the outcomes highlight the need to address non-stationarity, volatility, and poor signal-to-noise ratio, which are major issues. In a nutshell, the combination of classical and modern analytical frameworks is the way to go for developing more robust, adaptive automated trading strategies that can significantly change the dynamics of the stock market in terms of decision-making, risk management, and profitability.

The future of Time Series-Based Automated Trading Strategies research can leverage advancements in Transformer-based models, attention mechanisms, and hybrid statistical–ML–DL approaches to achieve higher prediction accuracy. Alternative data, real-time reinforcement learning, and further work on interpretability, efficiency, and overfitting will all contribute to a better, more adaptable model for the fast-changing world of finance.

REFERENCES

[1] O. Manta, V. Vasile, and E. Rusu, "Banking Transformation Through FinTech and the Integration of Artificial Intelligence in Payments," *FinTech*, vol. 4, no. 2, pp. 1–13, Apr. 2025, doi: 10.3390/fintech4020013.

[2] H. Prakash and C. Kapadia, "API-Driven Banking: How COVID-19 Remote Work Boosted Open Banking and Fintech Integrations," vol. 8, no. 10, pp. 514–519, 2021.

[3] V. Verma, "LSTM-based to Predicting Stock Market Trends Using Machine Learning and Sentiment Analysis," *Int. J. Res. Anal. Rev.*, vol. 8, no. 3, 2021.

[4] N. Malali, "AI Ethics in Financial Services: A Global Perspective," *Int. J. Innov. Sci. Res. Technol.*, vol. 10, no. 2, pp. 2456–2165, 2025, doi: /10.5281/zenodo.14881349.

[5] R. D. S. K. S. M. Rupali Atul Mahajan, Arup Kadia, Monika Singh, "Machine Learning Based Automated Trading Strategies for Indian Stock Market," *J. Electr. Syst.*, vol. 20, no. 2s, pp. 747–758, 2024, doi: 10.52783/jes.1572.

[6] S. B. Shah, "Advancing Financial Security with Scalable AI: Explainable Machine Learning Models for Transaction Fraud Detection," in *2025 4th International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE)*, 2025, pp. 1–7. doi: 10.1109/ICDCECE65353.2025.11034838.

[7] A. R. Bilipelli, "Forecasting the Evolution of Cyber Attacks in FinTech Using Transformer-Based Time Series Models," *Int. J. Res. Anal. Rev.*, vol. 12, no. 3, pp. 1–7, 2023.

[8] R. Q. Majumder, "Machine Learning for Predictive Analytics: Trends and Future Directions," *Int. J. Innov. Sci. Res. Technol.*, vol. 10, no. 04, pp. 3557–3564, 2025.

[9] W. Wang, "Machine Learning in Financial Time-series Data," *Adv. Econ. Manag. Polit. Sci.*, vol. 92, no. 1, pp. 293–299, 2024, doi: 10.54254/2754-1169/92/20231279.

[10] S. J. Wawge, "Evaluating Machine Learning and Deep Learning Models for Housing Price Prediction : A Review," *Int. J. Adv. Res. Sci. Commun. Technol.*, vol. 5, no. 11, pp. 367–377, 2025, doi: 10.48175/IJARSCT-25857.

[11] A. S. Wafi, H. Hassan, and A. Mabrouk, "Fundamental Analysis Models in Financial Markets – Review Study," *Procedia Econ. Financ.*, vol. 30, no. 15, pp. 939–947, 2015, doi: 10.1016/s2212-5671(15)01344-1.

[12] Vinay Singh, "AI-Driven Cash Flow Forecasting in ERP Systems: Integrating Economic Indicators and Real-Time Transaction Data Using LSTM-Based Time-Series Models," *J. Inf. Syst. Eng. Manag.*, vol. 10, no. 42s, pp. 238–248, 2025, doi: 10.52783/jisem.v10i42s.7879.

[13] W. Zeng, "Application of AR, MA, and ARMA Models in Financial Time Series Analysis," *Adv. Econ. Manag. Polit. Sci.*, vol. 141, no. 1, pp. 177–184, 2024, doi: 10.54254/2754-1169/2024.ga18862.

[14] I. M. Ghani and H. A. Rahim, "Modeling and Forecasting of Volatility using ARMA-GARCH: Case Study on Malaysia Natural Rubber Prices," in *IOP Conference Series: Materials Science and Engineering*, 2019. doi: 10.1088/1757-899X/548/1/012023.

[15] K. He, Q. Yang, L. Ji, J. Pan, and Y. Zou, "Financial Time Series Forecasting with the Deep Learning Ensemble Model," *Mathematics*, 2023, doi: 10.3390/math11041054.

[16] Y. Fan, "Financial Volatility Prediction Model Based on Denoising Autoencoder and Unstable Attention Mechanism," *Procedia Comput. Sci.*, vol. 261, pp. 45–52, 2025, doi: 10.1016/j.procs.2025.04.170.

[17] H. Kali, "Optimizing Credit Card Fraud Transactions Identification And Classification In Banking Industry Using Machine Learning Algorithms," *Int. J. Recent Technol. Sci. Manag.*, vol. 9, no. 11, pp. 1–12, 2024.

[18] J. Tanuwijaya and S. Hansun, "LQ45 stock index prediction using k-nearest neighbors regression," *Int. J. Recent Technol. Eng.*, vol. 8, no. 3, pp. 2388–2391, 2019, doi: 10.35940/ijrte.C4663.098319.

[19] I. Setiani, M. N. Tentua, and S. Oyama, "Prediction of Banking Stock Prices Using Naïve Bayes Method," in *Journal of Physics: Conference Series*, 2021. doi: 10.1088/1742-6596/1823/1/012059.

[20] A. Balasubramanian, "DYNAMIC DEPENDENCY MANAGEMENT IN SOFTWARE PROJECTS USING International Journal of Core Engineering & Management," *Int. J. Core Eng. Manag.*, vol. 7, no. 04, pp. 244–255, 2022.

[21] O. Limwattanapibool and S. Arch-int, "Determination of the appropriate parameters for K-means clustering using selection of region clusters based on density DBSCAN (SRCD-DBSCAN)," *Expert Syst.*, 2017, doi: 10.1111/exsy.12204.

[22] M. Huang, Q. Bao, Y. Zhang, and W. Feng, "A hybrid algorithm for forecasting financial time series data based on DBSCAN and SVR," *Inf.*, 2019, doi: 10.3390/info10030103.

[23] Y. Wang, J. Xu, S.-L. Huang, D. D. Sun, and X.-P. Zhang, "Assessing Uncertainty in Stock Returns: A Gaussian Mixture Distribution-Based Method," *Proc.*, vol. 1, no. 1, 2025.

[24] K. Olorunnimbe and H. Viktor, "Deep learning in the stock market—a systematic survey of practice, backtesting, and applications," *Artif. Intell. Rev.*, 2023, doi: 10.1007/s10462-022-10226-0.

[25] K. B. Thakkar and H. P. Kapadia, "The Roadmap to Digital Transformation in Banking: Advancing Credit Card Fraud Detection with Hybrid Deep Learning Model," in *2025 2nd International Conference on Trends in Engineering Systems and Technologies (ICTEST)*, IEEE, Apr. 2025, pp. 1–6. doi: 10.1109/ICTEST64710.2025.11042822.

[26] A. Yadav, C. K. Jha, and A. Sharan, "Optimizing LSTM for time series prediction in Indian stock market," in *Procedia Computer Science*, 2020. doi: 10.1016/j.procs.2020.03.257.

[27] V. Singh, "AI-Driven ERP Evolution: Enhancing Supply Chain Resilience with Neural Networks and Predictive LSTM Models," *Eur. J. Adv. Eng. Technol.*, vol. 12, no. 2, pp. 47–52, 2025.

[28] S. Nigam, "Forecasting time series using convolutional neural network with multiplicative neuron," *Appl. Soft Comput.*, vol. 174, p. 112921, 2025, doi: https://doi.org/10.1016/j.asoc.2025.112921.

[29] S. Almotairi, D. D. Rao, O. Alharbi, Z. Alzaid, Y. M. Hausawi, and J. Almutairi, "Efficient Intrusion Detection using OptCNN-LSTM Model based on hybrid Correlation-based Feature Selection in IoMT," *Fusion Pract. Appl.*, vol. 16, no. 1, 2024, doi: 10.54216/FPA.160112.

[30] A. M. Pattanayak, B. Sahoo, and A. Swetapadma, "A Deep Reinforcement Learning Technique for Stock Price Prediction and Trading Decision," in *2025 Second International Conference on Cognitive Robotics and Intelligent Systems (ICC - ROBINS)*, 2025, pp. 266–270. doi: 10.1109/ICC-ROBINS64345.2025.11086233.

[31] A. V, K. K. M, and K. N, "An ML based Stock Prediction and Automated Trading System using ALX," in *2025 5th International Conference on Pervasive Computing and Social Networking (ICPCSN)*, 2025, pp. 1574–1579. doi: 10.1109/ICPCSN65854.2025.11035240.

[32] Rajesh Dey, "Machine Learning-Based Automated Trading Strategies for the Indian Stock Market," *J. Inf. Syst. Eng. Manag.*, vol. 10, no. 26s, pp. 782–793, 2025, doi: 10.52783/jisem.v10i26s.4285.

[33] A. M. Al-Ali and A. I. Al-Alawi, "Stock Market Forecasting Using Machine Learning Techniques: A Literature Review," in *2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS)*, 2024, pp. 466–471. doi: 10.1109/ICETSIS61505.2024.10459681.

[34] S. Ahmad, M. A. Ansari, A. Mair, and S. Hussain, "Smart Market Insights: A Deep Learning Approach to Trend Analysis," in *2024 13th International Conference on System Modeling & Advancement in Research Trends (SMART)*, 2024, pp. 548–

555. doi: 10.1109/SMART63812.2024.10882505.

[35] S. Kumar, N. Pal, and A. M. Tripathi, “Improving Long Short-Term Memory (LSTM)-Based Stock Market Price Predictions in the Machine Learning Era,” in *2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT)*, 2024, pp. 923–928. doi: 10.1109/IC2PCT60090.2024.10486391.

[36] M. G. Ul-Haq, B. Purwandari, and K. Mahatma, “Predicting Market Manipulation in Stock Market using Supervised Machine Learning: A Case Study from the Indonesia Stock Exchange Unusual Market Activities,” in *2023 International Conference on Artificial Intelligence Robotics, Signal and Image Processing (AIRoSIP)*, 2023, pp. 182–187. doi: 10.1109/AIRoSIP58759.2023.10874005.

[37] A. I. Al-Alawi and Y. A. Alaali, “Stock Market Prediction using Machine Learning Techniques: Literature Review Analysis,” in *2023 International Conference on Cyber Management and Engineering, CyMaEn 2023*, 2023. doi: 10.1109/CyMaEn57228.2023.10050933.

[38] A. Julian, E. GaneshReddy, V. R. D. Reddy, and D. V. V Somasekhar, “Safe Trade – A Stock Recommender using Machine Learning Algorithms,” in *2023 International Conference on Computer Communication and Informatics (ICCCI)*, 2023, pp. 1–7. doi: 10.1109/ICCCI56745.2023.10128595.

