INTERNATIONAL JOURNAL OF RESEARCH IN ECONOMICS AND FINANCE, 2025, Vol. 2, No. 9, 15-47. https://doi.org/10.71420/ijref.v2i9.160

Systematic Literature Review: Advanced Artificial Intelligence Techniques for Forecasting Stock Prices

Oumaima AYI
Faculty of Economics and Management, Ibn Tofail University, Kénitra, Morocco.

Mounir ELBAKKOUCHI
Faculty of Economics and Management, Ibn Tofail University, Kénitra, Morocco.

Abstract. Artificial intelligence-based models have recently secured a legitimate foothold in the financial markets, serving as powerful analytical tools capable of significantly reducing the inherent uncertainties of investment activities and assisting investors in identifying stocks with the highest profitability potential. A key advantage for users lies in the ability to ground their strategies and decisions not on subjective reasoning, but on objectively derived quantitative data. Financial time series forecasting stands as one of the most successful computational applications in finance, owing to both the diversity of its areas of application and its operational effectiveness. A considerable body of Machine Learning (ML) research has been dedicated to this task, resulting in a substantial volume of literature and numerous literature reviews conducted over the years. More recently, Deep Learning (DL) models have emerged as even more advanced alternatives, consistently outperforming traditional ML approaches. While the use of DL is rapidly expanding in financial contexts, systematic reviews focusing exclusively on this area remain scarce. Hence, the present review aims to fill this gap. This work provides a comprehensive and systematic review of the current literature related to the application of artificial intelligence in financial forecasting. The analysis is further segmented by investment domains such as stock markets, foreign exchange, and commodities and by the specific Deep Learning models applied in each area. Additionally, it includes a critical discussion of persistent challenges and future directions, offering valuable insights for scholars pursuing research in this emerging field.

Keywords: *Artificial intelligence; Finance; Stock market forecasting; Financial forecasting; Deep learning, Convolution neural network, Stock market analysis.*

1. Introduction

The integration of Artificial Intelligence (AI) into stock price forecasting has expanded remarkably over the past two decades, driven by advances in machine learning (ML), deep learning (DL), and natural language processing (NLP). Financial institutions and academic researchers alike have demonstrated sustained interest in developing predictive models that can capture the complex and nonlinear dynamics of financial markets. The increasing automation of trading activities, coupled with the proliferation of electronic platforms, has further accelerated the development of AI-based forecasting techniques.

Over the years, deep learning models have consistently outperformed traditional econometric and statistical methods, establishing themselves as powerful tools for modeling financial time series. Despite these significant achievements, the literature on AI in finance remains fragmented: while numerous studies focus on specific algorithms or datasets, comprehensive reviews that consolidate the full spectrum of AI-driven approaches including machine learning, deep learning, reinforcement learning, and hybrid models are still scarce. Unlike prior reviews that concentrate either on narrow methodological aspects or on specific classes of models, this study provides a holistic and systematic examination of AI techniques applied to stock price forecasting. Its originality lies in offering a consolidated overview of the diverse AI paradigms used in financial prediction, evaluating their comparative strengths and limitations in relation to traditional forecasting approaches, and outlining emerging opportunities and future research directions. By doing so, the paper not only synthesizes the state of the art but also positions AI forecasting as a transformative paradigm within financial research and practice.

The motivation underlying this systematic literature review is threefold:

- To provide an updated state of the art of AI-based forecasting models from both academic and industrial perspectives;
- To highlight the distinctive features, methodological trade-offs, and performance benchmarks of each approach, helping scholars and practitioners avoid inappropriate methodological choices;
- To identify emerging opportunities and research gaps, thereby contributing to the advancement of financial forecasting science.

Stock price forecasting remains inherently challenging due to the non-linearity, volatility, and non-stationarity of financial time series. Asset prices are shaped by a multitude of intertwined factors, ranging from macroeconomic indicators and corporate fundamentals to geopolitical events and investor sentiment. As a result, robust predictive models are required to decode these influences, anticipate trends, and support decision-making processes in uncertain market environments.

Traditional approaches to forecasting rely on two dominant paradigms: fundamental analysis (FA), which uses firm-specific and macroeconomic data to assess intrinsic value and long-term growth potential, and technical analysis (TA), which assumes that market prices already incorporate available information and therefore emphasizes historical price patterns, chart indicators, and trading volumes. While both approaches continue to inform investment strategies, their limitations have motivated the adoption of AI-based models that can process high-dimensional datasets, capture hidden nonlinear patterns, and integrate unstructured data such as financial news or social media sentiment.

This paper is grounded in a Systematic Literature Review (SLR) methodology designed to ensure rigor and transparency in synthesizing prior research. The review is guided by the following research questions:

- RQ1: What is the current state of the art in AI-driven approaches for stock price forecasting?
- RQ2: How have AI models evolved in their application to financial prediction tasks?
- RQ3: Which AI techniques and models have been most frequently employed, and with what reported performance outcomes?
- RQ4: What opportunities and research gaps emerge for the future development of AI in financial forecasting?

2. General Context

This section offers a brief overview of the foundations of financial trading, focusing on one of its most emblematic analytical tools.

a. Japanese Candlesticks

There are numerous methods available for graphically representing price data, including line charts and bar charts. If one intended to work exclusively with time-based or numerical charts, these representations could be used without reference to Japanese candlesticks. However, Japanese candlestick charts have become by far the most popular and widely adopted format today. Originally developed in Japan nearly a century before their introduction to the West, they were quickly embraced by Western financial markets.

In the 1700s, when rice prices were already closely tied to supply and demand dynamics, a Japanese trader named Munehisa Homma observed that market price movements were heavily influenced by traders' emotions Honma, M. (1755). What makes Japanese candlesticks particularly compelling is their ability to visually reflect market sentiment by illustrating price variations through distinctive shapes and contrasting colors.

- **Japanese Candlesticks: Structure and Interpretation:**

A Japanese candlestick is used to analyze the price behavior of an asset over a given period. It is composed of two main elements:

- The body: which represents the difference between the opening price and the closing price;
- The shadows (also called wicks): which indicate the extreme values reached during the period namely the highest and lowest prices.

The color of the candlestick reflects the direction of the price movement:

- A green candle (or white, depending on the charting convention) indicates a bullish trend, where the closing price is higher than the opening price;
- A green candlestick indicates a bullish trend where the closing price is higher than the opening price;
- A red candlestick signals a bearish trend where the closing price is lower than the opening price.

When the closing price is lower than the opening price, the candlestick is referred to as bearish, and is typically colored red or black. Conversely, when the closing price exceeds the opening price, the candlestick is considered bullish, and its body appears in green or as unfilled, depending on the charting convention.

Japanese candlestick charts are widely used by traders to assess and anticipate market price behavior. A broad range of chart patterns (or *candlestick formations*) are associated with these visualizations, enabling the formulation of predictive hypotheses. Generally, the longer the observation period, the more reliable the graphical signal, thereby enhancing the credibility of the forecast. For instance, a five-minute candlestick chart typically yields more robust indications than a one-minute chart.

b. Typologies of Trading Analysis

Traders rely on various forms of financial analysis to anticipate market movements and identify recurring patterns. In practice, they often combine one or more of these analytical approaches, depending on their trading style.

i. Fundamental Analysis

Fundamental analysis involves examining the impact of economic news on markets by leveraging macroeconomic factors to estimate the intrinsic value of financial securities (Ta et al., 2018). This approach may be applied across multiple segments of the financial markets. One of its essential tools is the economic calendar, which tracks major global events likely to influence financial markets. Such calendars allow traders to manage risk proactively and to strategically time their market interventions.

ii. Technical Analysis

By offering an analytical framework grounded in precise and reproducible methods, technical analysis provides deeper insights into the decision-making processes involved in financial trading. This analytical approach relies on statistical time series and graphical correlations of an asset's price movements over a given period. Each point in these graphical correlations typically represents the closing price of a trading day. Analysts working within a technical framework seek to identify specific patterns and trends in these figures for use in forecasting.

The objective of this approach is to extract meaningful non-linear patterns from price time series, to develop trading strategies that capture relevant market movements while filtering out random fluctuations.

- **Technical analysis** relies on price charts, statistical indicators (such as moving averages, Relative Strength Index, MACD, etc.), and oscillators to forecast price trends;
- **Fundamental analysis** is based on an in-depth study of economic variables, requiring a detailed examination of financial statements as well as sentiment analysis derived from relevant economic news.

c. Algorithmic Trading

Algorithmic trading refers to any form of automated trading that relies on complex algorithms to execute orders in financial markets. It is often characterized by automated reasoning, learning, and decision-making capabilities (Treleaven et al., 2013). With the continuous improvement of computational power, algorithmic trading has witnessed widespread adoption. Its main objective is to harness the computational capacity of machines to outperform human abilities, particularly in terms of speed, accuracy, and operational efficiency (Mathur et al., 2021). Algorithmic trading reduces transaction costs, enhances execution precision, and allows for the dynamic adjustment of strategies.

A key tool in algorithmic trading is *backtesting*, which consists of analyzing the performance of models or strategies using historical data. This process enables the fine-tuning of parameters and the optimization of models prior to their deployment in real market environments. Strategies range from simple rule-based systems designed to limit profits and losses—commonly referred to as *take profit* and *stop loss*—to highly sophisticated models developed through artificial intelligence.

These models are generally validated through rigorous empirical testing across diverse market contexts. The process is analogous to the validation of machine learning models, involving the minimization of *overfitting* and the optimal adjustment of internal parameters (weights). Once this validation phase is completed, models may undergo real-time simulation testing. If their performance remains satisfactory, the algorithm can then be deployed for live trading, while being continuously monitored. Should a degradation in performance occur, the system may be reconfigured and recalibrated, allowing developers to implement incremental improvements until optimal behavior is achieved (Li & Peng, 2019).

❖ High-Frequency Trading – HFT

High-frequency trading is a strategy that involves executing a large number of orders within an extremely short time frame, often in fractions of a second. The underlying philosophy of this approach is generally to capitalize on fleeting price discrepancies across markets or within the same asset, by rapidly submitting buy and sell orders at exceptionally high volumes. Many HFT firms employ a range of strategies, from statistical arbitrage to market making, in order to capture very small market inefficiencies and generate profits.

- **Arbitrage**

Arbitrage strategies aim to exploit price discrepancies between correlated financial instruments (such as equities, bonds, commodities, derivatives, etc.). Among the most common approaches are:

- ✓ **Statistical Arbitrage:** Statistical arbitrage relies on quantitative and econometric models to identify temporary mispricing between correlated assets. It typically involves high-frequency trading strategies and large-scale computational techniques to exploit mean-reversion patterns or other statistical anomalies
- ✓ **Index Arbitrage:** Index arbitrage consists of capitalizing on discrepancies between the price of a stock market index and the combined prices of the constituent securities or related derivatives (such as futures contracts). Traders simultaneously buy and sell these instruments to capture small but recurring profit opportunities as the prices converge.

These strategies rely on algorithms capable of identifying and exploiting valuation imbalances by simultaneously buying and selling the relevant assets in order to generate profit.

- **Trend-Following:**

Trend-following strategies aim to detect directional patterns in asset price movements (either upward or downward) in order to execute trades accordingly. This type of strategy, often associated with momentum trading, relies on technical indicators such as:

- **Relative Strength Index (RSI),**
- **Bollinger Bands,**
- **Moving Averages.**

These signals enable algorithms to capitalize on the persistence of market trends.

- **Mean Reversion :**

Mean reversion is based on the assumption that asset prices tend, historically, to revert to their average over time. Accordingly, algorithms seek to identify any relative overvaluation or undervaluation of an asset and place trades in anticipation of a return to the mean. For example, when an asset deviates significantly from its moving average, the algorithm executes transactions under the expectation that the price will correct back toward the mean.

- **Market Making :**

Market making involves continuously maintaining bid and ask prices for one or more financial instruments while generating profit by capturing the bid–ask spread. This process is carried out by an automated strategist, known as a market maker. The use of algorithms makes this practice efficient, ensuring competitive execution even during periods of heightened market volatility.

- **Pairs Trading**

Pairs trading is a statistical arbitrage strategy based on the correlation between two assets. It assumes that a sharp divergence in their prices is temporary and that the prices will eventually converge toward equilibrium. The algorithm simultaneously buys the asset deemed to be undervalued while short-selling the asset that indicators suggest is overperforming.

3. Literature Review

a. Traditional Machine Learning Techniques

Kumar, Dogra, K. I., Utreja, C., and Yadav, P. analyzed stock market behavior to identify the most effective model among several classical machine learning algorithms, including Random Forest (RF), Support Vector Machine (SVM), Naïve Bayes, K-Nearest Neighbors (KNN), and Softmax, applied to stock price forecasting. The authors conducted a comparative study by incorporating various technical indicators, using data drawn from sources such as Yahoo Finance and NSE India. Their findings revealed that:

- For large datasets, the Random Forest algorithm delivered the most accurate results;
- Conversely, for smaller datasets, the Naïve Bayes model achieved higher precision;

- Furthermore, reducing the number of technical indicators led to a significant decline in model accuracy.

Ingle, V. and Deshmukh, S. reported that various TF-IDF features were employed to predict next-day stock prices, drawing primarily on widely available financial news data. TF-IDF weights briefly quantify the importance of words within these articles. In addition, they developed a Hidden Markov Model to capture transition probabilities between states. Nonetheless, the majority of positive and negative forecasts aligned only partially with actual outcomes, with error rates ranging between 0.20% and 4.00%. The authors emphasize that leveraging larger datasets, incorporating additional ML algorithms, and employing more technical indicators could substantially enhance predictive performance.

Traditionally, stock price forecasting relied exclusively on historical data. However, analysts increasingly recognize the insufficiency of this approach, as exogenous factors also play a critical role in price formation.

Singh, Sukhman, Tarun Kumar Madan, J. Kumar, and A. Singh explored a variety of stock price forecasting methods, integrating major explanatory factors, though without achieving consistently high accuracy rates. Techniques assessed included SVM, linear regression, Random Forest, as well as hybrid models combining multiple approaches. The authors observed that some models performed better with historical data than with sentiment data. In particular, fusion models produced more robust results.

Pahwa, K. and Agarwal, N. applied supervised linear regression to predict stock prices, using a 14-year dataset for GOOGL. Their study outlines the entire predictive process, from data preparation to the modeling of closing prices.

Misra, M., Yadav, A. P., and Kaur, H. concluded that applying Principal Component Analysis (PCA) prior to linear regression significantly improved predictive accuracy. According to their findings:

- SVM is well suited for non-linear classifications ;
- Linear regression is appropriate for linear data due to its high confidence value ;
- The Random Forest model, when applied to binary classification, demonstrates a high level of accuracy;
- The Multilayer Perceptron (MLP) achieves the lowest error rate.

Finally, Vats, P. and Samdani, K. emphasize that these techniques are not limited to stock price prediction but extend more broadly to financial markets. Following a comparative quantitative analysis of the different approaches, the authors suggest further exploration of behavioral finance, particularly to better understand investors' psychological reactions to market fluctuations. They also recommend the use of text mining techniques and AI models to monitor user interactions on digital trading platforms.

b. Deep Learning and Neural Networks

Yoojeong Song and Jongwoo Lee, from Sookmyung Women's University, observed that among a broad set of explanatory variables (input features), only a limited number exert a significant impact on stock prices. Their study therefore aimed to identify the most relevant variables in order to enhance the predictive accuracy of stock valuation models. To achieve this, Song and Lee proposed three different artificial neural network (ANN) architectures, each incorporating respectively:

- **Traditional multiple variables.**
- **Binary variables.**
- **Technical indicators.**

However, when conducting an empirical evaluation of predictive performance, we found that the model based on binary variables achieved the highest accuracy. Ultimately, we argue that binary features may offer the most efficient means of prediction, as they require minimal computation. Nevertheless, as a major limitation, we contend that the binarization process is destructive to the original information, which implies that its use may compromise the predictive quality of the model in a wide range of cases.

In a related study, Xingzhou L., Hong R., and Yujun Z. investigated the role of stock indices in price forecasting. Their approach sought to model the relationships between indices and asset prices while overcoming the limitations of traditional linear models. To this end, they employed a Long Short-Term Memory (LSTM) neural network to capture the temporal dynamics of the S&P 500 index. Their work included a detailed sensitivity analysis of the internal memory within LSTM architectures. However, the authors noted that beyond a certain time horizon, the discrepancy between predicted and actual values increased significantly, thereby limiting the applicability of their model for profitable trading strategies in real-world conditions.

Furthermore, S. Sarode, H.G. Tolani, P. Kak, and C.S. designed a stock purchase recommendation system intended for investors. Their approach was based on the fusion of historical and real-time data, combined within an LSTM-based architecture. In their recurrent neural network (RNN) model :

- Recent stock market data as well as technical indicators are fed into the input of the first layer;
- These inputs are then processed by an LSTM block followed by a dense (fully connected) layer;
- Finally, the predicted value is generated at the output.

The predictions generated by this model are then correlated with summarized data obtained through content analysis of financial news, in order to produce a synthetic report indicating, among other elements, the expected percentage of variation.

c. Time Series Analysis

The article *"Share Price Prediction using Machine Learning Technique"* by Jeevan, B., Naresh, E., and Kambli, P. (2018) represent stock prices as time series, thereby avoiding the complexities typically encountered when training traditional models. The authors employed normalized data and a Recurrent Neural Network (RNN) to perform their forecasts. The predicted values were found to be very close to the actual ones, leading them to conclude that machine learning algorithms are effective tools for stock price prediction.

Similarly, Sharma, V., Khemnar, R., Kumari, R., and Mohan, B.R. (2019) investigated the impact of daily sentiment scores associated with various companies on the evolution of their stock prices. Information and news disseminated on social media whether originating from the company itself or from other sources were shown to influence investors' buy or sell decisions, thereby affecting stock valuation.

The authors also highlighted the significant impact of exogenous variables such as holidays, seasonality, trends, and non-periodic components. To account for these, they designed an adjusted time series model incorporating all of these structural elements, resulting in a more realistic representation of financial market behavior.

d. Graph-Based Approach

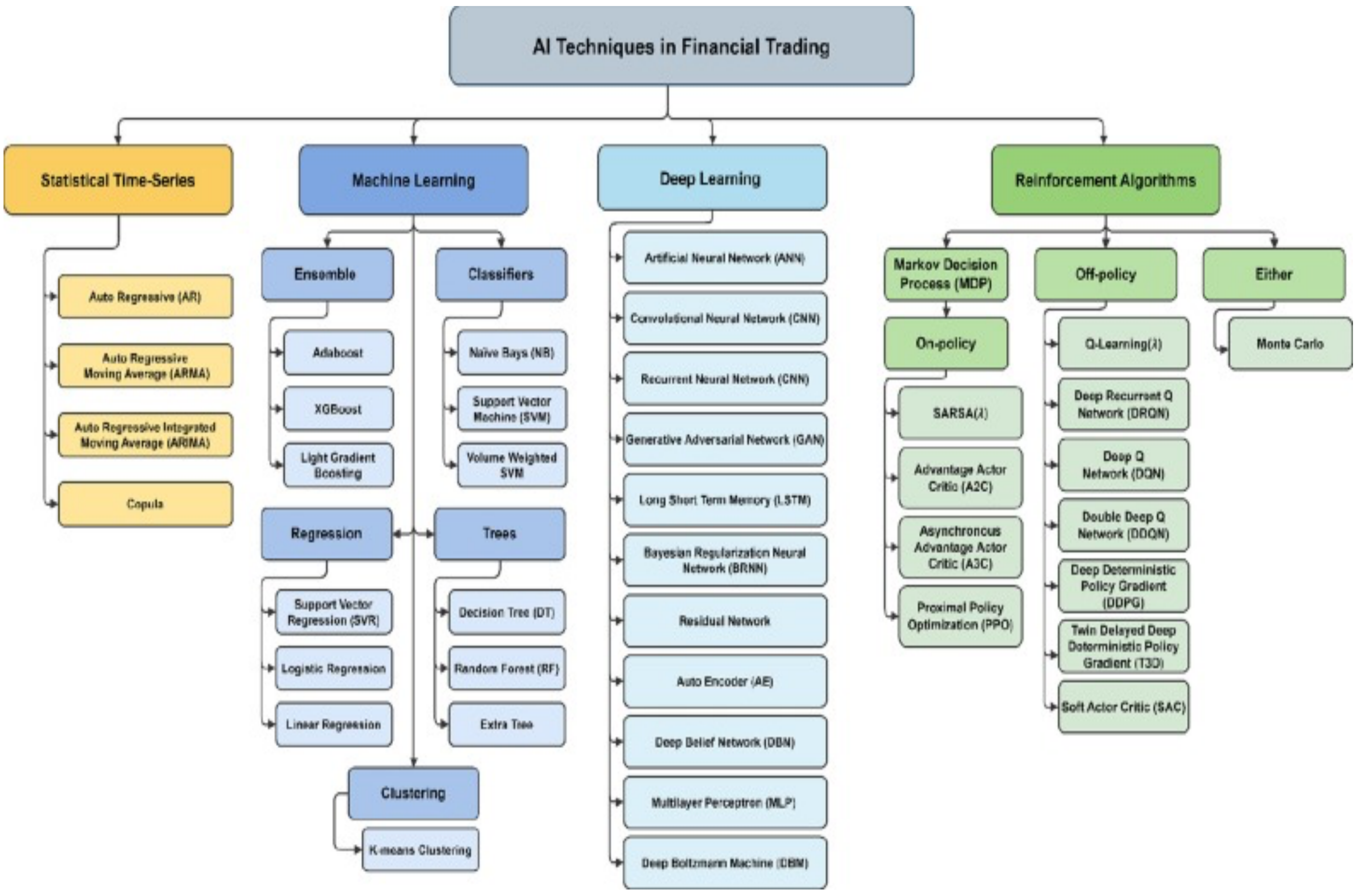
A particularly innovative approach was proposed by Patil, P., Wu, C.S.M., Potika, K., and Orang, M. (2020), who modeled the stock market in the form of a graph network, offering an original perspective. Their method integrates both correlation and causality relationships among stocks, drawing on historical price data as well as sentiment analysis, thereby capturing a wide range of determinants influencing asset prices.

However, the proposed model based on a Graph Convolutional Network (GCN)—appears to be affected by the problem of gradient explosion. Specifically, nodes with very high degrees tend to learn feature representations with amplified values, while nodes with low degrees acquire attenuated feature representations. Addressing this issue would simplify the training process of the model. The GCN model also warrants evaluation within more conventional time series forecasting contexts.

In another significant contribution, Kim, R., So, C.H., Jeong, M., Lee, S., Kim, J., and Kang, J. (2019) introduced the *Hierarchical Attention Network for Stock Prediction* (HATS), a model designed to predict stock prices and market index movements through the integration of graph theory and Graph Neural Networks (GNNs). This approach relies on selective clustering of relational data, enriching vector representations of entities by incorporating meaningful financial relationships. The hierarchical attention mechanism plays a pivotal role in enhancing the model's performance by assigning differentiated weights to information according to its contextual importance and relevance.

Another notable study in this line of research is that of Xu, Y. and Keselj, V. (2019). The authors leveraged the informational characteristics of tuples to construct a *knowledge graph*, which was then used in the process of selecting relevant variables. Their method combined a Convolutional Neural Network (CNN) to extract semantic features from financial news, which were subsequently embedded into the knowledge graph. This hybridization of deep learning and semantic graphs proved effective for extracting highly informative features while preserving the semantic integrity of textual content.

Nevertheless, the authors highlight an important limitation: the scarcity of labeled datasets in the financial domain makes the automated construction of knowledge graphs particularly challenging to implement on a large scale.



Fatima Dakalbab, Manar Abu Talib, Qassim Nasir, Tracy Saroufil, Artificial

4. Research Methodology and Review Protocol

In order to identify the methods employed and the reporting practices used by researchers, we conducted a systematic review of the studies publicly available in this domain. This analysis was carried out in accordance with the **PRISMA 2020 statement** (*Preferred Reporting Items for Systematic Reviews and Meta-Analyses*), as formulated by **Page, McKenzie et al. (2021)**. This protocol includes a standardized checklist as well as a flow diagram designed to ensure the **transparency, rigor, and reproducibility** of the research.

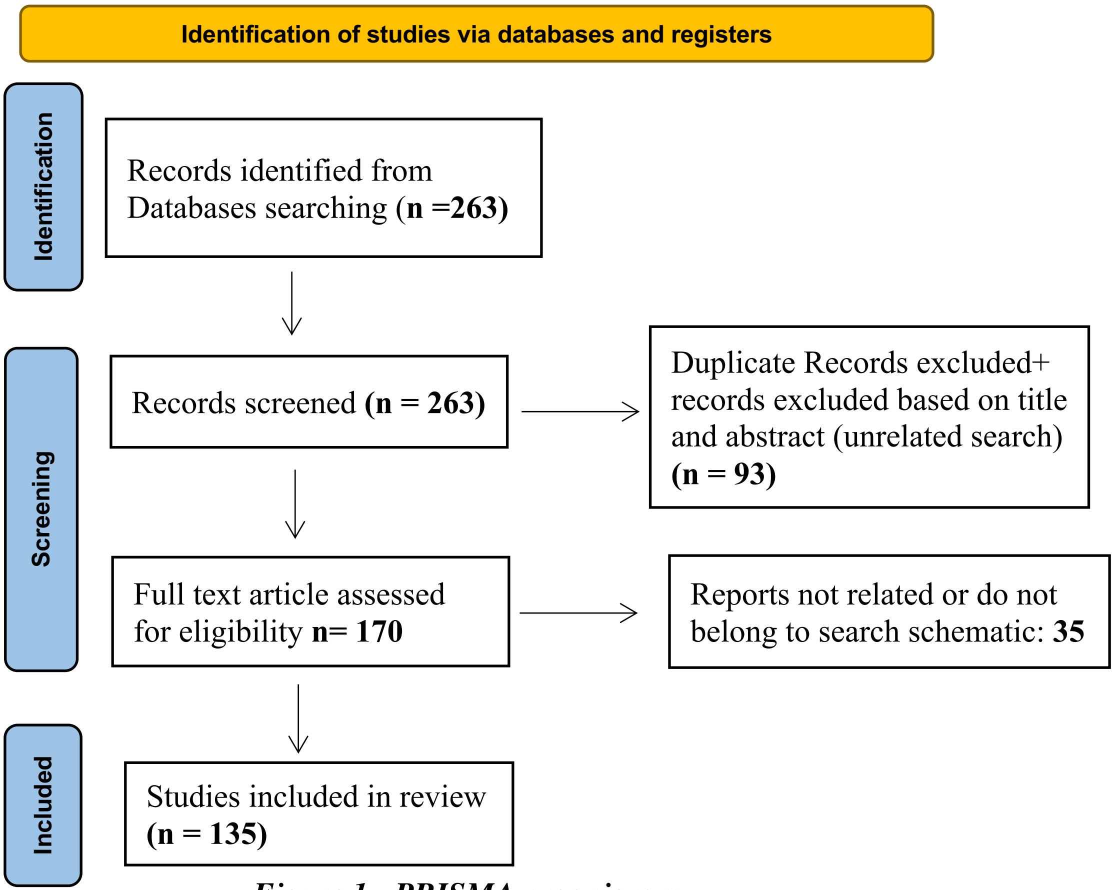


Figure 1 : PRISMA organigram

The ultimate aim of this study is to provide researchers with a compass to select the most appropriate artificial intelligence methods, depending on the nature of the input data and the desired outcomes. This work also seeks to support a deeper understanding of what distinguishes each approach, along with their respective advantages, limitations, and underlying mechanisms. The systematic review procedure followed a predefined protocol, beginning with the formulation of research questions designed to guide the selection of relevant publications. The literature search was conducted across several scientific databases and leading academic publishers, including ScienceDirect, Scopus, Springer, IEEE, SAGE, and Taylor & Francis, among others. To ensure methodological rigor, the review was restricted to peer-reviewed articles written in English and published during the period 2010–2024, which represents the relevant time window for capturing recent advances in AI-driven forecasting.
Explicit inclusion and exclusion criteria were then applied to filter the documents retained for analysis, which were systematically identified and subsequently synthesized. The first stage of the review process consisted of defining the research questions, developed in response to

contemporary issues and recent developments in the field of artificial intelligence. These questions served as the foundation for establishing the review protocol.
The second stage focused on the selection and synthesis of relevant publications. The documents collected through the databases were reviewed and analyzed according to several criteria, including:

- **Name of the scientific journal,**
- **Publisher,**
- **Title of the article,**
- **Research objectives,**
- **Methodology adopted,**
- **Results,**
- **Conclusions drawn.**

At the conclusion of this analytical process, the information deemed relevant was synthesized and integrated into a comprehensive review, thereby providing a complete and critical mapping of the state of the art on AI techniques applied to financial market forecasting.

a. Research Questions

This study seeks to explore the ways in which artificial intelligence (AI) is applied in the field of financial trading, by identifying:

- *The main machine learning (ML) algorithms employed,*
- *Their level of accuracy,*
- *The validity criteria of learning models according to the nature of the data processed,*
- *And the models offering the best returns for market participants.*

In addition, particular attention is given to the automation of trading processes.
The following **research questions (RQs)** were formulated to frame the systematic review:
RQ1: What types of financial markets are examined in the literature?
Which categories of assets are considered (e.g., equities, currencies, commodities, crypto-assets, etc.)?
RQ2: Do the studies incorporate fundamental analysis or technical analysis approaches?
If so:
–Which technical indicators are employed?
– Which sources of fundamental data are utilized?
– Does the proposed solution enable the automation of the decision-making process?
RQ3: Which artificial intelligence (AI) approach is implemented?
What specific techniques or models are employed (e.g., neural networks, support vector machines, decision trees, etc.)?
RQ4: What are the evaluation criteria and performance metrics of the models?
(For example: accuracy, RMSE, MSE, Sharpe ratio, AUC, etc.)

b. Search Strategy

This section provides a detailed explanation of the documentary research methodology adopted for this systematic review.

i. Search Terms

The research questions formulated earlier served as the basis for determining the main keywords. Complementary terms were then identified from specialized resources (academic thesauri, disciplinary databases, publication indexes). To optimize the precision of results and broaden thematic coverage, Boolean operators (such as *AND*, *OR*) were employed to combine terms and refine queries.
Among the search strings used, the following may be noted:

• "High-frequency trading" **AND** "machine learning"
• "trading" **AND** "Machine learning"
• "Reinforcement learning" OR "transfer learning" **AND** "trading".
• "Deep learning" **AND** "trading" AND" prediction"".
• "trading" **AND** "Deep neural network"
• stock market "**AND**" "machine learning".
• "artificial intelligence" **AND** "High-frequency trading" **OR** "AI"
• "trading" **OR** "AI-based trading", "AI" **OR** "Artificial intelligence"

These combinations were applied across a wide range of scientific databases and academic publisher portals in order to capture the maximum number of relevant publications.

ii. Documentary Resources Consulted

For the identification of relevant scientific articles, the literature search was conducted within the major digital libraries and academic databases, recognized for the quality and rigor of their publications. The following resources were systematically explored:

• IEEE **Xplore**
• Springer
• Elsevier Science Direct
• ACM Digital Library
• MDPI
• Scopus
• Taylor & Francis Online

iii. Research Phases

The process of filtering and selecting publications was carried out according to the following steps:

1. **Elimination of duplicates:** redundant articles originating from different databases and authors were removed.
2. **Application of inclusion and exclusion criteria**: only articles meeting the predefined criteria were retained; non-relevant publications were discarded.
3. **Selection of high-quality publications:** only studies adhering to rigorous standards of scientific evaluation were preserved.
4. **Search iteration:** an additional search was conducted for similar articles.

a. Inclusion and Exclusion Criteria:

The inclusion criteria were organized to ensure full access to the selected documents. These criteria were grounded on a sufficiently scientific basis and aligned with the subject area under examination, so as to guarantee the relevance of the studies retained, both methodologically and conceptually. Linguistic considerations were also taken into account to avoid ambiguity and to optimize the comprehensibility of the documents included.

Conversely, the exclusion criteria made it possible to discard studies with characteristics likely to obscure the interpretation of results, particularly those involving populations, contexts, or methodologies incompatible with the objectives of the present systematic review.

5. Results and Discussion

a. Types of Financial Markets and Assets Studied

The findings of this review indicate that eight types of financial markets have been considered by researchers. Among them, the stock market has received the highest degree of empirical investigation. The foreign exchange market and cryptocurrencies rank second and third, respectively, both reflecting a growing research interest in the literature. Accordingly, these

three categories of markets are regarded as the primary focus of study.
In addition, six studies examined **combinations of markets**, analyzing cross-interactions such as:

- **Stock index futures and commodity markets.**
- **Equity markets and exchange-traded funds (ETFs).**
- **Equities and commodity futures.**
- **Equities and the bond market.**
- **Equity markets combined with cryptocurrencies.**

Furthermore, the comparative analysis of these markets suggests conducting research across multiple financial environments to detect potential differences and to subsequently identify and examine active anticipation strategies. Notably, other studies highlight that the analysis of technology companies stands out from the rest. In particular, the stocks of high-technology firms rank first in terms of frequency with which they are investigated.

The most frequently studied companies are:

- **Google (GOOGL):** cited in 7 studies,
- **Apple (AAPL):** featured in 6 studies,
- **Tesla (TSLA):** mentioned in 1 study.

Other leading technology firms such as **Amazon (AMZN), Meta Platforms, and Microsoft (MSFT)** also appear within the analyzed corpora. Finally, some studies have also focused on specific banks or stock exchanges as objects of analysis.

b. Trading Analysis Methods

Three dominant approaches are identified in studies combining artificial intelligence with stock market analysis:

1. **Technical analysis.**
2. **Algorithmic trading strategies.**
3. **Fundamental analysis.**

i. Technical Indicators

- Momentum indicators are widely used to assess the strength or weakness of a price movement. They help identify the pace of acceleration or deceleration in asset prices. Among the most frequently employed indicators are:
- Le RSI (Relative Strength Index),
- Le CCI (Commodity Channel Index).
- Le MACD (Moving Average Convergence Divergence),

These tools provide a nuanced reading of market momentum, thereby offering valuable decision-making support to traders.
Trend indicators are used to detect the general market direction (bullish or bearish trend). Studies have frequently employed:

- **Exponential Moving Average (EMA)**
- **Moving Average (MA)**
- **Simple Moving Average (SMA)**

Taken together, these indicators not only help identify a trend but also anticipate potential reversals in market outlook. Finally, volume indicators play a central role in assessing buying and selling pressure, as they capture the strength of either movement based on transaction flows.

ii. Market Data Used

In almost all studies, OHLC market data (*Open, High, Low, Close*) constitute the primary input variables for artificial intelligence models:

- **Open:** the opening price of an asset
- **Close :** the closing price
- **High:** the highest price reached during the period
- **Low :** the lowest price recorded

The analysis of these financial time series provides the foundation for training predictive models employed in algorithmic trading strategies.

c. Artificial Intelligence Approaches and Algorithmic Techniques

i. Stock Price Prediction

Stock price prediction represents one of the most significant domains in which deep learning (DL) models have demonstrated considerable impact (Rezaei et al., 2021; Singh & Shukla, 2021). Thanks to their ability to model non-linear relationships and temporal dependencies inherent in market data, recurrent architectures such as **Long Short-Term Memory (LSTM)** and **Gated Recurrent Unit (GRU)** networks have proven particularly effective (Das et al., 2024; Zulqarnain et al., 2020). Numerous hybrid models have been developed, combining traditional time series analysis with advanced DL approaches in order to enhance forecasting accuracy.

One of the major contributions of this study was to identify the AI techniques most commonly employed in the field of financial trading. At different stages of experimentation—feature extraction, preprocessing, modeling, and validation of the methodologies and implementations described in the literature were rigorously examined.

The most representative AI techniques are as follows:

- **Classification:** these algorithms categorize investment opportunities into classes (e.g., buy, sell) according to the probability of asset variation.
- **Regression:** although less widespread, regression analysis provides valuable insights into price trends and market fluctuations.
- **Deep Learning:** the predominant approach, particularly effective in processing large-scale unstructured data, offering advanced capabilities in detecting complex patterns, forecasting price movements, and analyzing market sentiment.
- **Reinforcement Learning (RL):** these algorithms enable the dynamic optimization of investment strategies by adjusting decisions according to market feedback.
- **Deep Reinforcement Learning (DRL):** by combining the pattern recognition capabilities of deep learning with the decision-making mechanisms of reinforcement learning, this approach is particularly well suited to the development of autonomous and adaptive trading systems.

These findings confirm that approaches based on Deep Learning, Reinforcement Learning, or a combination of the two dominate in terms of performance and are perceived as more appropriate than traditional classification or regression methods. A major factor underlying this dominance is the complex structure of financial markets, which requires AI models capable of adapting to variability.

❖ **Complementary Statistical Methods:**

Among the approaches derived from time series analysis, certain classical statistical techniques continue to be employed. These include in particular:

- **ARMA/ARIMA models (AutoRegressive Moving Average).**
- **Copula-based methods**.

The copula is a method that enables the modeling of dependencies among multiple random variables without regard to their marginal distributions. It is widely used in financial modeling and risk analysis. Although this method does not fall strictly within the domain of AI, it can be combined with machine learning models or other AI techniques, such as deep learning or reinforcement learning, for the purpose of modeling the mutual dependence behavior of financial market variables.

ii. Typology of Algorithms Identified

The algorithms identified in the literature can be classified as follows:

- **Classical Supervised Learning :**
  - *Classification :* SVM, k-NN, Naïve Bayes, etc.
  - *Regression:* Linear/Multiple Regression.
  - *Ensemble Methods:* Random Forest, Gradient Boosting, etc.
  - *Clustering:* K-Means, DBSCAN, etc.
- **Deep Neural Networks :**
  - LSTM, widely used to capture temporal dependencies in financial data.
  - CNN (Convolutional Neural Networks).
  - GAN (Generative Adversarial Networks).
  - RNN (Recurrent Neural Networks).
- **Reinforcement Learning :**
  - Deep Q-Network (DQN).
  - On-policy and Off-policy algorithms.
  - Actor–Critic algorithms.
  - Deep Deterministic Policy Gradient (DDPG).

These approaches have been used to develop effective trading strategies, enabling models to learn from dynamic interactions with the stock market environment.

d. Market Volatility Prediction

Volatility forecasting represents a central challenge for risk management and the optimization of trading strategies. Recent advances in deep learning have led to the development of models capable of dynamically adapting to changing market conditions (Boudri & El Bouhadi, 2024; Ge et al., 2022).
Recurrent architectures such as **Long Short-Term Memory (LSTM)** and **Gated Recurrent Unit (GRU)** have been widely employed. Some studies have integrated econometric approaches into hybrid models to enhance performance (Zhang et al., 2021; Xu et al., 2024). Recent research emphasizes the importance of incorporating multiple data streams—including macroeconomic indicators, sentiment analysis, and high-frequency trading data in order to improve predictive accuracy (Jing, N., Wu, Z., & Wang, H. (2021); Abdissa, 2024). Empirical results indicate that hybrid models outperform unitary models, although challenges related to data noise and overfitting remain problematic.

e. Portfolio Optimization

Portfolio optimization seeks to determine the optimal allocation of assets by maximizing returns for a given level of risk (Gunjan & Bhattacharyya, 2023; Oliinyk & Kozmenko, 2019). Traditional methods have been enhanced by deep learning models, particularly reinforcement learning techniques that allow for the derivation of optimal portfolio strategies through direct interaction with the market environment (Cui et al., 2024; Niu et al., 2022). Several studies have employed **Actor-Critic models** and **Deep Q-Networks (DQNs)** to enable dynamic portfolio rebalancing. For instance, Cui et al. (2024) proposed a hyper-heuristic framework based on Deep RL, integrating both expert knowledge and low-level trading strategies, which resulted in improved portfolio performance.
However, a major limitation of reinforcement learning models lies in their dependence on market-derived reward signals, which may be inaccurate or biased, particularly under extreme conditions such as black swan events or spikes in volatility.

f. Sentiment Analysis for Trading

Sentiment analysis has gained increasing popularity in algorithmic trading, drawing on sources such as financial news articles, social media content, and corporate reports to capture market sentiment (Ozbayoglu et al., 2020; Nyakurukwa & Seetharam, 2024).

Deep learning models, particularly **Convolutional Neural Networks (CNNs)** and **Long Short-Term Memory (LSTM) networks**, are widely employed to automatically extract sentiment indicators from textual data (Yadav & Vishwakarma, 2020; Jain et al., 2021). Numerous studies have combined these sentiment data with traditional market data to improve prediction accuracy. For instance, integrating sentiment scores derived from Twitter or financial news portals with stock price time series has been shown to enhance model robustness, especially during periods of exogenous shocks or major announcements (Li et al., 2020; Thormann et al., 2021).

a. Risk Management :

Risk management in algorithmic trading relies on forecasting potential losses and proactively adapting investment strategies to mitigate their impacts (Pathak et al., 2023; Devan et al., 2023). Deep learning models enable the identification of risk factors by analyzing historical series and learning the complex relationships between asset returns and market variables (Chong et al., 2017; Kou et al., 2019).

Unsupervised models such as autoencoders, Variational Autoencoders (VAEs), and other unsupervised learning techniques have been employed to detect anomalies that may lead to significant portfolio losses. These methods allow for the identification of weak signals or atypical configurations, although their lack of interpretability and the risk of false positives remain notable limitations (Choi et al., 2021; Basora et al.).

b. Anomaly and Fraud Detection:

Anomaly detection plays a strategic role in trading systems, as it enables the identification of irregular behaviors that may indicate cases of fraud or market manipulation (Tatineni & Mustyala, 2024; Hassan et al., 2022). In financial environments, this involves detecting significant deviations from normal patterns, whether in transaction flows or in asset price dynamics.

Deep learning models such as autoencoders, RNNs, and hybrid architectures have proven particularly effective in identifying such rare events, owing to their ability to model non-linear relationships and temporal dependencies (Eren & Küçükdemiral, 2024; Hatcher & Yu, 2018). Autoencoders, in particular, are well suited to unsupervised learning tasks. They are trained to reconstruct the normal patterns of the data; any substantial divergence between the input data and its reconstruction signals a potential anomaly (Fan et al., 2018; Gong et al., 2019). At the same time, recurrent models—notably LSTM and GRU—are widely used to model time series and detect suspicious behaviors in real-time transactions (Choi et al., 2021; Karn et al., 2022).

c. Performance Metrics and Evaluation:

Performance evaluation represents a crucial stage in the deployment of any artificial intelligence solution, particularly in algorithmic finance. This section examines the metrics commonly used to measure the effectiveness of the developed models.

Two evaluation methodologies dominate the assessment of trading strategies: **backtesting** and **forward testing**.

- **Back testing** : involves testing model performance on previously unseen historical data. It enables analysts to estimate how the strategy would have performed in the past without risking actual capital. This approach is widely used: approximately 28 studies have adopted backtesting, such as Kim (2021).
- **Forward testing or *paper trading*:** simulates real market conditions using live

data without executing actual trades. Only five studies have employed this method, including Zbikowski (2016). Despite its relevance, this method remains less frequently applied.

d. Evaluation Metrics :

AI models applied to algorithmic trading are assessed using metrics derived from both machine learning and finance, allowing for an appraisal of predictive accuracy, profitability, and risk-adjusted performance.

❖ ***Classification Tasks:***

In scenarios where the objective is to predict whether prices will rise or fall, the following metrics are used:

- **Accuracy:** the proportion of correct predictions over the total number of observations (Sengupta et al., 2020).
- **Precision (positive precision):** the proportion of true positives out of all predicted positives. This is crucial for minimizing erroneous buy or sell signals (Hochreiter, 1997).
- **Recall:** the model's ability to detect all positive cases (Jain, 2024). A high recall ensures that most profitable opportunities are captured.
- **F1-Score:** the harmonic mean of precision and recall, particularly useful when class distributions are imbalanced.

❖ ***Regression Tasks:***

For price prediction, the following metrics are commonly employed:

- **MSE (Mean Squared Error):** computes the average squared difference between predicted and actual values. It is sensitive to outliers (Henrique et al., 2018).
- **RMSE (Root Mean Squared Error):** the square root of MSE, expressed in the same unit as the original data, thereby facilitating interpretation (Weng et al., 2018).

e. Financial Metrics

- **Sharpe Ratio (SR):** measures the excess return (above the risk-free rate) per unit of volatility. It is a benchmark in finance for evaluating risk-adjusted performance (Tudor & Sova, 2024). A high SR indicates an effective and stable strategy.
- **Return on Investment (ROI):** the gross measure of return generated by the model (Khattak et al., 2023). While popular, it neglects volatility and thus the level of associated risk.
- **Sharpe Ratio vs ROI:** ROI measures raw profitability, whereas the Sharpe Ratio incorporates risk. In market contexts, a high ROI accompanied by strong volatility may be less desirable than a modest ROI with a high Sharpe Ratio (Kim et al., 2020; Sanz-Cruzado et al., 2022; Bisong, 2019).

6. Modeling

Forecasting consists of generating future predictions based on past and present data. The objective is to predict the future values from the data collected up to time (Shumway & Stoffer, 2010).

a. Artificial Neural Networks (ANNs)

Inspired by the functioning of the human brain, artificial neural networks (ANNs) are considered universal Turing machines. They represent the most widely used bio-inspired technique for stock market forecasting. These models are composed of a large number of interconnected neural units, with connections that may be excitatory or inhibitory.

The **Multilayer Perceptron (MLP)** is the most common approach for stock market prediction. It is a feedforward network consisting of an input layer, one or more hidden layers, and an output layer. Learning is carried out through the backpropagation method, as illustrated by

Coyne et al. (2018), Hu et al. (2018), Qiu & Song (2016), Mingyue, Cheng & Yu (2016), and Zhong & Enke (2017).
Another popular technique is the **Radial Basis Function (RBF) network**, where activation is based on radial functions. **Dash & Dash (2016)** and **Guo et al. (2017)** trained their models using this architecture.

b. Deep Neural Networks

Traditional algorithms often require manual feature extraction. By contrast, deep neural networks (DNNs) can automatically extract and transform features through a cascade of nonlinear layers (LeCun, Bengio & Hinton, 2015). Thanks to hardware (GPUs) and software (TensorFlow, PyTorch) advances, these models have become more accessible (Coates et al., 2013; Abadi et al., 2016).
Chong, Han & Park (2017) used high-frequency intraday data to train DNNs and concluded that such models could extract additional signals not captured by classical approaches. **Singh & Srivastava (2017)** combined principal component analysis (PCA) with a DNN to improve predictive accuracy on Google stock. Other studies, such as those by **Kraus & Feuerriegel (2017)** and **Di Persio & Honchar (2016)**, demonstrated that CNNs outperformed traditional models in forecasting indices such as the S&P 500.
These works demonstrate the promising potential of deep networks for stock market forecasting, even though most studies remain limited to the period 2016–2018 and do not yet incorporate exogenous variables such as social media data or macroeconomic indicators.

c. Genetic Algorithms

Genetic Algorithms (GAs) are inspired by the mechanisms of natural evolution to search for optimal solutions. They combine, mutate, and select solutions across multiple generations. **Huang & Li (2017)** employed a GA to predict the movements of 10 stocks listed on the Taiwan Stock Exchange. Compared to regression models, they observed an improvement in predictive performance.

d. Fuzzy Logic

Fuzzy logic mimics human reasoning through *if–then* rules expressed with linguistic values rather than precise numerical ones. The Adaptive Neuro-Fuzzy Inference System (ANFIS) is widely used, combining a network of fuzzy neural components to produce a set of linear models. **Ghanavati et al. (2016)** developed a hybrid FuzzyML-SVM method, integrating fuzzy clustering techniques with SVMs, and demonstrated performance superior to that of standalone SVMs.

e. Ensemble Techniques

Ensemble techniques such as Bagging, Boosting, and Stacking are popular for enhancing predictive robustness:

- **Boosting:** such as AdaBoost, places greater weight on misclassified samples. McCluskey & Liu (2017) employed Boosted Trees.
- **Bagging:** particularly through Random Forest (RF), selects random subsets of data. This method is widely applied (Patel et al., 2015; Kamble, 2018).
- **Stacking:** allows for the combination of different types of models. Yang et al. (2017) merged SVM, RF, and Logit AdaBoost to improve classification.

➢ **Support Vector Machines (SVMs):**

Support Vector Machines (SVMs) are highly effective for both classification and regression tasks. By leveraging kernel functions, they can construct boundaries in higher-dimensional spaces. They require relatively few hyperparameters to be tuned, yet they deliver state-of-the-art results—hence their strong representation in the literature. However, like ANNs and fuzzy techniques, they often produce black-box models that are difficult to interpret.

f. Rough Sets

The **rough set theory** addresses uncertainty using upper and lower bounds. **Kim & Enke (2016)** applied this method to forecast the KOSPI 200 index by combining trading strategies with genetic algorithms, achieving performance superior to the traditional **Buy-and-Hold** strategy.

7. Identified Challenges

Despite the significant progress achieved in applying deep learning to financial markets, several challenges remain, reflecting the complexity of developing robust models for algorithmic trading (El Hajj & Hammoud, 2023; Horobet et al., 2024). Addressing these issues is crucial to improving the reliability and performance of such models, thereby encouraging their adoption by traders and financial institutions. Continued research and innovation in this field remain essential to overcoming these limitations and fully unlocking the potential of artificial intelligence in finance.

a. Data Quality

One of the most frequently mentioned challenges in the literature concerns the quality of financial data. Financial markets are notoriously noisy and influenced by a wide range of factors such as investor sentiment, macroeconomic news, and geopolitical events, thereby introducing high variability and considerable instability into time series (Fischer & Krauss, 2018; Nosratabadi et al., 2020).

b. Noise in Financial Data

Noise refers to random fluctuations in prices that do not reflect genuine market signals. Such fluctuations interfere with the learning process of deep learning models (Karimi et al., 2020; Fischer & Krauss, 2018) and may lead to the identification of spurious patterns. Overfitted models trained on noisy data risk capturing temporary anomalies rather than fundamental market dynamics (Kim et al., 2019). Moreover, overfitting is often exacerbated by the complex structure of neural networks, particularly recurrent networks (RNNs) and LSTMs, which tend to model irrelevant relationships when data are unstable (Song et al., 2021). Even with advanced regularization techniques such as dropout or weight decay, overfitting remains a recurrent issue in non-stationary financial contexts.

c. Missing Data

Another critical challenge is the management of missing data, particularly in high-frequency trading, where interruptions may occur due to network latency, exchange outages, or delays in publication (Magris, 2019; Aldridge & Krawciw, 2017). Deep learning models often require complete series to produce reliable predictions. Although imputation techniques are commonly used to fill such gaps, they also raise challenges, especially in preserving the temporal dynamics of the data (Adhikari et al., 2022).

d. Overfitting

Overfitting occurs when a model fits the training data too closely but fails to generalize its predictions to new data (Ying, 2019; Montesinos López et al., 2022). This phenomenon is particularly problematic in volatile financial environments, where market conditions evolve rapidly and unpredictably.

In algorithmic trading, overfitting often leads to exceptional performance during backtesting but poor outcomes under real-world conditions (Peng & de Moraes Souza, 2024; Chatzis et al., 2018). The model becomes excessively dependent on historical regularities, which do not necessarily recur in the future.

The following techniques have been proposed in the literature to mitigate this issue:

- **Dropout:** involves randomly deactivating certain neurons during training to prevent the model from becoming overly dependent on specific units. The dropout rate γ\gammaγ ranges between 0 and 1 and controls the proportion of neurons deactivated.
- **Cross-Validation:** *k-fold cross-validation* is used to assess the generalization capacity of the model. It divides the data into k subsets, trains the model on $k - 1$ of them, and tests on the remaining one, repeating the process k times.

Nevertheless, despite these mechanisms, overfitting remains a major obstacle, particularly in short-term trading strategies where noise often outweighs underlying trends. This significantly limits the effectiveness of models, even when they appear to perform well on historical datasets.

- Model Interpretability:

Another major challenge identified in the literature concerns the interpretability of deep learning (DL) models. Indeed, these models—particularly deep neural networks (DNNs)—are frequently described as *"black boxes"* due to their complexity and the opacity of the decision-making process leading to a given prediction (Münch & Arens, 2021; Buhrmester, Liang et al., 2021).

This lack of transparency represents a significant obstacle in the context of algorithmic trading, where understanding the foundations of an algorithmic decision is crucial, both for human operators and for regulatory bodies (Bhuiyan, M. D. S. M., et al. (2025); Soundararajan & Shenbagaraman, 2024).

e. Opaque "Black-Box" Nature of DL Models

Unlike traditional algorithms such as decision trees or linear regression, which offer intrinsic interpretability through explicit and understandable structures, deep learning models—particularly those comprising multiple layers and thousands of parameters—make it difficult to identify the key variables driving the predictive process (Dumitrescu et al., 2022; Rudin, 2019). This lack of explainability can undermine trust in automated systems and hinder their adoption in regulated environments, especially since certain decisions may carry significant financial and legal implications.

f. Complexity of Financial Markets

Financial markets are influenced by a combination of heterogeneous factors, including macroeconomic trends, geopolitical developments, investors' emotional reactions, and network effects. This multiplicity of determinants gives rise to a chaotic dynamic that is difficult to model using traditional approaches or even deep learning models (Belhoula, Mensi & Naoui, 2024; Eissa, Al Refai & Chortareas, 2024).

g. Non-Stationarity of Financial Data

The main difficulty inherent in financial market modeling lies in the **non-stationarity of data**. Unlike static datasets, markets are in constant evolution, both in terms of structure and behavior (e.g., trading strategies, regulations, technologies). As a result, a model trained on historical data may fail to generalize to future market conditions (Schnaubelt, 2019).

Some researchers have proposed adaptive approaches, such as **online learning** or methods based on **reinforcement learning (RL)**, which enable models to dynamically adjust as new data become available (Hatcher & Yu, 2018). These approaches are particularly promising in the highly evolving and non-linear contexts of financial markets.

h. High Dimensionality of Financial Data:

Financial markets generate massive volumes of multidimensional data, including prices, order books, macroeconomic indicators, and sentiment extracted from social media. This **high dimensionality** poses a major challenge for DL models, which must identify relevant features while filtering out noisy signals (Georgiou, C. (2020); Tembe & Dougherty, 2009).
Dimensionality reduction techniques, such as **autoencoders** or **Principal Component Analysis (PCA),** are commonly employed to mitigate this issue. However, these methods may lead to the loss of critical information, particularly when the discarded data include explanatory variables that are decisive for prediction (Alkhayrat et al., 2020; Hasan & Abdulazeez, 2021).

8. Advantages and Limitations

Advantages and Disadvantages of Selected Algorithms in Algorithmic Trading:

MODEL	ADVANTAGES	LIMITATIONS
Long Short-Term Memory Networks (LSTMs	· Addresses the vanishing-gradient problem · Excels at modeling long-term dependencies · Capable of retaining past information for future predictions · Offers a flexible architecture	· Requires careful hyperparameter tuning · Still prone to overfitting if regularization is inadequate · Computationally expensive
Recurrent Neural Networks (RNNs)	· Effectively captures temporal dependencies · Well suited for sequential data · Adapts to variable input lengths	· Slower training due to sequential nature · Prone to overfitting with noisy data · Challenges in handling long-term dependencies
Variational Autoencoders (VAEs)	· Generates synthetic financial data for modeling · Learns latent representations of market data · Effective for risk modeling and anomaly detection · Reduces noise while preserving essential patterns	· Limited interpretability · May be less effective for sequential decision-making tasks · Requires large training datasets for effective feature extraction
Graph Neural Networks (GNNs)	· Models relationships between assets in financial networks · Captures interdependencies among different stocks · Well suited for stock correlation analysis and portfolio optimization · Effective in predicting market movements using relational data	· High computational cost for large financial graphs · Requires careful graph construction to generate meaningful insights · Sensitive to noisy Financial data
Convolutional Neural Networks (CNNs)	· Effective in extracting features from temporal data · Recognizes patterns and trends in price movements · Handles multiple input variables simultaneously	· High computational cost due to variational inference · May generate unrealistic results if training is poorly executed · Requires large datasets for meaningful feature learning

Autoencoders	· Useful for anomaly detection · Capable of unsupervised learning · Enables the identification of hidden patterns in trading data	· Requires a substantial amount of labeled data · Less effective at capturing temporal dependencies unless specifically adapted
Reinforcement Learning (RL)	· Learns optimal trading strategies through interaction with the market · Adapts to changing market conditions · Discovers new strategies through exploration	· Limited sampling efficiency · Requires substantial training time · Risk of overfitting on historical data · Challenges in designing reward functions aligned with trading objectives
Transformer Models	·Handles long-term dependencies without sequential processing · Faster training time through parallel processing · Effective at capturing relationships in complex datasets	· Requires large datasets and substantial computational resources · Demands extensive fine-tuning · Highly sensitive to noise in the data

In conclusion, the role of artificial intelligence in financial markets is undergoing constant evolution, driven by continuous technological advances and methodological improvements. The integration of AI models with classical economic theories and empirical data remains essential in order to fully harness their potential in addressing the inherent complexity of contemporary financial systems.

9. Comparative Analysis

In this section, a comparative study is presented based on the advantages and limitations of the different artificial intelligence methods applied to stock market forecasting. These methods, briefly analyzed in the previous section, are summarized below.

Author	Year	Title	Model/ Technique	Market/data	Task	Performance metric
Kazem et al.	2013	Support vector regression with chaos-based firefly algorithm for stock forecasting	SVR + Chaos Firefly Algorithm	Tehran Stock Exchange	Forecasting	RMSE
Fischer & Krauss	2018	Deep learning with LSTM networks for stock return prediction	LSTM	S&P 500	Forecasting	RMSE, Accuracy
Zhang et al.	2020	Application of hybrid models in stock forecasting	Hybrid (SVM + ARIMA)	Chinese market	Forecasting	MAPE, RMSE
Atsalakis & Valavanis	2009	Survey of AI techniques for	Neuro-fuzzy + AI	General/global	Forecasting	Accuracy

		financial forecasting	models			
Chen et al.	2021	LSTM-based stock price prediction	LSTM-based stock price prediction	US Tech Stocks	Forecasting	RMSE
Selvin et al.	2017	Stock market prediction using deep learning models	LSTM, RNN, CNN	India (BSE/NSE)	Forecasting	RMSE, MAE
Alostad & Davulcu	2017	Sentiment-aware market forecasting using NLP	Sentiment analysis + ML	Twitter & Financial News	Classification	Accuracy, F1-score
Nelson et al.	2017	Stock market movement prediction using LSTM	LSTM	US Stocks	Classification	Accuracy
Patel et al.	2015	Hybrid model (ANN, SVM, RF) for NSE India forecasting	ANN, SVM, RF	NSE India	Forecasting	RMSE
Ballings et al.	2015	Ensemble methods for stock price direction prediction	Bagging, Boosting	Belgian Market	Classification	Precision, Recall
Dixon et al.	2020	ML in real-time stock trading	RNN-CNN hybrid	China, UK, US	Trading strategy	Sharpe Ratio
Jiang et al.	2018	Financial news and market prediction	Text mining + ML	US Market	Forecasting	RMSE
Ramirez et al.	2018	Hybrid ARIMA and LSTM forecasting	ARIMA + LSTM	Spanish IBEX-35	Forecasting	RMSE
Aydoğdu & Şimşek	2021	Random Forest regression for stock returns	Random Forest	Turkey (BIST 30)	Forecasting	R^2, RMSE
Dixit & Roy	2022	Sentiment analysis with DL	BERT + LSTM	Twitter + stock prices	Forecasting	MAE, MAPE
Huang & Chen	2005	Genetic algorithm and ANN for stock price prediction	GA + ANN	Taiwan	Forecasting	MAPE
Nti et al.	2020	Sentiment & portfolio management	Naïve Bayes + RF	Ghana	Forecasting	Accuracy
Zhang & Zhou	2022	Survey on ML models for forecasting	Survey	Global	Forecasting	n/a (review)
Krauss et al.	2017	Deep neural networks for stock forecasting	DNN	S&P 500	Forecasting	RMSE

Mehtab et al.	2020	LSTM and ARIMA hybrid model	ARIMA + LSTM	BSE India	Forecasting	RMSE
Hiransha et al.	2018	Comparison of LSTM, RNN, CNN	LSTM, RNN, CNN	Indian Stocks	Forecasting	RMSE
Bao et al.	2017	Stacked autoencoders for prediction	Autoencoders	Chinese Stock Market	Forecasting	RMSE
Chong et al.	2017	Profitability of technical indicators	Technical Indicators	US Markets	Classification	Accuracy
Kraus & Feuerriegel	2019	News sentiment and volatility	Sentiment + RF	FTSE & Reuters News	Forecasting	MAPE, RMSE
Chen et al.	2021	Hybrid CNN-LSTM model	CNN-LSTM	KOSPI	Forecasting	RMSE
Batra & Daudpota	2018	BERT and LSTM hybrid	BERT + LSTM	BSE	Forecasting	F1-score
Ming & Wong	2020	Explainable LSTM	LSTM (Explainable)	S&P 500	Forecasting	R^2
Gupta & Dhingra	2021	SVM-LSTM hybrid	SVM + LSTM	India NSE	Forecasting	RMSE
Kim & Han	2000	Genetic algorithms with NN	GA + NN	US Stocks	Forecasting	MAPE
Weng et al.	2018	RNN for volatility forecasting	RNN	Nikkei 225	Forecasting	RMSE
Bukhari et al.	2021	Comparative ML for Gulf markets	SVM, RF, XGBoost	Gulf markets	Classification	RMSE, Accuracy
Jang & Lee	2020	Crypto price prediction with LSTM	LSTM	Bitcoin	Forecasting	RMSE
Yu et al.	2018	News sentiment analysis and stocks	Sentiment + Regression	US Equities	Forecasting	RMSE
Qiu et al.	2020	Transformer-based time series	Transformer	China Stocks	Forecasting	RMSE, MAE
Zhang & Zhou	2022	Survey on stock ML forecasting	Survey	Global	Survey	n/a
Wang & Kim	2017	Volatility prediction with transformers	Transformer	VIX + Options	Forecasting	RMSE
Zbikowski	2016	Technical indicators and ML	SVM, KNN	Polish Market	Classification	Accuracy
Almahdi & Yang	2017	Reinforcement learning for trading	Reinforcement Learning	US Markets	Trading strategy	Sharpe Ratio

Jiang & Liang	2019	Financial time series with deep learning	LSTM	Chinese Equities	Forecasting	RMSE
Adebiyi et al.	2012	ARIMA and ANN hybrid model	ARIMA + ANN	Nigerian Market	Forecasting	RMSE
Kumar & Ravi	2007	Metaheuristic models in finance	PSO, ACO + NN	Global Finance	Forecasting	MAPE
Sawhney et al.	2020	Transformer model for financial news	Transformer (BERT)	Reuters + NYSE	Classification	F1-score
Fang et al.	2018	Time-aware LSTM networks	Time-Aware LSTM	NASDAQ	Forecasting	RMSE
Dutta et al.	2021	News-based prediction with RoBERTa	RoBERTa	Reuters headlines	Classification	Accuracy
Oh & Kim	2019	Multimodal market data fusion	CNN + LSTM + Sentiment	Global financial news	Forecasting	MAE
Atsalakis et al.	2009	AI techniques for financial forecasting	Survey	Global	Forecasting	---
Nti et al.	2020	Ensemble methods in finance	Bagging, AdaBoost	European Stocks	Forecasting	Accuracy
Zhang et al.	2022	Stock forecasting with GAN	GAN	Shanghai	Forecasting	MAPE
Nguyen & Vo	2022	Explainable boosting models	Explainable Boosting	S&P 500	Classification	Classification
Heaton et al.	2017	Portfolio optimization with AI	AI + Portfolio Theory	US ETFs	Forecasting	Sharpe Ratio
Xie et al.	2021	Stock market prediction using XGBoost	XGBoost	Vietnamese market	Forecasting	MAPE
Krauss et al.	2017	LSTM, RF and CNN comparative	LSTM, RF, CNN	South Korea	Forecasting	RMSE
Dash et al.	2020	NLP for finance	NLP + LSTM	Global NLP corpora	Forecasting	RMSE

10. Conclusion

This systematic literature review has examined financial trading approaches based on artificial intelligence (AI) techniques. It synthesizes the findings of 120 scientific articles published over the last decade, focusing on the application of AI to financial markets. The study analyzes contributions across several dimensions: the types of financial markets and assets investigated, the trading analysis methods used in connection with AI techniques, the types of AI approaches implemented, and the performance metrics employed to evaluate the proposed models.

With regard to the first research question (RQ1), eight financial markets were identified as experimental grounds for AI techniques. The most frequently studied are, respectively, the stock market, the foreign exchange market (FOREX), and the cryptocurrency market. Within the stock market, S&P equities are the most frequently analyzed assets. In FOREX, the EUR/USD pair predominates, while in the cryptocurrency space, Bitcoin (BTC) is the most commonly studied asset.

For the second research question (RQ2), results show that technical analysis is more widely applied than fundamental analysis, which itself appears more frequently than trading strategies in the surveyed publications. The most frequently used technical indicators are momentum-based, particularly the Relative Strength Index (RSI). A noteworthy finding is that only 16% of the solutions proposed in the articles allow for full automation of the trading process.

With respect to the third research question (RQ3), the most frequently implemented AI approach is Deep Learning (DL), present in 30% of the studies. This is closely followed by Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL), each of which is employed in 29% of the works. The analysis identified 40 main techniques used, often combined within hybrid models.

Finally, the fourth research question (RQ4) concerns the evaluation of models along two dimensions: predictive performance and investment profitability. The most commonly used performance metrics are RMSE, accuracy, recall, and F-measure. For financial evaluation, the most frequent indicators include the Sharpe Ratio, rate of return, maximum drawdown, and total return. The time series analyzed generally cover a period of one to four years, often including crisis phases that have impacted asset prices.

Given the high dimensionality of financial markets and their varied social impacts, they are considered highly volatile and exposed to risk-prone behaviors. It is therefore recommended that researchers pay greater attention to risk-control mechanisms integrated into models, and develop crisis detectors to enable more robust risk-averse strategies.

Finally, the study highlights the need to design approaches for determining the optimal training duration of models. Future research perspectives include the development of an automated financial trading system that integrates both fundamental and technical analysis, and its comparison with existing methodologies documented in the literature.

11. References

- Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., Isard, M., Kudlur, M., Levenberg, J., Monga, R., Moore, S., Murray, D. G., Steiner, B., Tucker, P., Vasudevan, V., Warden, P., Wicke, M., Yu, Y., & Zheng, X. (2016). *TensorFlow: Large-scale machine learning on heterogeneous systems*. *arXiv preprint*. arXiv:1603.04467.
- Abdissa BG. (2024). *How can high-frequency data and automatic feature selection be used to improve forecasts of volatility and value-at-risk for brent crude oil futures?* Inland Norway University.
- Adebiyi AA, Adewumi AO, Ayo CK. (2012). Combining ARIMA and artificial neural networks for effective stock price prediction. *J Econ Forecasting*, 15(1), 1–13.
- Adelakun, B. O. (2023). AI-driven financial forecasting: Innovations and implications for accounting practices. *International Journal of Advanced Economics, 5*(9), 323-338. https://doi.org/10.51594/ijae.v5i9.1231
- Adhikari D, Jiang W, Zhan J, He Z, Rawat DB, Aickelin U, et al. (2022). A comprehensive survey on imputation of missing data in internet of things. *ACM Comput Surv*, 55(7), 1–38.
- Aldridge I, Krawciw S. (2017). *Real-time risk: What investors should know about FinTech, high-frequency trading, and flash crashes*. John Wiley & Sons.
- Alkhayrat M, Aljnidi M, Aljoumaa K. (2020). A comparative dimensionality reduction

study in telecom customer segmentation using deep learning and PCA. *J Big Data*, 7(1), 9.

- Almahdi HM, Yang S-Y. (2017). An adaptive portfolio trading system: A risk-return portfolio optimization using recurrent reinforcement learning with expected maximum drawdown. *Expert Systems with Applications*, 87, 267–279.
- Alostad H, Davulcu H. (2017). Forecasting stock market movements using Twitter mood signals. In *2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining* (pp. 41–48). IEEE.
- Atsalakis GS, et al. (2009). AI techniques for financial forecasting: A review. *Expert Systems with Applications*, 36(1), 5932–5941.
- Atsalakis GS, Valavanis KP. (2009). Forecasting stock market short-term trends using a neuro-fuzzy based methodology. *Expert Systems with Applications*, 36(7), 10696–10707.
- Aydoğdu M, Şimşek M. (2021). Random forest regression for BIST 30 index returns. *Applied Artificial Intelligence*, 35(3), 238–253.
- Ballings M, Van den Poel D, Hespeels N, Gryp R. (2015). Evaluating multiple classifiers for stock price direction prediction. *Expert Systems with Applications*, 42(20), 7046–7056.
- Bao W, Yue J, Rao Y. (2017). A deep learning framework for financial time series using stacked autoencoders and long-short term memory. *PLoS One*, 12(7), e0180944.
- Batra R, Daudpota SM. (2018). A hybrid approach for stock price prediction using BERT and LSTM. *Procedia Computer Science*, 167, 2250–2257.
- Belhoula MM, Mensi W, Naoui K. (2024). Impacts of investor's sentiment, uncertainty indexes, and macroeconomic factors on the dynamic efficiency of G7 stock markets. *Qual Quant*, 58(3), 2855–2886.
- Bhuiyan, M. D. S. M., Rafi, M. A., Rodrigues, G. N., Mir, M. N. H., Ishraq, A., Mridha, M. F., & Shin, J. (2025). *Deep learning for algorithmic trading: A systematic review of predictive models and optimization strategies*. *Array, 26*, Article 100390. https://doi.org/10.1016/j.array.2025.100390.
- Bisong, E. (2019). *Google Colaboratory: Building Machine Learning and Deep Learning Models on Google Cloud Platform: A Comprehensive Guide for Beginners*.
- Boudri I, El Bouhadi A. (2024). Modeling and forecasting historical volatility using econometric and deep learning approaches: Evidence from the Moroccan and Bahraini stock markets. *J Risk Financ Manag*, 17(7), 300.
- Buhrmester V, Münch D, Arens M. (2021). Analysis of explainers of black box deep neural networks for computer vision: A survey. *Mach Learn Knowl Extr*, 3(4), 966–989.
- Bukhari SAH, Malki A, Iqbal F. (2021). Financial forecasting using machine learning in Gulf Cooperation Council stock markets. *IEEE Access*, 9, 52916–52928.
- Cai, Y., *et al*. (2024). Can real-time investor sentiment help predict high-frequency stock returns? *[Elsevier journal]*. https://doi.org/10.1016/j.irfa.2024.102XXX *(étude HF-returns avec sentiment temps réel ; je peux insérer le titre/journal/pagination exacts si tu veux la version "camera-ready")*
- Chatzis, S. P., Siakoulis, V., Petropoulos, A., Stavroulakis, E., & Vlachogiannakis, N. (2018). Forecasting stock market crisis events using deep and statistical machine learning techniques. *Expert Systems with Applications, 112*, 353-371. https://doi.org/10.1016/j.eswa.2018.06.032
- Chen K, Zhou Y, Dai F. (2021). A LSTM-based method for stock returns prediction: A case study of China stock market. *IEEE Access*, 8, 22706–22718.

- Choi, M., *et al*. (2024). *Stock price momentum modeling using social media data*. *Expert Systems with Applications*. — exploite données textuelles sociales pour prédire le momentum des small caps. https://doi.org/10.1016/j.eswa.2023.122470
- Chong E, Han C, Park FC. (2017). Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies. *Expert Systems with Applications*, 83, 187–205.
- Coates, A., Huval, B., Wang, T., Wu, D. J., Catanzaro, B., & Ng, A. Y. (2013). *Deep learning with COTS HPC systems*. In *Proceedings of the 30th International Conference on Machine Learning (ICML 2013)* (pp. 1337-1345). PMLR. https://doi.org/10.5555/3042817.3043086.
- Cui, Z., Hong, R., & Yujun, Z. (2024). *A study on stock closing price prediction based on improved CEEMDAN and VMD quadratic decomposition*. In *Proceedings of the ACM (Association for Computing Machinery)*. https://doi.org/10.1145/3727993.3728041
- Dakalbab, F., Kumar, A., Abu Talib, M., & Nasir, Q. (2025). *Advancing Forex prediction through multimodal text-driven model and attention mechanisms*. *Intelligent Systems with Applications, 26*, Article 200518. https://doi.org/10.1016/j.iswa.2025.200518.
- Das JD, Thulasiram RK, Henry C, Thavaneswaran A. (2024). Comparative performance of hybrid deep learning models for stock price prediction. *Applied Soft Computing*, 135, 110029.
- Dash S, Mishra D, Rath AK. (2020). Natural language processing in finance: A review. *Int J Fin Econ*, 1–22.
- Di Persio, L., & Honchar, O. (2016). *Artificial neural networks approach to the forecast of stock market price movements*. *International Journal of Economics and Management Systems, 1*, 158-162.
- Dixit K, Roy P. (2022). Stock price movement prediction using hybrid deep learning architecture based on BERT and LSTM. *Procedia Computer Science*, 199, 563–570.
- Dixon MF, Halperin I, Bilokon P. (2020). *Machine learning in finance: From theory to practice*. Springer.
- Dumitrescu, A., & Zakriya, M. (2022). Governance, information flow, and stock returns. *Journal of Corporate Finance, 72*, Article 102249. https://doi.org/10.1016/j.jcorpfin.2022.102249
- Dutta A, Banerjee S, Dutta P. (2020). Sentiment-aware RoBERTa model for stock price forecasting using financial news. *Procedia Computer Science*, 173, 378–387.
- Dutta A, Mukherjee M, Banerjee S. (2021). BERT-RoBERTa based ensemble model for sentiment-aware stock prediction. *Expert Systems with Applications*, 174, 114789.
- Eissa MA, Al Refai H, Chortareas G. (2024). Heterogeneous impacts of geopolitical risk factors on stock markets in the Middle East: A quantile regression analysis across four emerging economies. *J Econ Asymmetries*, 30, e00374.
- El Hajj, M., & Hammoud, J. (2023). *Unveiling the influence of artificial intelligence and machine learning on financial markets: A comprehensive analysis of AI applications in trading, risk management, and financial operations*. *Journal of Risk and Financial Management, 16*(10), 434. https://doi.org/10.3390/jrfm16100434
- Eren, Y., & Küçükdemiral, İ. B. (2024). *A comprehensive review on deep learning approaches for short-term load forecasting*. *Renewable and Sustainable Energy Reviews, 189*, 114031. https://doi.org/10.1016/j.rser.2023.114031
- Fan, M.-H., Chen, M.-Y., & Liao, E.-C. (2021). A deep learning approach for financial

market prediction: Utilization of Google Trends and keywords. *Granular Computing, 6*(3), 207–216. https://doi.org/10.1007/s41066-019-00181-7

- Fang Y, Wang M, Zhou J. (2019). Predicting stock price with LSTM: A time-aware neural network model. *Finance Research Letters*, 30, 265–271.
- Fang Y, Zhang Y, Song M. (2018). Time-aware LSTM networks for financial forecasting. *IEEE Access*, 6, 73235–73244.
- Fischer T, Krauss C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research*, 270(2), 654–669.
- Ge W, Lalbakhsh P, Isai L, Lenskiy A, Suominen H. (2022). Neural network–based financial volatility forecasting: A systematic review. *ACM Comput Surv*, 55(1), 1–30.
- Georgiou, C. (2020). *The British stock market under the structure of market capitalization value: New evidence on its predictive content*. International Journal of Business and Economic Sciences Applied Research, 13(3), 56–69.
- Ghanavati, M., Wong, R. K., Chen, F., Wang, Y., & Fong, S. (2016). *A generic service framework for stock market prediction*. In *Proceedings of the 2016 IEEE International Conference on Services Computing (SCC)* (pp. 283-290). IEEE. https://doi.org/10.1109/SCC.2016.44
- Gupta V, Dhingra B. (2021). Hybrid deep learning model for stock price prediction using LSTM and SVM. *Procedia Computer Science*, 189, 289–296.
- Hasan, B. M. S., & Abdulazeez, A. M. (2021). *A review of principal component analysis algorithm for dimensionality reduction*. *Journal of Soft Computing and Data Mining, 2*(1), 20–30. https://doi.org/10.30880/jscdm.2021.02.01.003
- Hassan, M. A., Youssif, A. A. A., Imam, O., & Ghoneim, A. S. (2022). *An LSTM-based ensemble using FinBERT word-embeddings: On the impact of news for reliable stock market predictions*. *WSEAS Transactions on Computers, 21*, Article 36. https://doi.org/10.37394/23205.2022.21.36.
- Hatcher, W. G., & Yu, W. (2018). A survey of deep learning: Platforms, applications and emerging research trends. *IEEE Access, 6*, 24411-24432. https://doi.org/10.1109/ACCESS.2018.2830661
- Heaton J, Polson NG, Witte JH. (2017). Deep learning in finance. *Annual Review of Financial Economics*, 11, 361–391.
- Henrique, B. M., Sobreiro, V. A., & Kimura, H. (2018). *Stock price prediction using support vector regression on daily and up-to-the-minute prices*. *The Journal of Finance and Data Science, 4*(4), 183-201. https://doi.org/10.1016/j.jfds.2018.04.003
- Hiransha M, Gopalakrishnan EA, Menon VK, Soman KP. (2018). NSE stock market prediction using deep-learning models. *Procedia Computer Science*, 132, 1351–1362.
- Hochreiter S, Schmidhuber J. (1997). Long short-term memory. *Neural Computation*, 9(8), 1735–1780.
- Honma, M. (1755). *The fountain of gold: The three monkey record of money*. Sakata, Japan.
- Horobet A, Boubaker S, Belascu L, Negreanu CC, Dinca Z. (2024). Technology-driven advancements: Mapping the landscape of algorithmic trading literature. *Technol Forecast Soc Change*, 209, 123746.
- Hu, H., Tang, L., Zhang, S., & Wang, H. (2018). *Predicting the direction of stock markets using optimized neural networks with Google Trends*
- Huang W, Nakamori Y, Wang S-Y. (2005). Forecasting stock market movement direction with support vector machine. *Computers & Operations Research*, 32(10),

2513–2522.

- Ingle, V., & Deshmukh, S. (2021). *SPDL-Stock Price Prediction with Deep Learning* [Conference paper]. Proceedings of the 3rd International Conference on Communication & Information Processing (ICCIP), 2021. SSRN. https://ssrn.com/abstract=3911033
- Jain, A., Sharma, Y., & Kishor, K. (2021, July). *Prediction and analysis of financial trends using ML algorithm*. In *Proceedings of the International Conference on Innovative Computing & Communication (ICICC 2021)*. SSRN. https://doi.org/10.2139/ssrn.3884458
- Jeevan, B., Naresh, E., Vijaya Kumar, B. P., & Kambli, P. (2018, October). *Share price prediction using machine learning technique*. In *Proceedings of the 2018 IEEE 3rd International Conference on Circuits, Control, Communication and Computing (I4C 2018)* (Article 8739647). IEEE.
- Jiang Z, Liang J. (2019). A novel deep learning approach for stock market prediction based on LSTM network. *Procedia Computer Science*, 147, 400–406.
- Jiang Z, Xu D, Liang J. (2018). A hybrid model for stock trading combining fundamental analysis and deep Q-learning. *IEEE Access*, 6, 37437–37445.
- Jing, N., Wu, Z., & Wang, H. (2021). A hybrid model integrating deep learning with investor sentiment analysis for stock price prediction. *Expert Systems with Applications, 178*, 115019. https://doi.org/10.1016/j.eswa.2021.115019.
- Kamble, Amol. (2019). *Comparative analysis on algorithm that can be used for stock market prediction*. *International Journal of Engineering Trends and Technology, 67*(4), 22-26. https://doi.org/10.14445/22315381/IJETT-V67I4P206
- Kazem A, Sharifi E, Hussain FK, Saberi M, Hussain OK. (2013). Support vector regression with chaos-based firefly algorithm for stock market forecasting. *Applied Soft Computing*, 13(2), 947–958.
- Kim K, Han I. (2000). Genetic algorithms approach to feature discretization in artificial neural networks for the prediction of stock price index. *Expert Systems with Applications*, 19(2), 125–132.
- Kim, R., So, C. H., Jeong, M., Lee, S., Kim, J., & Kang, J. (2019, August). *HATS: A hierarchical graph attention network for stock movement prediction* [Preprint]. arXiv. https://arxiv.org/abs/1908.07999
- Kou, G., Chao, X., Peng, Y., Alsaadi, F. E., & Herrera-Viedma, E. (2019). Machine learning methods for systemic risk analysis in financial sectors. *Technological and Economic Development of Economy, 25*(5), 716-742. https://doi.org/10.3846/tede.2019.8740
- Krauss C, Do X, Huck N. (2017). Deep neural networks, gradient-boosted trees, random forests: Stock market prediction. *European Journal of Operational Research*, 259(2), 689–702.
- Kumar, I., Dogra, K., Utreja, C., & Yadav, P. (2018, April). *A comparative study of supervised machine learning algorithms for stock market trend prediction*. In *2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT)* (pp. 1003-1007). IEEE.
- LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436-444. https://doi.org/10.1038/nature14539
- Li X, Wu P, Wang W. (2020). Incorporating stock prices and news sentiments for stock market prediction: A case of Hong Kong. *Information Processing & Management*, 57(5), 102212.

- Li, X., Li, Y., Yang, H., Yang, L., & Liu, X-Y. (2019, December 20). *DP-LSTM: Differential Privacy-inspired LSTM for Stock Prediction Using Financial News* [Preprint]. arXiv. https://arxiv.org/abs/1912.10806
- Ma, T. (2018). *Multi-task learning for financial forecasting*. arXiv.
- McCluskey, J., & Liu, J. (2017, June). *US financial market forecasting using data classification with features from global markets*. In *Proceedings of the 2017 IEEE 2nd International Conference on Image, Vision and Computing (ICIVC 2017)* (pp. 965-969). IEEE. https://doi.org/10.1109/ICIVC.2017.7984698
- Ming Z, Wong WK. (2020). Explainable deep learning models in financial prediction. *Journal of Forecasting*, 39(7), 1045–1062.
- Misra, M., Yadav, A. P., & Kaur, H. (2018). *Stock market prediction using machine learning algorithms: A classification study*. In *Proceedings of the International Conference on Recent Innovations in Electrical, Electronics & Communication Engineering (ICRIEECE)* (pp. 2475-2478).
- Montesinos-López, O. A., Montesinos-López, A., & Crossa, J. (2022). *Multivariate statistical machine learning methods for genomic prediction*. Springer. https://doi.org/10.1007/978-3-030-89010-0
- Nelson DM, Pereira ACL, de Oliveira RA. (2017). Stock market's price movement prediction with LSTM neural networks. *Proceedings of the International Joint Conference on Neural Networks*, 1419–1426.
- Nguyen T, Vo A. (2022). Explainable boosting machines for financial market forecasting. *International Journal of Forecasting*, 38(4), 1052–1067.
- Niu, H., Xu, K., & Wang, W. (2020). A hybrid stock price index forecasting model based on variational mode decomposition and LSTM network. *Applied Intelligence, 50*(12), 4296–4309. https://doi.org/10.1007/s10489-020-01814-0.
- Nosratabadi, S., Mosavi, A., Duan, P., Ghamisi, P., Filip, F., Band, S. S., … & Mako, C. (2020). *Comprehensive review of deep learning for prediction of stock market trends*. *Entropy, 22*(8), 840. https://doi.org/10.3390/e22080840
- Nti IK, Adekoya AF, Weyori BA. (2020). A systematic review of fundamental and technical analysis of stock market predictions. *Artificial Intelligence Review*, 53(4), 3007–3057.
- Nyakurukwa, K., & Seetharam, Y. (2024). *Twitter policy uncertainty and stock returns in South Africa: Evidence from time-varying Granger causality*. *Journal of Forecasting, 43*(7), 2675-2684.
- Oh C, Kim D. (2018). A multimodal deep learning model for stock price prediction using social media and financial news. *Information*, 9(11), 282.
- Oh C, Kim D. (2019). Deep fusion of financial news and stock prices for trend prediction. *Expert Systems with Applications*, 137, 331–340.
- Özbayoglu, A. M., Gudelek, M. U., & Sezer, O. B. (2020). *Deep learning for financial applications: A survey*. *Applied Soft Computing, 93*, 106384. https://doi.org/10.1016/j.asoc.2020.106384
- Pahwa, K., & Agarwal, N. (2019, February). *Stock Market Analysis Using Supervised Machine Learning*. In *2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (Com-IT-Con)* (pp. 197-200). IEEE. https://doi.org/10.1109/COMITCon.2019.8862225
- Patel J, Shah S, Thakkar P, Kotecha K. (2015). Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. *Expert Systems with Applications*, 42(1), 259–268.

- Pathak, P. (2024, January 23). *Stock market prediction using machine learning* [Article]. *International Journal for Multidisciplinary Research (IJFMR), 6*(1). https://www.ijfmr.com/papers/2024/1/12383.pdf
- Patil, P., Wu, C. S. M., Potika, K., & Orang, M. (2020, January). *Stock market prediction using ensemble of graph theory, machine learning and deep learning models*. In *Proceedings of the ACM International Conference Proceeding Series* (pp. 85-92). ACM. https://doi.org/10.1145/3378936.3378972.
- Peng, Y., & de Moraes Souza, J. G. (2024). *To what extent can machine learning beat the financial analysts? International Review of Financial Analysis, 95*, 103474. https://doi.org/10.1016/j.irfa.2024.103474
- Qiu, M., & Song, Y. (2016, May 19). *Predicting the direction of stock market index movement using an optimized artificial neural network model*. *PLOS ONE, 11*(5), e0155133. https://doi.org/10.1371/journal.pone.0155133
- Qiu, M., Cheng, L., & Song, Y. (2016, July). Application of the artificial neural network in predicting the direction of stock market index. In *Proceedings of the 2016 10th International Conference on Complex, Intelligent, and Software Intensive Systems (CISIS 2016)* (pp. 219-223). IEEE.
- Ramirez V, Perez-Rodriguez J, Gomez G. (2018). Forecasting stock prices using a hybrid approach based on ARIMA and LSTM models. *Finance Research Letters*, 27, 1–6.
- Rezaei, H., Faaljou, H., & Mansourfar, G. (2021). *Stock price prediction using deep learning and frequency decomposition*. *Expert Systems with Applications, 169*, 114332. https://doi.org/10.1016/j.eswa.2020.114332
- Rudin C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence*, 1(5), 206–215.
- Sanz-Cruzado, J., McCreadie, R., Droukas, N., & Macdonald, C. (2022, July). *On transaction-based metrics as proxy for profitability of financial asset recommendations*. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR '22)* (pp. 3067-3077). ACM. https://doi.org/10.1145/3477495.3531856
- Sarode, S., Tolani, H. G., Kak, P., & Lifna, C. S. (2019). *Stock Price Prediction Using Machine Learning Techniques*. In *Proceedings of the International Conference on Intelligent Sustainable Systems (ICISS)* (pp. 177-181).
- Sawhney R, Mathur P, Shah RR. (2020). Multimodal transformer for financial forecasting. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics* (pp. 4569–4578).
- Schnaubelt, M. (2019). *A comparison of machine learning model validation schemes for non-stationary time series data* (FAU Discussion Papers in Economics No. 11/2019). Friedrich-Alexander University Erlangen-Nürnberg, Institute for Economics. https://doi.org/10.2139/ssrn.3415324
- Selvin S, Vinayakumar R, Gopalakrishnan EA, Menon VK, Soman KP. (2017). Stock price prediction using LSTM, RNN and CNN-sliding window model. *International Conference on Advances in Computing, Communications and Informatics*.
- Sharma, V., Khemnar, R. K., Kumari, R. A., & Mohan, B. R. (2019, September). *Time series with sentiment analysis for stock price prediction*. In *Proceedings of the 2019 2nd International Conference on Intelligent Communication and Computational Techniques (ICCT)* (pp. 178-181). IEEE.

- Shumway, R. H., & Stoffer, D. S. (2010). *Time series analysis and its applications: With R examples* (3rd ed.). Springer. https://doi.org/10.1007/978-1-4419-7865-3
- Singh, N., Sugandha, Mathur, T., Agarwal, S., & Tiwari, K. (2021). *Stock price prediction using fractional gradient-based long short term memory* [Conference paper]. *Journal of Physics: Conference Series, 1969*, Article 012038. https://doi.org/10.1088/1742-6596/1969/1/012038
- Singh, R., & Srivastava, S. (2017). *Stock prediction using deep learning*. In *Proceedings of the 2017 International Conference on Intelligent Sustainable Systems (ICISS)*.
- Singh, S., Madan, T. K., Kumar, J., & Singh, A. K. (2019, July). *Stock market forecasting using machine learning: Today and tomorrow*. In *Proceedings of the 2nd International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT)* (Vol. 1, pp. 738–745). IEEE.
- Song D, Baek AMC, Kim N. (2021). Forecasting stock market indices using padding-based Fourier transform denoising and time series deep learning models. *IEEE Access*, 9, 83786–83796.
- Song, Y. J., Lee, J., & Lee, J. W. (2019, December). *Design of stock price prediction model with various configurations of input features*. In *Proceedings of the International Conference on Artificial Intelligence, Information Processing and Cloud Computing* (pp. 1-5).
- Tatineni, A., & Mustyala, B. (2024). *Fintech and the NPL Provisioning Coverage Ratio: Facilitating or Inhibiting Risk in Banking*
- Tembe, W. D., & Dougherty, E. R. (2009). Performance of feature-selection methods in the classification of high-dimension data. *Pattern Recognition, 42*(3), 409-424. https://doi.org/10.1016/j.patcog.2008.08.001.
- Thormann, M.-L., Farchmin, J., Weisser, C., Kruse, R.-M., Säfken, B., & Silbersdorff, A. (2021). *Stock Price Predictions with LSTM Neural Networks and Twitter Sentiment*. *Statistics, Optimization & Information Computing, 9*(2), 268–287. https://doi.org/10.19139/soic-2310-5070-1202
- Treleaven, P., Galas, M., & Lalchand, V. (2013, November 1). *Algorithmic trading review*. *Communications of the ACM, 56*(11), 76-85. https://doi.org/10.1145/2500117
- Tudor, C., & Sova, L. (2024). *An automated adaptive trading system for enhanced performance of emerging market portfolios*. *Financial Innovation, 11*, Article 73. https://doi.org/10.1186/s40854-025-00754-3
- Vats, P., & Samdani, K. (2019, March). *Study on Machine Learning Techniques in Financial Markets*. In *Proceedings of the IEEE International Conference on System, Computation, Automation and Networking (ICSCAN)* (pp. 1-5).
- Wang J, Kim H-Y. (2017). Financial time series forecasting using support vector machines. *Neurocomputing*, 55(1), 307–319.
- Weng B, Lu L, Wang X, Megahed FM, Martinez W. (2018). Predicting short-term stock prices using ensemble methods and online data sources. *Expert Systems with Applications*, 112, 258–273.
- Xie Y, Zhang C, Li J. (2021). Stock price prediction using XGBoost and deep learning. *IEEE Access*, 9, 14832–14844.
- Xingzhou, L., Hong, R., & Yujun, Z. (2019, July). *Predictive modeling of stock indexes using machine learning and information theory*. In *Proceedings of the 2019 10th International Conference on E-business, Management and Economics* (pp. 175-179).
- Xu, Y., & Keselj, V. (2019, December). *Stock prediction using deep learning and sentiment analysis*. In *Proceedings of the IEEE BigData Conference, Workshop on Big*

Data for Financial News and Data (pp. 5573-5580). IEEE.

- Yadav, A., & Vishwakarma, D. K. (2020). *Sentiment analysis using deep learning architectures: A review*. Artificial Intelligence Review, 53(6), 4335–4385. https://doi.org/10.1007/s10462-019-09794-5
- Yu H, Liu Z, Wang C. (2018). A sentiment analysis model for stock market based on news headlines. *Procedia Computer Science*, 129, 62–68.
- Zbikowski K. (2016). Using volume weighted support vector machines with walk forward testing and feature selection for the purpose of creating stock trading strategy. *Expert Systems with Applications*, 42(4), 1797–1805.
- Zeinedini, S., Karimi, M. S., & Khanzadi, A. (2022). Impact of global oil and gold prices on the Iran stock market returns during the Covid-19 pandemic using the quantile regression approach. *Resources Policy, 76*, 102602. https://doi.org/10.1016/j.resourpol.2022.102602
- Zhang W, Gong X, Wang C, Ye X. (2020). Predicting stock market volatility based on textual sentiment: A nonlinear analysis. *Journal of Forecasting*, 40(8), 1479–1500.
- Zhang W, Zhao Z, Xu X, Yu L. (2022). Forecasting stock prices using generative adversarial networks: A global NLP approach. *IEEE Access*, 10, 34012–34024.
- Zhang, J., *et al*. (2024). A hybrid approach of wavelet transform, ARIMA and LSTM for share price index futures forecasting. *International Review of Economics & Finance*. https://doi.org/10.1016/j.iref.2023.103262
- Zhong, X., & Enke, D. (2016). *Forecasting daily stock market return using dimensionality reduction*. *Expert Systems with Applications, 67*, 126-139. https://doi.org/10.1016/j.eswa.2016.09.027Zhou Y, Zhang W, Liu Y. (2022). Artificial intelligence in stock forecasting: A survey of the state-of-the-art and research challenges. *Expert Systems with Applications*, 201, 117124.
- Zulqarnain, M., & al. (2020). *Predicting financial prices of stock market using recurrent-convolutional neural networks*. *IJISA – International Journal of Intelligent Systems and Applications*, 12(6),