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Deep learning for algorithmic trading: A systematic review of predictive models and optimization strategies

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ABSTRACT

Algorithmic trading has revolutionized financial markets, offering rapid and efficient trade execution. The integration of deep learning (DL) into these systems has further enhanced predictive capabilities, providing sophisticated models that capture complex, non-linear market patterns. This systematic literature review explores recent advancements in the application of DL algorithms to algorithmic trading with a focus on optimizing financial market predictions. We analyze and synthesize the key DL architectures, such as recurrent neural networks (RNN), long short-term memory (LSTM), convolutional neural networks (CNN), and hybrid models, to evaluate their performance in predicting stock prices, volatility, and market trends. The review highlights current challenges, such as data noise, overfitting, and interpretability, while discussing emerging solutions and future research directions. Our findings provide a comprehensive understanding of how DL reshapes algorithmic trading and its potential to improve decision-making processes in volatile financial environments.

1. Introduction

Algorithmic trading has transformed the financial markets by automating the process of executing trades, relying on pre-programmed instructions and sophisticated mathematical models to achieve speed and efficiency unattainable by human traders [1,2]. This shift from manual to algorithmic trading has allowed market participants to capitalize on minute price discrepancies and market inefficiencies with remarkable precision, especially in high-frequency trading (HFT), where milliseconds can define success or failure [3,4]. The financial sector's increasing reliance on computational power to process vast volumes of market data in real-time has laid the groundwork for advanced techniques like machine learning (ML) and deep learning (DL) to optimize trading strategies and market predictions [5–7].

Deep learning, a subset of machine learning, has gained significant attention in recent years due to its ability to handle vast amounts of unstructured data, such as price time series, social media sentiment, and economic indicators [8–10]. Unlike traditional machine learning algorithms, deep learning models, particularly neural networks, excel at identifying complex, non-linear patterns, making them ideal for analyzing chaotic and highly volatile financial markets [11,12]. DL architectures like Recurrent Neural Networks (RNNs) [13], Long Short-Term Memory (LSTM) networks [14], Convolutional Neural Networks (CNNs) [15], and hybrid models have shown promise in predicting stock prices, detecting market trends, and managing portfolio risks [16,17].

Financial market predictions have traditionally been challenging due to market volatility, noise, and unpredictability [18,19]. However, introducing DL algorithms offers an unprecedented opportunity to improve predictive accuracy by modeling dynamic relationships that elude traditional statistical methods [20,21]. While conventional algorithmic trading strategies have been driven primarily by technical indicators, DL enables incorporating a broader array of inputs, such as historical market data, macroeconomic factors, and textual data from news and social media [22]. This shift presents an opportunity for algorithmic trading systems to execute trades and actively adapt and optimize strategies based on predictive insights drawn from complex data sets.

Despite the considerable promise of deep learning in algorithmic trading, the literature remains fragmented, with many studies focusing

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on isolated aspects of DL without providing a comprehensive view of its applications across various trading strategies [23,24]. Previous reviews have often concentrated either on broader machine learning applications in finance or on specific DL techniques applied to narrow problem sets, such as stock price prediction [25]. As a result, there is a notable gap in the systematic synthesis of research that encompasses both the range of DL models used and their practical efficacy in optimizing algorithmic trading.

The financial markets are characterized by increasing complexity, driven by globalization, technological advancements, and the proliferation of high-frequency trading [26,27]. Traditional trading models struggle to cope with the volume and velocity of data generated, while financial regulations and market structure changes require ever more adaptive and intelligent trading systems [28,29]. The demand for more robust predictive models necessitates a review that explores how DL techniques are being leveraged to optimize these systems, overcoming the limitations of earlier approaches.

This systematic literature review aims to fill this gap by providing a structured and comprehensive analysis of deep learning's applications in algorithmic trading. This paper seeks to identify trends, challenges, and emerging opportunities by critically evaluating existing research. Given the growing influence of artificial intelligence (AI) in finance, this review is crucial for guiding future research and development in algorithmic trading systems that are more predictive, adaptive, and ultimately more profitable. This paper makes the following key contributions to the intersection of deep learning (DL) and algorithmic trading:

- The paper examines how deep learning algorithms are currently being applied to various financial markets. It explores a broad spectrum of DL architectures, including RNN, LSTM, CNN, and hybrid models, used across different financial instruments such as stocks, commodities, and foreign exchange. The review identifies how these models are employed for diverse prediction tasks, including price trends and market volatility forecasting.
- This study critically evaluates the challenges and limitations of using deep learning in optimizing financial market predictions. It highlights key issues such as the difficulty of managing noisy and incomplete data, the risk of overfitting in complex models, and the lack of interpretability in DL models due to their black-box nature. Additionally, the review explores the computational intensity required for large-scale financial datasets, providing insights into practical and theoretical barriers to adoption.
- The paper outlines emerging opportunities in the use of DL for algorithmic trading. It identifies promising areas for further investigation, such as the development of new DL architectures, the integration of hybrid models that combine deep learning with reinforcement learning or traditional methods, and the use of advanced data integration techniques like attention mechanisms and transformers. These opportunities point to ways in which DL can enhance predictive power and operational efficiency in financial markets.

By synthesizing the current state of research, this paper provides a consolidated understanding of deep learning's role in algorithmic trading and lays the groundwork for future advancements. These contributions are intended to drive both academic inquiry and practical applications in financial technology, offering novel insights into optimizing trading strategies through advanced predictive models.

The paper is structured as follows: Section 2 provides an overview of existing reviews in the field, summarizing key studies and methodologies. Section 3 outlines the review methodology used to collect and analyze relevant literature. Section 4 presents the theoretical background, covering foundational concepts and models. Section 5 discusses the results and findings from the reviewed studies. Section 6 identifies challenges in the field, such as data quality and model complexity. Section 7 offers a discussion of these challenges and suggests future research directions. Finally, Section 8 concludes the paper, summarizing key insights and recommendations.

2. Existing reviews

Numerous reviews have examined the role of ML and DL in financial applications, especially in the domain of algorithmic trading [30–32]. These reviews typically focus on isolated components, such as specific algorithms, data types, or market scenarios [33]. However, few offer a systematic synthesis across diverse DL models and their application to various financial markets. Table 1 shows several key reviews that have contributed to the understanding of DL in trading while highlighting their limitations.

For instance, Biju et al. [34] quantitatively analyze ML, AI, and DL literature through bibliometric methods, identifying trends and research themes such as ESG scoring and geographical insights. They also highlight algorithmic bias concerns, although they note the lack of empirical research on advanced automated financial technologies and issues with traceability and replicability in deep learning systems. Similarly, Sonkavde et al. [6] review recent ML and DL techniques for stock price prediction, proposing a generic framework for prediction and classification. While their work focuses on ensemble models, they acknowledge limitations such as insufficient exploration of ensemble methods and the missed integration of sentiment analysis, which could enhance model predictive power.

Salehpour et al. [32] provide a holistic view of cutting-edge machine learning applications in algorithmic trading, emphasizing real-world performance and the risks of overfitting and interpretability. They stress that their review may not encompass all emerging techniques in this rapidly evolving field. Ayitey et al. [35] focus on machine learning algorithms applied to forex market forecasting from 2010 to 2021. Their meta-analysis evaluates model performance but is limited by the quality of included studies and a lack of standardization in model evaluation metrics.

Joiner et al. [38] offer insights into financial asset price forecasting models, highlighting research gaps in data warehousing integration and algorithmic trading's impact on market liquidity. However, they face limitations in comparability due to inconsistent reporting metrics and the reliance on specific datasets. Cohen et al. [37] integrate human behavior and social media sentiment with traditional data for algorithmic trading, enhancing predictions of price movements. However, they emphasize the risks associated with algorithmic misinterpretation during extreme price movements and the challenges of data quality.

Lastly, Singh et al. [31] review learning methods such as DL, RL, and DRL in finance, presenting a framework for applying these techniques to financial problems. They identify limitations such as their narrow exploration of single-agent settings and the neglect of data quality issues.

These existing reviews provide a foundation but highlight the fragmented nature of research in the application of deep learning to algorithmic trading. Our systematic review seeks to fill these gaps by providing a comprehensive overview of the diverse DL models, their applications, challenges, and future research directions.

3. Review methodology

This section outlines the methodology used to conduct a systematic review of DL applications in algorithmic trading. By following a structured and rigorous approach, we aim to ensure that the review is both comprehensive and replicable, allowing future researchers to build on our findings.

3.1. Systematic review protocol

This study follows a systematic literature review (SLR) methodology, guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol [39,40]. The PRISMA approach is designed to ensure transparency, rigor, and replicability in conducting systematic reviews [41]. By adhering to this protocol, we structured

Table 1
Summary of key reviews on DL in algorithmic trading, their contributions, and limitations.

Ref.	Year	Systematic review	Dataset description	Technological advancements	Results analysis	Challenges & future work	Contribution	Limitations
[36]	2025	✓	×	×	×	×	This paper integrates AI and ML techniques to enhance stock market prediction accuracy, addresses research gaps in emerging data sources, connects predictive models to economic sustainability, and employs a systematic review methodology for comprehensive analysis.	This paper highlights the lack of standardized data frameworks, limited real-time adaptability, the high computational complexity of reinforcement learning techniques, and the potential oversight of indirect competitors, which may impact the accuracy and practicality of predictive models.
[34]	2024	✓	×	✓	×	×	This paper contributes to finance research by quantitatively analyzing ML, AI, and DL literature through bibliometric methods, identifying trends, research themes like ESG scoring, and geographical insights. It also highlights algorithmic bias concerns and advocates for future research directions addressing disruptive innovations in finance.	The paper lacks empirical research on advanced automated financial technologies, highlights algorithmic biases in critical areas, and discusses issues with traceability and replicability in deep learning systems. Additionally, it identifies an absence of governance and ambiguity in the effectiveness of AI/ML over traditional analytical tools.
[6]	2023	✓	×	✓	×	✓	This paper reviews recent machine learning and deep learning techniques for stock price prediction, implements various models, and conducts a comparative analysis with a focus on ensemble models. It also proposes a generic framework for prediction and classification, discussing the implications and limitations of current methodologies, and guiding future research.	The paper's limitations include insufficient exploration of ensemble methods, lack of detailed hyperparameter tuning strategies, inadequate adaptation framework for the evolving stock market, focus on specific stocks limiting generalizability, and missed integration of sentiment analysis, which could enhance model predictive power.
[32]	2023	✓	×	✓	×	×	This paper reviews cutting-edge machine learning applications in algorithmic trading, validating previous advancements, evaluating real-world performance, and identifying limitations for future research. It offers a holistic view of the field, providing insights for practitioners and policymakers on responsible innovation at the intersection of technology and finance.	The paper highlights several limitations, including the risks of overfitting, challenges with interpretability, reliance on large datasets, instability in reinforcement learning, and increased complexity in hybrid methods. Additionally, the review may not encompass all emerging techniques in the fast-evolving field of machine learning in trading.
[35]	2023	✓	×	✓	×	✓	This paper provides a comprehensive review of machine learning algorithms applied to forex market forecasting (2010–2021). It evaluates the design of evaluation techniques, conducts a meta-analysis of model performance using metrics like MAE and RMSE, identifies trends (LSTM, ANN), and highlights future research directions to improve prediction accuracy.	The meta-analysis is limited by the quality of included studies, with poor designs and biases affecting overall findings. A lack of standardization in model evaluation metrics complicates comparisons. The paper focuses solely on machine learning methods, potentially overlooking other forecasting techniques. Dataset division methodology is also questioned.
[37]	2022	×	×	✓	×	×	The paper integrates human behavior and social media sentiment with traditional data for algorithmic trading, enhancing predictions of price movements. It combines technical, fundamental, and sentiment analysis, offers practical guidance for traders, and reviews advanced techniques for improved trading outcomes, emphasizing adaptability and pattern recognition.	The paper highlights several limitations, including the risk of algorithmic misinterpretation during extreme price movements, dependence on data quality, challenges in forecasting due to market complexity, poor algorithm performance under "Black Swan" conditions, and the significant transaction costs associated with high-frequency trading systems.

(*continued on next page*)

Table 1 (*continued*).

Ref.	Year	Systematic review	Dataset description	Technological advancements	Results analysis	Challenges & future work	Contribution	Limitations
Ours	–	✓	✓	✓	✓	✓	This review comprehensively evaluates the application of deep learning in algorithmic trading, highlighting advancements, results analysis, and future directions. It also identifies critical research gaps and discusses the implications of deep learning technologies in finance.	This review has several limitations, including potential publication bias from underreported negative results and a focus on English-language studies, which may exclude relevant research. Additionally, varying study quality affects transparency in methodologies, and the review is limited to the literature available up to 2018–2024.

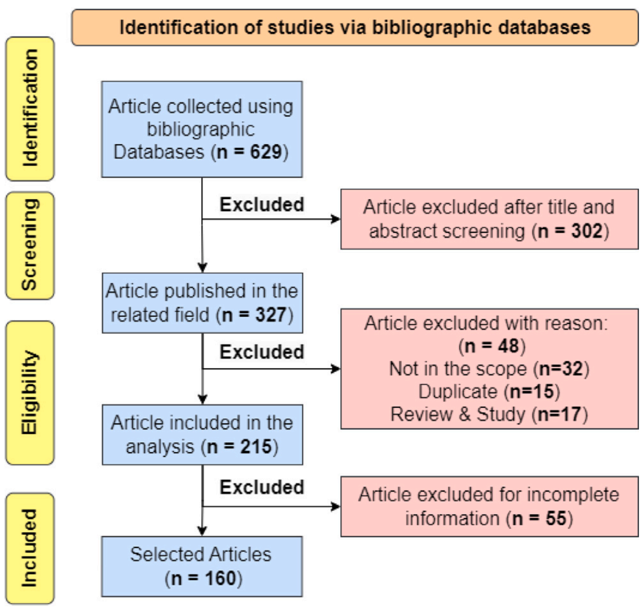

Fig. 1. PRISMA flow diagram detailing the stages of the systematic literature review process, including study identification, screening, eligibility assessment, and final inclusion.

our review process into several key stages: defining research questions, developing a search strategy, selecting relevant studies, assessing their quality, and synthesizing the findings. The overall process is visually represented in Fig. 1, which outlines the key steps taken during the systematic review, ensuring clarity and reproducibility.

3.2. Research questions (RQs)

The review was structured to address the following key research questions (RQs) presented in Table 2:

Table 2
Key research questions (RQs) for deep leaning based algorithmic trading review.

Research question	Description
RQ1: How are deep learning algorithms currently being applied in algorithmic trading across different financial markets? This question examines the types of DL models, their application in various financial instruments (e.g., stocks, commodities, foreign exchange), and the nature of the predictions they produce (e.g., price trends, volatility).	Sections 4 & 5
RQ2: What are the key challenges and limitations associated with using DL in optimizing financial market predictions? This includes both practical challenges such as data quality, computational demands, and overfitting, as well as theoretical limitations, such as the interpretability of models and their generalizability across markets.	Section 6
RQ3: What are the future opportunities for improving algorithmic trading performance using DL techniques? This question explores emerging trends in DL research, including new architectures, hybrid models, and the integration of advanced data sources that may offer better predictive power and efficiency in financial markets.	Section 7

3.3. Search strategy

To ensure comprehensive coverage of relevant literature, we developed a structured search strategy, outlined in Table 3.

Table 3
Search strategy for systematic review.

Component	Description
Databases Searched	• IEEE Xplore • SpringerLink • Google Scholar • arXiv
Search Keywords	• "Deep Learning" • "Algorithmic Trading" • "Financial Market Prediction" • "Stock Price Forecasting" • "Reinforcement Learning" • "Neural Networks in Trading" • "Market Volatility Prediction" • "Convolutional Neural Networks in Finance" • "Recurrent Neural Networks in Trading" • "High-Frequency Trading using AI" • "Long Short-Term Memory in Financial Markets" • "AI-driven Algorithmic Trading Strategies" • "Financial Time-Series Forecasting" • "Sentiment Analysis for Trading" • "Machine Learning in Portfolio Optimization"
Search Techniques	Combination of keywords and Boolean operators such as AND, OR, and NOT to refine search results and identify relevant studies.
Timeframe for Publication	2020–2024 (to capture the most recent advancements in DL applications in algorithmic trading).
Manual Search	Manual searches in reference lists of key papers to ensure no relevant studies were missed.

3.4. Study selection criteria

The inclusion and exclusion criteria for study selection were defined as presented in Table 4.

3.5. Quality assessment

To assess the methodological rigor of the selected studies, we applied a quality assessment framework that evaluated the following criteria:

- **Relevance:** The study's relevance to the research questions and its contribution to understanding DL applications in algorithmic trading.
- **Rigor:** The robustness of the study's experimental design, including the evaluation metrics and comparison to baseline models.

Table 4
Inclusion and exclusion criteria for study selection.

Criteria	Inclusion	Exclusion
Focus	Studies applying deep learning models to algorithmic trading or financial market prediction.	Studies focusing solely on traditional machine learning or statistical models without incorporating deep learning.
Type of Studies	Empirical studies, case studies, or review papers reporting performance metrics.	Studies that do not provide sufficient details on methods, model configurations, or performance metrics.
Publication Year	Studies published between 2010 and 2023.	Studies published before 2010.
Source	Peer-reviewed journals or high-quality conference proceedings.	Non-peer-reviewed articles, opinion pieces, or grey literature (e.g., blog posts, non-academic reports).
Language	Articles published in English.	Articles not written in English.
Dataset Transparency	Studies that describe the datasets used, including source, size, and features.	Studies that do not disclose the datasets or fail to provide sufficient dataset details.
Model Reproducibility	Studies providing detailed model parameters, code, or steps for replication.	Studies lacking reproducibility, including insufficient details for replicating the deep learning model.
Financial Instruments	Studies focusing on diverse financial instruments, including stocks, commodities, and foreign exchange.	Studies limited to very niche or non-mainstream financial instruments without broader applicability.
Comparison to Baselines	Studies that compare deep learning models to baseline models (e.g., traditional ML models or statistical approaches).	Studies that do not provide comparative analysis or performance benchmarking.

- **Replicability:** The transparency of the study's methodology, including the availability of datasets, model parameters, and reproducible code.
- **Publication Quality:** Preference was given to studies published in reputable journals and conferences with a high citation index.

Each study was scored on a scale of 1 (low) to 5 (high) for each criterion, and only studies with an overall score of 3 or higher were included in the final analysis.

3.6. Data extraction and synthesis

For each selected study, the following data were extracted:

- **Year of publication:** To track the temporal distribution of studies and trends over time.
- **DL models used:** The specific deep learning architectures employed (e.g., CNN, RNN, LSTM, hybrid models).
- **Financial markets examined:** The type of financial instruments studied (e.g., stocks, commodities, foreign exchange) and their respective markets.
- **Evaluation metrics:** Performance measures such as accuracy, precision, recall, Sharpe ratio, return on investment (ROI), etc.
- **Challenges and limitations:** Key challenges identified in applying DL to algorithmic trading (e.g., data quality, overfitting, model interpretability).

The results were synthesized using a narrative synthesis approach, categorizing studies based on DL model types, prediction tasks, and performance outcomes. Where appropriate, comparisons were made between the effectiveness of different models and their applications across various financial markets.

4. Theoretical background

Understanding the theoretical underpinnings of algorithmic trading and the application of deep learning is essential for grasping their roles in modern financial markets [42,43]. This section outlines the foundational concepts and methodologies employed in algorithmic trading, followed by a discussion on how deep learning techniques have revolutionized financial predictions and trading strategies.

4.1. Algorithmic trading

Algorithmic trading involves using computer algorithms to automatically execute the buying and selling of financial assets according to specific, pre-established criteria [44,45]. These algorithms can execute trades at speeds and frequencies far beyond the capability of human traders. Algorithmic trading strategies are primarily designed to optimize execution efficiency, minimize trading costs, and exploit market inefficiencies [46,47]. The key strategies employed in algorithmic trading include:

- **High-Frequency Trading (HFT):** This involves executing a large number of orders at extremely high speeds, usually in fractions of a second. The goal is to exploit minute price differentials across markets or within the same asset by rapidly buying and selling large volumes. HFT firms often employ statistical arbitrage and market-making strategies to capture profits from tiny market inefficiencies.
- **Arbitrage:** Arbitrage trading strategies seek to profit from price discrepancies between related financial instruments, such as stocks, bonds, commodities, or derivatives. These strategies include *statistical arbitrage* and *index arbitrage*, where algorithms identify and exploit mispricings by simultaneously buying and selling the assets involved.
- **Trend-Following:** These algorithms detect patterns in the movement of asset prices, such as upward or downward trends, and execute trades accordingly. Trend-following strategies, such as momentum trading, typically rely on technical indicators like moving averages, relative strength indices (RSI), and Bollinger Bands.
- **Mean Reversion:** Mean reversion strategies are based on the idea that asset prices tend to return to their historical average over time. Algorithms using this approach detect when an asset is either overvalued or undervalued and place trades, anticipating that the price will move back toward the average.
- **Market Making:** This approach entails consistently offering buy and sell prices for financial assets. Market makers earn profits from the bid–ask spread and provide liquidity to markets. Algorithms automate this process, ensuring orders are executed efficiently and at competitive prices.
- **Pairs Trading:** This is a type of statistical arbitrage where two correlated assets are traded simultaneously. The strategy assumes that when the price of one asset diverges significantly from its paired asset, the prices will eventually converge. An algorithm buys the underperforming asset and sells the outperforming one, profiting from their convergence.

Table 5 compares key algorithmic trading strategies based on their description, key features, and use cases.

Fig. 2 provides a comprehensive overview of AI techniques used in algorithmic trading. The diagram categorizes these techniques into four main groups: Statistical Time-Series Methods, Machine Learning, Deep Learning, and Reinforcement Learning (RL). In this literature, we focus exclusively on deep learning models, providing a detailed description of each model shown in Fig. 2 in the following Section 4.2. Additionally, we review previous studies that have applied these models in algorithmic trading, highlighting their effectiveness and applications in financial markets.

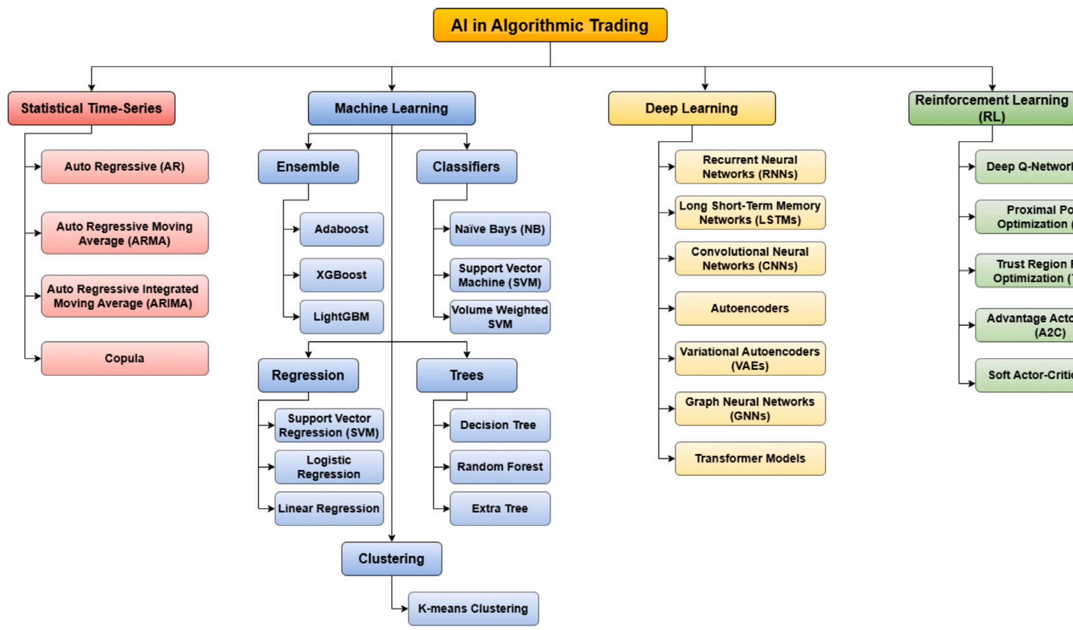

Fig. 2. Overview of different AI models for Algorithmic Trading.

Table 5
Comparison of algorithmic trading strategies.

Trading strategy	Description	Key features and use cases
High-Frequency Trading (HFT)	Executes a large number of orders at extremely high speeds, often in milliseconds, to exploit small price differentials.	Utilized by institutional traders; exploits inefficiencies in highly liquid markets through rapid trading.
Arbitrage	Exploits price discrepancies between related financial instruments or markets by simultaneously buying and selling to lock in profits.	Includes statistical arbitrage and index arbitrage; commonly applied across different asset classes (e.g., stocks, bonds, commodities).
Trend-Following	Detects price trends (upward or downward) and executes trades in the direction of the trend. Relies on technical indicators to confirm trends.	Popular in momentum trading; uses indicators such as moving averages, RSI, and Bollinger Bands; suitable for medium- to long-term strategies.
Mean Reversion	Assumes that prices will revert to their historical mean over time. Trades are made when assets are deemed overbought or oversold.	Based on the statistical concept of reversion to the mean; often used in markets with cyclical behavior.
Market Making	It refers to the ongoing process of offering both buy and sell prices for a financial asset, generating profit from the difference between the bid and ask prices.	Provides liquidity to the market; algorithms automate order execution to reduce latency and ensure competitive pricing.
Pairs Trading	A statistical arbitrage strategy where two correlated assets are traded simultaneously. The idea is to bet on their prices converging.	Buys the underperforming asset and sells the outperforming asset; works well with assets that have a historical correlation.

4.2. Deep learning in financial predictions

DL has emerged as a pivotal technology in financial markets, enabling sophisticated modeling of non-linear relationships and effective processing of vast amounts of data [20,48,49]. In algorithmic trading, various DL models have been developed to predict market trends, optimize trading strategies, and enhance decision-making processes.

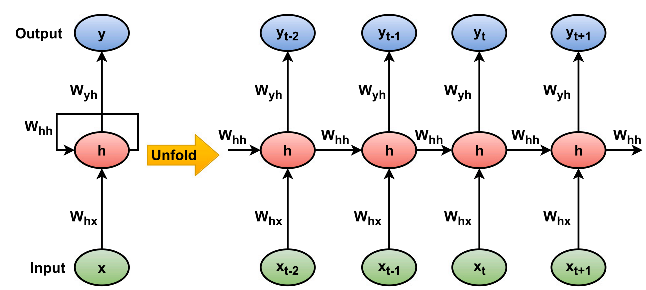

Fig. 3. Architecture of RNN.

4.2.1. Recurrent Neural Networks (RNNs)

RNNs are particularly adept at time-series forecasting in financial markets due to their inherent ability to capture temporal dependencies [50,51]. An RNN maintains a hidden state h_t that updates with each new time step t, based on the previous hidden state h_{t-1} and the current input x_t:

$$h_t = \sigma(W_h h_{t-1} + W_x x_t + b_h) \tag{1}$$

In this equation, W_h and W_x represent the weight matrices, b_h is a bias term, and σ is a non-linear activation function, typically chosen as *tanh* or *ReLU*. While RNNs are powerful, they often struggle with long-term dependencies due to the vanishing gradient problem.

Fig. 3 illustrates the structure of an RNN, where the hidden state h_t captures information from previous time steps, allowing the model to make predictions based on historical data. RNNs have been successfully applied in algorithmic trading for predicting stock price movements based on historical prices and trading volumes, as well as forecasting currency exchange rates by analyzing historical currency data [52,53].

A recent contribution by Lu et al. [52] focuses on the efficiency of prediction results in big data analysis, emphasizing the importance of data preprocessing methods. The proposed Time-series RNN (TRNN) for stock price prediction incorporates trading volume and employs sliding windows to process time series data. By expanding the price–volume relationship from one dimension to two, the TRNN model strengthens the influence of recent trading volumes on current stock prices. The study contrasts the TRNN with conventional RNN and LSTM models,

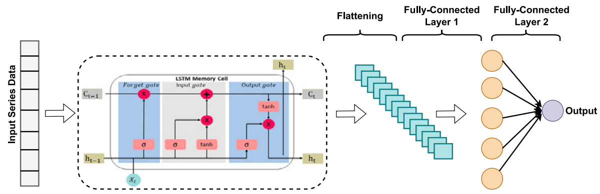

Fig. 4. Architecture of LSTM.

highlighting its increased efficiency and accuracy, while also exploring its potential applications in other areas.

Zhao et al. [54] presents a stock price trend prediction model utilizing RNN, LSTM, and GRU, enhanced by an attention mechanism. The results indicate that the GRU-M and LSTM-M models outperform the RNN-M model, with the GRU-M model achieving slightly better performance. The study concludes that two layers are optimal for performance, as deeper networks may slow the learning rate and underperform with limited training data. Aldhyani et al. [55] introduce a hybrid CNN-LSTM framework for predicting stock market prices, achieving high R-squared values of 98.37% for Tesla and 99.48% for Apple. However, the study notes the absence of sentiment analysis from financial investigations, which could limit prediction robustness. The findings also suggest that current AI stock prediction models have not yet achieved full accuracy, indicating opportunities for further enhancement.

4.2.2. Long Short-Term Memory Networks (LSTMs)

LSTMs are a specialized type of RNN designed to overcome the vanishing gradient problem [14,56]. LSTMs utilize memory cells that regulate the flow of information using three gates: the input gate, the forget gate, and the output gate [14]. The cell state C_t and hidden state h_t are updated as follows:

$$\begin{aligned}
f_t &= \sigma(W_f[h_{t-1}, x_t] + b_f) \\
i_t &= \sigma(W_i[h_{t-1}, x_t] + b_i) \\
\tilde{C}_t &= \tanh(W_C[h_{t-1}, x_t] + b_C) \\
C_t &= f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \\
o_t &= \sigma(W_o[h_{t-1}, x_t] + b_o) \\
h_t &= o_t \cdot \tanh(C_t)
\end{aligned} \tag{2}$$

In this formulation, f_t, i_t, and o_t correspond to the forget, input, and output gates, respectively. Fig. 4 illustrates the LSTM architecture, demonstrating the flow of information through the cell state and gates. Each gate plays a crucial role in regulating data flow and maintaining long-term dependencies.

A recent study by Billah et al. [57] compared the Simple Moving Average (SMA), Exponential Moving Average (EMA), and LSTM models for stock price prediction. The study found that while LSTM significantly outperforms SMA and EMA in short-term forecasting, with an RMSE of 12.312 and MAPE of 2.06%, SMA and EMA are better suited for long-term predictions. The paper also highlighted the limitations of LSTM in long-term prediction due to the complexity of the stock market, noting that the findings were based on datasets from only six companies, which may limit generalizability. Additionally, Zhang et al. [58] introduced a novel CNN-BiLSTM-Attention model for stock price prediction, which achieved superior accuracy compared to LSTM, CNN-LSTM, and CNN-LSTM-Attention models. Despite its robustness and effectiveness, the study noted limitations regarding external factors and the model's generalizability due to the lack of testing on North American market data. Gulmez et al. [59] further enhanced LSTM by optimizing it with the Artificial Rabbits Optimization algorithm (LSTM-ARO) for stock price prediction. Their model outperformed traditional ANN and GA-optimized LSTM models in terms of MSE, MAE, MAPE, and R-squared, although the study did not address the model's performance in volatile market conditions.

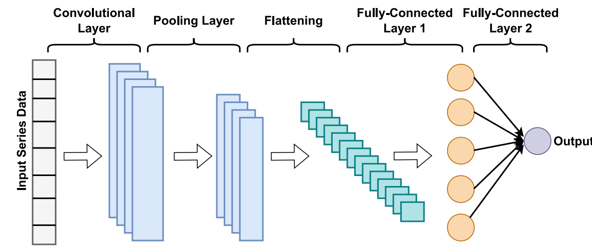

Fig. 5. Architecture of CNN.

Xu et al. [60] presented a hybrid LSTM-GARCH framework that integrates deep learning with classical econometric models to improve volatility risk prediction. The hybrid model achieved a lower MSE of 0.604 compared to standalone models, highlighting its utility in financial risk management. However, its performance was sensitive to parameter selection and input data quality, potentially affecting broader applicability. Lastly, Zhang et al. [53] investigated the influence of investor sentiment on stock market volatility using an LSTM model, finding a significant negative correlation, particularly during crises. The study demonstrated that sentiment indices outperform historical data models for short-term volatility predictions but noted limitations due to the small sample size and dictionary-based sentiment analysis methods.

4.2.3. Convolutional Neural Networks (CNNs)

CNNs have demonstrated significant potential in financial market predictions by treating time-series data as one-dimensional signals [61,62]. This application enables CNNs to automatically identify significant features from historical price data using their convolutional layers. By uncovering patterns and trends that are often overlooked in conventional financial analysis, CNNs improve the precision of predictions. Additionally, their ability to efficiently process large datasets makes them well-suited for high-frequency trading environments, where timely and precise forecasts are essential for successful trading strategies [63,64]. The convolution operation for a one-dimensional input x_t with a filter w can be defined as:

$$y_t = (x * w)(t) = \sum_{i=0}^{k-1} x_{t+i} w_i \tag{3}$$

where k denotes the kernel size and w_i represents the filter weights. Fig. 5 depicts the CNN architecture designed for one-dimensional financial time series, showcasing how convolutional layers extract significant features that can be used for predicting market behavior.

In algorithmic trading, CNNs have been applied to identify patterns in historical price charts, which aids in trend prediction. Hoseinzade et al. [65] present CNNpred, a CNN-based framework for stock market prediction that utilizes diverse variables beyond traditional indicators, enhancing prediction accuracy. Their framework demonstrates significant performance improvements on major stock indices and successfully extracts higher-level features from varied data sources. However, the authors acknowledge limitations due to the complexity of variable interactions in financial data, suggesting that traditional CNN filters may not be optimal and calling for further research to address these challenges. Similarly, Lu et al. [66] introduce a novel CNN-BiLSTM-AM method for predicting stock closing prices, effectively combining CNN for feature extraction, BiLSTM for temporal dependencies, and an attention mechanism to enhance accuracy. Tested over 1000 trading days of the Shanghai Composite Index, this approach achieved the highest prediction accuracy with a mean absolute error (MSE) of 21.952. The study highlights the need for further parameter optimization and broader validation in other time series prediction fields.

Chung et al. [67] propose a method to optimize CNN architecture using a Genetic Algorithm (GA) for stock market prediction, demonstrating the effectiveness of deep learning in financial forecasting.

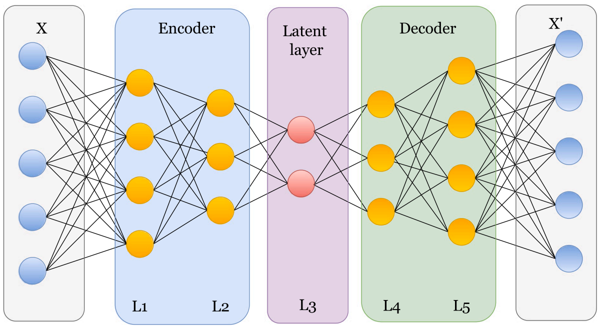

Fig. 6. Architecture of Autoencoders.

The GA-optimized CNN outperforms traditional models, validated by statistical tests. However, its effectiveness relies on the fitness function's definition and faces challenges due to the stock market's inherent complexity and noise, underscoring the need for further exploration of advanced deep-learning techniques in this domain. In another study, Mehtab et al. [68] developed deep learning models for predicting NIFTY 50 stock prices, achieving high forecasting accuracy, particularly with the univariate encoder–decoder convolutional LSTM model. They emphasize fast execution, with the univariate CNN model processing in about 11.17 s. However, limitations include the inherent randomness in stock prices affecting accuracy, reliance on historical data for predictions, and the complexity of models requiring significant computational resources and expertise.

4.2.4. Autoencoders

Autoencoders are unsupervised neural networks designed for dimensionality reduction and latent feature extraction [69,70]. The model comprises an encoder that transforms input data x into a latent representation z and a decoder that reconstructs x from z:

$$\begin{aligned} z &= \sigma(W_e x + b_e) \quad \text{(Encoder)} \\ \hat{x} &= \sigma(W_d z + b_d) \quad \text{(Decoder)} \end{aligned} \tag{4}$$

Here, W_e and W_d are the weight matrices for the encoder and decoder, respectively. Fig. 6 shows the autoencoder structure, highlighting the encoder–decoder architecture used for reconstructing input data. This capability is beneficial for feature extraction and anomaly detection in financial datasets.

In algorithmic trading, autoencoders have been employed for anomaly detection, which helps identify irregular trading patterns or fraudulent activities. A notable contribution by Soleymani et al. [71] introduces DeepBreath, a novel deep reinforcement learning framework for portfolio management. This framework combines a restricted stacked autoencoder for feature selection with a CNN for investment policies, demonstrating superior performance against expert strategies in return on investment while maintaining scalability and efficiency. However, the study acknowledges challenges in addressing settlement risk and potential difficulties in generalizing to unforeseen market conditions. In another study, Zhang et al. [72] explore the use of autoencoders for stock-index tracking, demonstrating their superiority over traditional models, particularly with portfolios of fewer than 30 stocks. The effectiveness of specific autoencoder architectures in capturing complex market representations is highlighted, although the findings may be limited by dataset specificity and insufficient hyperparameter optimization, potentially affecting generalizability.

Bao et al. [73] present a novel deep-learning framework that combines wavelet transforms, stacked autoencoders, and LSTM networks for stock price forecasting, incorporating macroeconomic variables to enhance predictive accuracy. This model outperforms others in various financial markets, demonstrating effective predictive performance. However, it is time-consuming and may require advanced hyperparameter selection, with its generalizability limited by specific market conditions. Jung et al. [74] introduce a hybrid autoencoder-LSTM model for forecasting foreign exchange volatility, showing improved prediction accuracy over traditional LSTM models, especially with data variability and outliers. The findings underscore the model's sensitivity to extreme outliers and its dependency on data quality, which may limit generalizability to other currencies or timeframes.

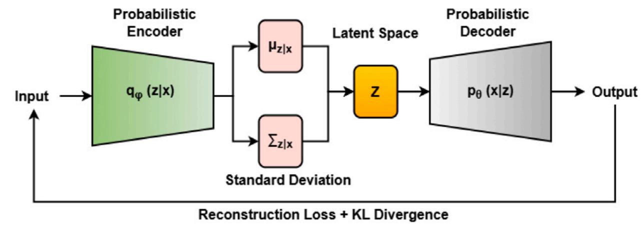

Fig. 7. Architecture of Variational Autoencoders (VAE).

4.2.5. Variational Autoencoders (VAEs)

Variational Autoencoders (VAEs) are a generative model that learns a probabilistic mapping from data to a latent space and can generate new data samples by sampling from this latent space [75,76]. Unlike traditional autoencoders, VAEs impose a distributional prior on the latent variables, making them suitable for tasks such as anomaly detection, denoising, and generation of new instances in financial data analysis [77]. The encoder outputs parameters of the posterior distribution, while the decoder attempts to reconstruct the data by sampling from this distribution.

The VAE framework is defined as:

$$q_\phi(z|x) = \mathcal{N}(z; \mu_\phi(x), \sigma_\phi^2(x)) \tag{5}$$

where $\mu_\phi(x)$ and $\sigma_\phi(x)$ represent the mean and standard deviation of the variational approximation of the posterior distribution. The decoder is then trained to maximize the likelihood of data points given the latent variables sampled from the prior distribution.

Fig. 7 illustrates a VAE's structure, highlighting the model's probabilistic nature where the encoder learns to approximate the posterior distribution of latent variables. VAEs have been applied in financial market prediction tasks, including generating synthetic stock data and detecting anomalies in high-frequency trading patterns [78,79].

Recent work by Xu et al. [78] leverages VAEs for stock market prediction, demonstrating that VAEs can generate new sequences of stock prices for stress testing and simulate different market conditions. Similarly, Li et al. [79] use VAEs to model uncertainty in stock returns, achieving better robustness in their predictions compared to traditional models. However, the study highlights the challenge of selecting an appropriate prior distribution and the difficulty of generalizing the model to various market conditions.

4.2.6. Graph Neural Networks (GNNs)

GNNs are designed to process data represented as graphs, capturing the relationships between nodes and their neighbors [80,81]. In financial markets, where entities such as stocks, companies, or even countries are interconnected through complex relationships, GNNs have been applied to capture dependencies between different financial instruments [63,82]. The GNN model operates by iteratively aggregating information from neighboring nodes to update the state of each node, making it highly effective for learning from structured data such as financial networks [83,84].

The general message-passing operation in a GNN is given by:

$$h_i^{(k+1)} = \sigma\left(W^{(k)} \cdot h_i^{(k)} + \sum_{j \in \mathcal{N}(i)} \frac{1}{c_{ij}} \cdot W^{(k)} \cdot h_j^{(k)}\right) \tag{6}$$

where $h_i^{(k)}$ represents the hidden state of node i at the k-th layer, $\mathcal{N}(i)$ denotes the neighbors of node i, and c_{ij} is a normalization constant. The function σ is a non-linear activation function, typically ReLU or sigmoid.

GNNs have been applied in financial prediction tasks such as modeling stock price movements by considering the correlations between different assets and companies. For instance, Yilmaz et al. [85] integrate graph representations with time series data for financial forecasting, employing an ensemble of deep neural networks. Their model achieves a 23.52% annual return on the DOW30 index, significantly outperforming heuristic trading strategies. By leveraging both temporal dependencies and graph-based relationships, the model enhances predictive accuracy. However, challenges remain regarding the model's complexity, its reliance on historical data, and the necessity for broader market validation to confirm its robustness across varying financial conditions.

Beyond forecasting, GNNs have also been employed to detect fraudulent financial market activities. Chen et al. [86] propose a multi-modal GNN framework for identifying market manipulation in high-frequency trading. The model constructs dynamic trading networks to capture intricate interactions among traders, achieving an accuracy of 98.7% with an 8.3 ms latency. This real-time capability is crucial for regulatory agencies and financial institutions aiming to mitigate fraudulent activities. However, the approach faces computational challenges due to the intensive nature of high-frequency trading data and remains sensitive to sudden market fluctuations, necessitating further architectural refinements to enhance adaptability. Another key application of GNNs in finance is anomaly detection in trading behavior. Li et al. [87] introduce a novel GNN-based architecture designed to detect anomalies in high-frequency trading data. Their model improves real-time processing efficiency and enhances detection accuracy by 15% over conventional methods. Additionally, it achieves a 15%–20% higher F1-score, demonstrating its robustness across different market conditions. Despite these advantages, the model's effectiveness is constrained by its reliance on high-quality data, implementation complexity, and potential limitations in generalizing across diverse financial datasets.

GNNs have also been utilized to rank investors based on trading behaviors and social network interactions. Baltakys et al. [88] develop a graph-based ranking tool that evaluates investors by their level of suspicious trading activity, leveraging social connections to enhance predictability. The results indicate a high level of accuracy in identifying potentially fraudulent investors, offering valuable insights for regulatory oversight. However, challenges such as dependency on specific data sources, difficulty in generalizing findings across different financial markets, and the complexity of modeling social interactions introduce limitations that require careful interpretation in regulatory contexts.

While GNNs offer significant advancements in financial applications, they still face key challenges such as scalability, feature selection, and sensitivity to the choice of graph structure. Future research should explore adaptive GNN architectures that dynamically refine graph representations based on evolving market conditions. Additionally, hybrid models that integrate GNNs with other deep learning techniques may further enhance predictive power and resilience in financial decision-making.

4.2.7. Transformer models

Transformers have recently gained attention in algorithmic trading due to their ability to handle long-range dependencies in sequential data without the limitations of recurrent architectures [89,90]. Unlike traditional RNNs, which process data sequentially, Transformers use a mechanism called self-attention, allowing them to analyze input data in parallel. This enables the model to weigh the importance of different parts of the input sequence, making it particularly effective for financial time-series analysis [91,92].

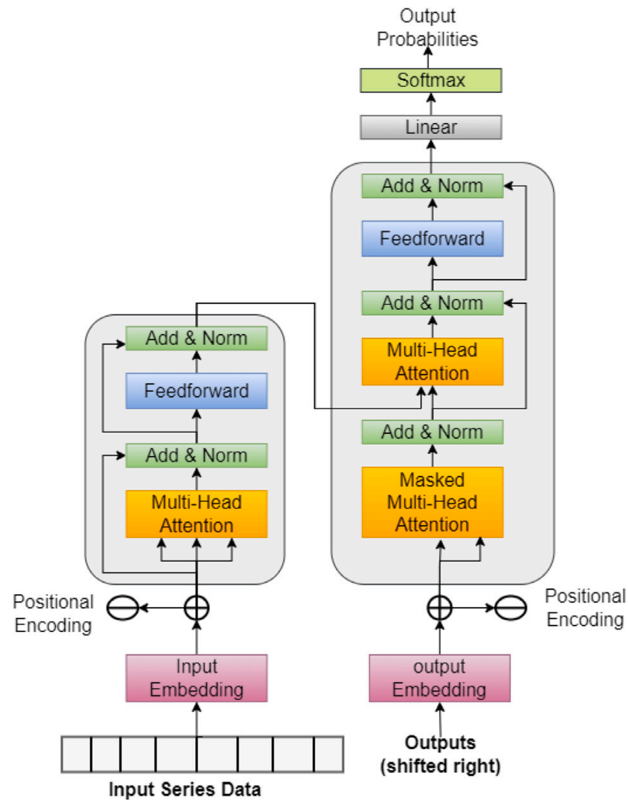

Fig. 8. Architecture of Transformer.

The self-attention mechanism computes a score for each pair of input elements, which determines how much focus to place on each element in the sequence. Given an input sequence represented as a matrix X, the self-attention function can be expressed as follows:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{7}$$

In this equation:

- Q (queries), K (keys), and V (values) are derived from the input sequence X through learned linear transformations.
- d_k is the dimensionality of the keys, serving as a scaling factor to stabilize gradients during training.
- The softmax function normalizes the attention scores to produce a distribution that indicates how much focus each input should receive.

Transformers in Fig. 8, are built on an encoder–decoder architecture. The encoder transforms the input sequence into continuous representations, while the decoder uses these representations to generate the output sequence. In the context of financial predictions, the encoder can analyze historical price movements and other relevant features, while the decoder can generate forecasts or trading signals.

Recent contributions have shown the potential of Transformer models in financial forecasting. Wang et al. [89] introduced the Adaptive Long-Short Pattern Transformer (ALSP-TF), which enhances stock price forecasting by improving representation across varying context scales. The model incorporates a learnable self-attention mechanism and graph self-supervised regularization, outperforming state-of-the-art methods on multiple exchange datasets by capturing both short- and long-term volatility patterns. However, the study highlights challenges such as the model's complexity, dependence on data quality, and limited validation across different markets.

Bilokon et al. [93] compared Transformer and LSTM-based models for financial time series prediction using high-frequency limit order book data. Their work introduced a new LSTM-based model (DLSTM) and a Transformer architecture, showing that while Transformers excel at absolute price prediction, LSTMs are superior for predicting price differences. However, the focus on specific data types and the exclusion of models like FEDformer and Autoformer, which have limitations with stationary data, pose constraints on broader applications. Lezmi et al. [90] explored Transformer models for time series forecasting in finance, particularly in trend-following strategies and portfolio optimization. The study highlighted the models' capability to capture long-range dependencies but observed performance declines in volatile markets after 2020. The authors also discussed challenges like the low signal-to-noise ratio in financial data, the difficulty in model generalization, and the need for continuous recalibration.

Finally, Tran et al. [91] introduced a novel neural network layer that combines bilinear projection and attention mechanisms to improve financial forecasting in multivariate time-series data. The model enhances interpretability by focusing on temporal information and achieves state-of-the-art results in predicting mid-price movements with minimal computational resources. Despite its strengths, the model faces limitations, including potential underfitting with large datasets and generalizability concerns due to the specific nature of the data used.

In summary, Transformer models provide a robust framework for algorithmic trading by leveraging self-attention mechanisms to capture intricate patterns in financial time-series data [94,95]. Their ability to process data in parallel, combined with recent advancements in training and architecture design, positions them as a powerful tool for enhancing prediction accuracy and strategy development in dynamic financial markets.

4.2.8. Reinforcement Learning (RL)

RL has gained prominence in algorithmic trading for its ability to learn optimal trading policies through interaction with the trading environment [96,97]. Unlike traditional supervised learning approaches, RL focuses on training an agent to make decisions by taking actions a_t at each time step t to maximize cumulative rewards R_t. The agent receives feedback from the environment based on its actions, which informs its future decision-making process.

The learning process in RL is governed by the Bellman equation, which captures the relationship between the current state s_t, action a_t, and the expected cumulative reward:

$$Q(s_t, a_t) = r_t + \gamma \max_{a'} Q(s_{t+1}, a') \tag{8}$$

In this equation:

- $Q(s_t, a_t)$ denotes the action-value function, representing the expected utility of taking action a_t in state s_t.
- r_t is the immediate reward received after taking action a_t.
- γ is the discount factor (ranging from 0 to 1) that determines the importance of future rewards. A γ close to 0 prioritizes immediate rewards, while a γ close to 1 emphasizes long-term rewards.
- $\max_{a'} Q(s_{t+1}, a')$ signifies the best possible future reward obtainable from the subsequent state s_{t+1} after taking action a_t.

In algorithmic trading, RL has been applied to develop dynamic trading strategies that adapt to changing market conditions. Recent work by Khan et al. [98] integrates reinforcement learning techniques, such as Deep Q-learning and Proximal Policy Optimization, to improve trading performance. RL models adapt dynamically to market complexities and outperform traditional models, though challenges like overfitting, data quality issues, and high computational demands remain. The study also highlights regulatory and ethical concerns due to the autonomous nature of RL-based strategies but showcases how RL enhances decision-making in trading environments.

Li et al. [99] presented a deep RL-based trading agent that enhances DQN and A3C algorithms for dynamic financial environments. The model leverages Stacked Denoising Autoencoders (SDAEs) and LSTMs for feature extraction and integrates practical mechanisms like n-step rewards. This agent outperforms baseline models by generating higher profits and robust risk-adjusted returns. However, sensitivity to extreme market conditions and partial observability are limitations that require further research, particularly in the context of multi-asset trading. Huang et al. [100] proposed an efficient deep SARSA algorithm for stock trading, combining Deep Reinforcement Learning (DRL) with a BiLSTM-Attention network for enhanced feature recognition. The model achieved an impressive 582.17% Cumulative Return and a Sharpe Ratio of 1.86 on the IXIC dataset, surpassing both traditional and DRL-based strategies. Despite the promising results, the paper lacks a discussion on the challenges associated with the real-world deployment of such models.

In summary, Deep Learning models, including RNNs, LSTMs, CNNs, Autoencoders, Transformers, and Reinforcement Learning, have demonstrated significant potential in financial predictions, particularly in algorithmic trading. These models leverage the strengths of neural networks to analyze complex patterns in historical data, leading to improved predictive performance and enhanced decision-making capabilities [101,102]. The advantages and disadvantages of the discussed algorithms in algorithmic trading are summarized in Table 6.

4.3. Role of deep learning in financial markets

Deep learning has become a pivotal tool in financial markets due to its ability to model complex, non-linear relationships that traditional machine learning models struggle to capture [103–105]. Unlike linear regression models or decision trees, DL can handle vast amounts of unstructured data (e.g., time-series data, text from news articles, and social media sentiment) and learn hidden patterns that drive market behavior [106,107].

The main strength of DL in finance is its ability to automate feature extraction, allowing models to discover intricate relationships between variables without the need for extensive manual preprocessing [108,109]. For instance, in the case of stock price prediction, DL models can combine technical indicators, macroeconomic factors, and textual data to produce more accurate forecasts. Recent studies, such as those by Billah et al. [57] and Long et al. [110], demonstrate how advanced architectures like LSTM and hybrid models significantly improve forecasting accuracy compared to traditional approaches.

In comparison to traditional machine learning, DL models are more adept at handling high-dimensional and noisy data, which is characteristic of financial markets. This has led to improved performance in a wide range of financial applications, including price forecasting, portfolio optimization, risk management, and algorithmic trading strategies [31,111]. For example, Xu et al. [60] introduced a hybrid LSTM-GARCH framework that enhances volatility risk prediction, demonstrating the effective integration of deep learning with classical econometric models.

However, despite their success, DL models face challenges such as overfitting, interpretability, and computational complexity. These challenges highlight the need for further research into hybrid models, model interpretability, and advanced optimization techniques [112,113]. Biju et al. [34]) emphasize the importance of addressing algorithmic biases and the lack of governance in AI/ML applications in finance, advocating for future research directions to enhance the reliability of these models.

Recent advancements also indicate a growing focus on improving model robustness and generalizability. For instance, the work of Ghani et al. [114] on the GARCH-MIDAS model highlights the need for a broader understanding of economic policy uncertainty's impact on market volatility, particularly in emerging economies. This suggests that while DL models are powerful, their application should

Table 6
Advantages and disadvantages of algorithms in algorithmic trading.

Model	Advantages	Disadvantages
Recurrent Neural Networks (RNNs)	• Captures temporal dependencies effectively • Suitable for sequential data • Adapts to varying input lengths	• Struggles with long-term dependencies • Slower training due to sequential nature • Prone to overfitting with noisy data.
Long Short-Term Memory Networks (LSTMs)	• Addresses vanishing gradient issue • Excels in modeling long-term dependencies • Can remember past information for future predictions • Flexible architecture	• Computationally intensive • Requires careful tuning of hyperparameters • May still overfit if not regularized properly
Convolutional Neural Networks (CNNs)	• Effective in extracting features from time-series data • Recognizes patterns and trends in price movements • Processes multiple input features simultaneously	• Requires extensive labeled data • Less effective for temporal dependencies unless adapted
Autoencoders	• Useful for anomaly detection • Capable of unsupervised learning • Identifies hidden patterns in trading data	• Limited interpretability • May not be effective for sequential decision-making tasks • Requires extensive training data for effective feature extraction
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 crucial patterns	• High computational cost due to variational inference • May produce unrealistic outputs if poorly trained • Requires large datasets for meaningful feature learning
Graph Neural Networks (GNNs)	• Models relationships between assets in financial networks • Captures interdependencies between different stocks • Suitable for analyzing stock correlations and portfolio optimization • Effective in predicting market movements using relational data	• High computational cost for large financial graphs • Requires careful graph construction for meaningful insights • Sensitive to noisy financial data
Transformer Models	• Handles long-range dependencies without sequential processing • Faster training due to parallel processing • Effective in capturing relationships in complex datasets	• Requires large datasets and substantial computational resources • Extensive fine-tuning needed • Sensitive to noise in the data
Reinforcement Learning (RL)	• Learns optimal trading strategies through market interaction • Adapts to changing market conditions • Discovers novel strategies through exploration	• Sample inefficiency • Requires extensive training time • May overfit to historical data • Difficult to implement reward functions that align with trading goals

be complemented with an understanding of economic and financial contexts.

In conclusion, the role of deep learning in financial markets is evolving, driven by continuous advancements in technology and methodologies. The integration of DL models with traditional economic theories and real-world data remains crucial for maximizing their potential in addressing the complexities of financial systems.

5. Results and findings

This section provides an in-depth analysis of selected studies focused on deep learning (DL) applications in algorithmic trading [115]. We categorize the studies based on the specific financial applications they target, such as stock price prediction, market volatility prediction, portfolio optimization, sentiment analysis, automated trading strategies, risk management, and anomaly detection [57,60,116–118]. Each subsection reviews the key contributions and limitations of prominent DL models, providing a holistic view of the effectiveness and applicability of these models in trading environments.

5.1. Overview of selected studies based on applications

The integration of DL in algorithmic trading has facilitated the development of models that can handle vast datasets, uncover intricate patterns, and make informed predictions in real-time [119,120]. As the financial landscape evolves, researchers have explored various applications of deep learning techniques to enhance trading strategies and risk management. These studies offer important insights into how deep learning enhances decision-making and adjusts to swiftly evolving market dynamics, emphasizing both its potential and the challenges encountered in real-world applications.

5.1.1. Stock price prediction

The prediction of stock prices has been one of the primary areas where deep learning models have made a significant impact [116,121]. The ability to model the non-linear and temporal dependencies in market data makes recurrent architectures such as LSTM and GRU highly effective [50,122]. Several hybrid models that combine traditional time-series analysis with advanced DL techniques have been developed to enhance predictive accuracy.

Table 7 summarizes key papers in stock price prediction, focusing on the deep learning architectures used, the datasets analyzed, their contributions, and the limitations identified in their approaches.

5.1.2. Market volatility prediction

Market volatility prediction is crucial for risk management and optimizing trading strategies. Volatility forecasting has seen advancements through the use of DL models that can dynamically adjust to changing market conditions [127,128]. RNN-based models like LSTM and GRU have been extensively applied, with some hybrid models integrating econometric approaches to improve performance [53,60].

Recent studies have emphasized the significance of incorporating multiple data streams, including macroeconomic indicators, sentiment analysis, and high-frequency trading data, to enhance the predictive accuracy of volatility models [129,130]. The findings suggest that hybrid models outperform single-model approaches, but data noise and overfitting remain challenges. As shown in Table 8, a variety of models have been applied to different datasets, each with specific contributions and limitations.

5.1.3. Portfolio optimization

Portfolio optimization involves determining the best asset allocation to maximize returns for a given level of risk [133,134]. Traditional optimization methods have been enhanced by deep learning models,

Table 7
Summary of selected studies on stock price prediction.

Ref.	Year	Model	Contribution	Limitation
[57]	2024	LSTM	The paper compares SMA, EMA, and LSTM models for stock price prediction. It demonstrates LSTM's superiority in short-term forecasting with an RMSE of 12.312 and MAPE of 2.06%, while SMA and EMA perform better in long-term predictions.	The paper highlights LSTM's weakness in long-term stock price prediction, where SMA and EMA perform better. Additionally, it acknowledges the stock market's inherent complexity, which affects prediction reliability, and notes the limited generalizability of the findings due to the use of datasets from only six companies.
[123]	2024	Variational Mode Decomposition (VMD)	The paper introduces a novel two-stage prediction model combining variational mode decomposition (VMD) and ensemble learning methods, outperforming fourteen other models in stock price prediction. The model effectively decomposes time series data and enhances prediction accuracy, demonstrating superior performance in empirical validation with multiple evaluation metrics.	The two-stage model has high computational complexity due to the decomposition and ensemble learning processes. Its performance heavily depends on the quality of the VMD algorithm, and suboptimal decomposition can reduce prediction accuracy. Additionally, the model's generalizability to other time series domains remains unexplored.
[124]	2024	GARCH-AI	The paper introduces a hybrid model integrating GARCH with AI techniques like LSTM, GRU, and Transformers to enhance stock price forecasting in African markets. Results show that GARCH-LSTM outperforms standalone models in metrics such as RMSE, MAE, MAPE, and R-squared, demonstrating improved prediction accuracy and robustness.	The paper's limitations include a primary focus on volatility dynamics rather than direct stock price prediction, which may restrict broader financial forecasting applications. Additionally, it uses Airtel stock data from a limited time frame, limiting generalizability to other markets, financial instruments, or diverse market conditions.
[125]	2024	GRA-WD- BiLSTM	The paper introduces a GRA-WD-BiLSTM hybrid model to predict stock prices using environmental factors like air quality and weather. It achieved high prediction accuracies of 95.93% for SSEC, 93.02% for SZI, and 97.07% for HSI, showcasing the model's effectiveness across multiple stock indices.	The study's limitations include constraints in selecting environmental data due to equipment and data availability, restricting the influencing factors used. Additionally, it did not account for seasonal variations in environmental factors, which may affect the accuracy of stock price predictions.
[58]	2023	CNN-BiLSTM	The paper presents a novel CNN-BiLSTM-Attention model for stock price prediction, achieving superior accuracy compared to LSTM, CNN-LSTM, and CNN-LSTM-Attention models. Tested on various stock indices, including the CSI 300, it demonstrates robustness and effectiveness, although it has limitations regarding external factors and market data generalizability.	The model's limitations stem from its reliance on stock trading data, which is affected by various external factors. Additionally, the authors did not evaluate the model using North American market data, potentially restricting its generalizability. Future research should incorporate multi-source information and test diverse datasets to overcome these limitations.
[59]	2023	LSTM	The paper presents an optimized deep LSTM network enhanced by the Artificial Rabbits Optimization algorithm for stock price prediction. Using DJIA index stocks, the LSTM-ARO model outperforms other models, including traditional ANN and GA-optimized LSTMs, based on metrics like MSE, MAE, MAPE, and R-squared.	The paper does not address the LSTM-ARO model's performance in volatile market conditions or its adaptability to diverse stock datasets. Additionally, its reliance on historical data may overlook sudden market changes and external factors that can significantly impact stock prices, limiting the model's robustness and applicability.
[126]	2023	BiLSTM-MTRAN- TCN	The paper presents a novel BiLSTM-MTRAN-TCN model for stock price prediction, improving prediction accuracy and stability over traditional methods. It achieves R^2 improvements of 0.3% to 15.6% and reduces RMSE by 24.3% to 93.5%, demonstrating strong generalization across different stock indices and time periods.	The model, while enhancing prediction accuracy, may struggle to capture all market dynamics due to the unpredictable nature of financial markets. Additionally, the paper lacks a thorough discussion of the computational costs and scalability of the proposed method, raising concerns about its applicability in real-time scenarios.

particularly reinforcement learning approaches that learn optimal portfolio strategies through interaction with the market environment [117,135].

Studies in this domain have applied actor-critic models and deep Q-networks (DQN) for dynamic portfolio rebalancing. For instance, Cui et al. [117] utilized a novel Deep RL hyper-heuristic framework, demonstrating improved portfolio performance through the integration of expert knowledge and low-level trading strategies. However, a key limitation of RL models is their dependence on accurate reward signals from the market, which can lead to suboptimal performance during extreme market conditions, such as black swan events or sudden volatility spikes.

A summary of selected studies on portfolio optimization is provided in Table 9, highlighting their contributions and limitations.

5.1.4. Sentiment analysis for trading

Sentiment analysis has become popular in trading by using news articles, social media content, and financial reports to assess market sentiment [30,141]. DL models, such as CNNs and LSTMs, are frequently used to analyze text data and extract sentiment features that impact market behavior [142,143].

Several studies have incorporated sentiment analysis with traditional market data to enhance prediction models. For instance, integrating sentiment scores from Twitter or financial news with stock price data can lead to better forecasting, especially during major market events [149,150]. However, the noisy nature of social media data and the ambiguity in sentiment classification pose significant challenges, as illustrated in Table 10.

5.1.5. Risk management

Effective risk management in algorithmic trading involves predicting potential losses and optimizing trading strategies to mitigate risks [119,151]. Deep learning models help identify risk factors by analyzing historical data and learning complex relationships between asset returns and market variables [152,153].

Autoencoders, Variational Autoencoders (VAE), and other unsupervised learning techniques have been deployed to detect anomalies that could lead to portfolio losses. These models are valuable in identifying outliers, but the lack of interpretability and the potential for false positives remain concerns [154,155]. The following Table 11 summarizes key studies in this area, including contributions and limitations of different deep learning models used for risk management.

Table 8
Summary of selected studies on market volatility prediction.

Ref.	Year	Model	Contribution	Limitation
[60]	2024	LSTM-GARCH	The paper presents a hybrid LSTM-GARCH framework that enhances volatility risk prediction in financial markets by integrating deep learning with classical econometric models. The hybrid model significantly outperforms standalone models, achieving an MSE of 0.604, thus providing a more accurate tool for volatility forecasting in financial risk management.	The hybrid model's performance is sensitive to parameter selection and input data quality, potentially impacting its predictive capabilities. Additionally, the study primarily uses historical data from the Nasdaq 100 Index, which may limit the findings' generalizability to other financial markets or asset classes, reducing broader applicability.
[114]	2024	GARCH-MIDAS	This study enhances understanding of economic policy uncertainty's impact on stock market volatility in emerging economies, particularly Pakistan, using the GARCH-MIDAS model. It finds the US EPU index significantly predicts volatility, while indices from Pakistan and China show limited predictive power, even during economic upheavals like COVID-19.	The study's focus on a limited number of countries (US, China, UK, and Pakistan) may hinder the generalizability of findings to other emerging markets. Additionally, the lack of significant predictive information from Pakistan and China's EPU indices suggests potential data or model limitations that require further investigation.
[131]	2022	VU-GARCH-LSTM	The paper introduces the VU-GARCH-LSTM hybrid model, enhancing stock market volatility prediction by 21.03% in RMSE compared to existing models. It emphasizes the significance of data distribution characteristics and shows improved performance in predicting abnormal financial events, addressing limitations in capturing complex fluctuations in financial time-series data.	The paper acknowledges challenges in GARCH-type models regarding their ability to capture complex fluctuations and nonlinear correlations in financial time-series data. It suggests that further modifications to the model's concave function could enhance prediction performance, indicating that there is still potential for improvement in the hybrid modeling approach.
[53]	2021	LSTM	The paper investigates how investor sentiment from the Xueqiu forum impacts stock market volatility in China, revealing a significant negative correlation, especially during crises. It demonstrates that sentiment indices can effectively predict short-term volatility, outperforming historical data models, while suggesting a causal relationship where volatility influences sentiment.	The paper's limitations include a relatively small sample size of 1,230 observations, which may restrict the generalizability of the findings. Additionally, the dictionary-based sentiment analysis method may overlook nuanced sentiments, suggesting a need for integrating machine learning techniques. Finally, the predictive power diminishes for long-term volatility predictions.
[132]	2021	HAR-based framework	This paper highlights the predictive role of speculative sentiment on gold market volatility, demonstrating its significant impact on forecast accuracy. Results indicate that incorporating sentiment improves models, leading to better cumulative returns and Sharpe ratios, thereby enhancing investment strategies. Further research is needed to explore complex market dynamics.	The paper notes that the relationship between speculative sentiment and volatility is complex, potentially overlooking certain market dynamics, which calls for additional research. Furthermore, its focus on high-frequency data may not accurately reflect long-term trends or behaviors in the gold market, limiting the generalizability of the findings.
[19]	2019	ARIMA	The paper presents an ARIMA model tailored for predicting stock market movements in the Indian stock market, achieving an average deviation of approximately 5% mean percentage error. It demonstrates the model's effectiveness in real-world applications while emphasizing the importance of time series analysis and its potential across various fields.	The paper acknowledges that the ARIMA model, while effective, cannot guarantee 100% accuracy due to the unpredictability of auto-regressive processes. It also notes the necessity for stationary time series data, complicating the modeling process if differencing is required. Additionally, external factors affecting stock prices are not explored.

5.1.6. Anomaly detection and fraud detection

Anomaly detection plays a crucial role in safeguarding trading systems by identifying irregularities and suspicious activities that may indicate fraud or market manipulation [162,163]. In trading environments, detecting anomalies involves recognizing deviations from normal patterns in transaction data or stock price movements. DL models, such as autoencoders, RNN, and hybrid models, have shown promise in capturing these rare events due to their ability to model non-linear patterns and temporal dependencies [164,165].

Autoencoders, particularly, are effective in unsupervised learning tasks like anomaly detection, as they are trained to reconstruct normal patterns in data [166,167]. When the input deviates significantly from expected behavior, reconstruction error increases, signaling potential fraud. Similarly, RNN-based models, especially LSTM and GRU, are employed to model temporal sequences and detect unusual behavior in real-time transactions [154,168].

Table 12 provides a summary of notable studies applying DL models for anomaly and fraud detection in trading systems, outlining key contributions and their respective limitations.

5.1.7. Supply chain forecasting

Supply chain forecasting is essential for predicting product demand, managing inventory levels, and optimizing logistics, which are critical for operational efficiency and cost reduction [176,177]. Various machine learning models have been applied to improve forecasting accuracy by capturing complex temporal patterns and external factors [178,179].

Nguyen et al. [180] presented an LSTM-based method for multivariate time series forecasting and anomaly detection using an LSTM Autoencoder with OCSVM. While improving prediction accuracy, the model focuses on past anomalies, faces data access challenges, and produces single-value outputs, limiting its applicability in complex multivariate scenarios. This highlights the importance of addressing both temporal dependencies and external anomalies in supply chain forecasting. Punia et al. [181] proposed a cross-temporal forecasting framework (CTFF) using LSTM networks to enhance forecast coherency in retail supply chains. It achieved lower MAE, MSE, and MAPE with statistically significant improvements, with confidence levels exceeding 95%. However, its effectiveness depends on high-quality data, may not generalize to other industries, and involves complex implementation, limiting adoption by smaller organizations. This model addresses forecast accuracy in the retail context, contributing to the growing body of work focusing on improving forecast consistency and accuracy in supply chains.

Belhadi et al. [181] introduced a hybrid RotF-LB ensemble approach to forecast credit risk in agriculture 4.0 investments. By identifying 22 key variables and offering practical guidelines for SMEs and FSPs, the model improves forecasting accuracy, utilizing data from 216 SMEs,

Table 9
Summary of selected studies on portfolio optimization.

Ref.	Year	Model	Contribution	Limitation
[117]	2024	Deep Reinforcement Learning	The paper presents a novel Deep RL hyper-heuristic framework for multi-period portfolio optimization, integrating expert knowledge for enhanced asset allocation. Evaluated on five capital market instances, it shows significant performance gains over traditional methods, with implications for investment strategies and regulatory frameworks, despite challenges from real-world constraints and market variability.	The paper identifies several limitations, including the complexity of real-world constraints, such as cardinality and turnover, which create a nonconvex search space. Additionally, the approach's effectiveness may fluctuate with changing market conditions, and the inherent complexity of DRL algorithms presents computational challenges in larger problem instances, affecting scalability.
[136]	2024	Method of Moving Asymptotes (MMA)	The paper presents a new portfolio optimization method that directly optimizes portfolio weights through constrained penalized regression, enhanced by AutoML for model selection and hyperparameter tuning. Tested on M6 competition data, the approach achieved a 9.5% return and a 5.045 information ratio, surpassing traditional strategies.	The paper acknowledges challenges with financial data complexity, including noise and non-stationarity, which may hinder accurate asset dependency modeling. Despite a penalization term, overfitting remains a concern in high-dimensional settings. Additionally, the method's success is highly dependent on data quality, potentially affecting model accuracy.
[137]	2024	Quantile Regression Neural Network	The paper introduces a novel performance measure integrating non-Gaussianity and systemic risk into portfolio optimization, extending the Conditional Value-at-Risk framework. It demonstrates superior profitability and resilience in backtesting, especially during crises, outperforming benchmark strategies, even with transaction costs included, highlighting practical applicability in market distress.	The paper's limitations include a focus on the US market, potentially reducing the generalizability of findings to other regions. Its complex implementation, requiring advanced technical expertise and computational resources, may limit accessibility. Additionally, reliance on specific modeling assumptions may introduce biases if market conditions differ from those assumed.
[138]	2022	CNN-BiLSTM	This paper integrates a CNN-BiLSTM model with the Markowitz mean–variance (MV) model to enhance stock selection and portfolio optimization. Experimental results show improved performance over traditional models, especially in terms of the Sharpe ratio and risk. A five-stock portfolio is identified as optimal for individual investors.	The study's limitations include its focus on Thai stock data, limiting broader applicability. Hyperparameters were manually tuned, and external factors, such as political events, were not considered. Additionally, the model's time complexity was not addressed, potentially affecting real-world implementation and computational efficiency.
[139]	2021	Random Forest	This paper integrates traditional time series models with machine learning and deep learning techniques like Random Forest, SVR, LSTM, DMLP, and CNN for stock return prediction. It finds that Random Forest, combined with portfolio optimization models, yields the best results, though high turnover rates reduce profitability.	The study's limitations include the use of only simple historical returns as input features, excluding technical indicators or economic factors that could enhance model accuracy. Additionally, the high turnover rates in the RF-based portfolio models significantly reduce overall profitability, indicating a need for further research to address these challenges.
[140]	2021	XGBoost	This paper presents a hybrid model combining machine learning and mean–variance optimization for portfolio construction, achieving superior prediction accuracy and improved returns. The results demonstrate enhanced performance over traditional methods and benchmark models, emphasizing the importance of stock selection and the complexity of input data in investment decision-making.	The paper acknowledges challenges in accurately predicting complex input data, which can impact prediction accuracy. It also highlights that transaction costs were primarily analyzed as unilateral, potentially overlooking real-world trading implications. Additionally, the model's effectiveness heavily depends on hyperparameter optimization, necessitating robust techniques to avoid suboptimal performance.

195 enterprises, and 104 FSPs. Limitations include sample selection bias, dimensionality challenges, and a need for comparisons with more advanced EML techniques. This research emphasizes the need for hybrid models to address forecasting challenges in niche sectors, such as agriculture. Weng et al. [182] proposed a hybrid LightGBM-LSTM model for supply chain sales forecasting, offering high accuracy, efficiency, and interpretability. This model enhances inventory management and demand planning, outperforming traditional methods in prediction speed and providing insights into sales influences. However, its complexity demands more computational resources, relies on data quality, and may have limited generalizability across industries. Weng et al.'s work complements other research by demonstrating the efficacy of hybrid models in balancing accuracy with interpretability and efficiency.

Table 13 summarizes some studies, highlighting the different models used, their contributions to supply chain forecasting, and the limitations that must be addressed for broader application.

These studies demonstrate the effectiveness of deep learning and hybrid models in supply chain forecasting by capturing temporal dependencies, external influences, and multi-task requirements, offering scalable solutions for improving operational performance.

5.2. Datasets and resources

In deep learning applications for algorithmic trading, the choice of dataset is crucial, as it significantly impacts model performance and predictive accuracy. Various datasets, each with unique features and characteristics, can be utilized for different tasks such as stock price prediction, volatility forecasting, anomaly detection, and sentiment analysis. Table 14 shows ten noteworthy datasets commonly used in deep learning research related to algorithmic trading, along with a summary highlighting their references, names, and descriptions.

The Astock dataset [184] focuses on the China A-shares market, containing 40,963 stock-specific news items annotated with trading actions. It features 24 stock factors and is divided into in-distribution and out-of-distribution splits, supporting stock movement classification and simulated trading. The Stock Market Dataset [185] offers historical daily prices of NASDAQ-traded stocks and ETFs, retrieved via Yahoo Finance, with each ticker's data stored in CSV format. The NIFTY-50 Stock Market Data [186] provides daily stock price history and trading volumes for fifty stocks in India's NIFTY-50 index from January 1, 2000, to April 30, 2021, including individual CSV files for each stock and metadata updated monthly for ongoing analysis. The StockNet dataset [187] includes two years of stock price movements for 88 stocks across nine sectors, along with Twitter data. It features both

Table 10
Summary of selected studies on sentiment analysis for trading.

Ref.	Year	Model	Contribution	Limitation
[118]	2024	LLM	The paper explores the use of LLMs like OPT, BERT, and FinBERT for financial sentiment analysis, demonstrating their superior performance in market prediction. The OPT model achieved a 74.4% accuracy in predicting stock returns and generated a 355% gain from a long-short strategy between 2021–2023.	The paper highlights challenges in adopting LLMs for financial analysis, including the need for technical expertise, computational resources, and funding. It also acknowledges the complexity of interpreting textual data and suggests that further research is needed to explore additional models and refine techniques for financial text analysis.
[144]	2024	CNN, LSTM, and GRU-CNN	This paper introduces a sentiment analysis framework for Turkish financial tweets using DL models like CNN, LSTM, and GRU-CNN. The CNN model with pre-trained word embedding achieved the highest accuracy for binary classification (83.02%) and multi-class classification (72.73%), highlighting the effectiveness of deep learning for sentiment analysis in resource-limited languages.	The paper highlights potential data collection bias due to specific keyword usage, which may skew sentiment representation. Additionally, Turkish tweets' ambiguity complicates pre-processing, impacting model performance. The research also notes the limited amount of sentiment analysis work in Turkish compared to English, indicating a gap for future studies.
[145]	2024	JST and TS-LDA	This paper addresses a research gap by applying aspect-based sentiment analysis (JST and TS-LDA) to predict Bitcoin's directional returns, using polarity, subjectivity, and LDA topics as features. It demonstrates enhanced model performance through ROC AUC and accuracy, providing interpretable topics and leveraging diverse textual data sources.	The paper's limitations include cryptocurrency data sources providing short comments, limiting analysis depth. Additionally, classifying comments based on parent posts may lead to incorrect subject assignments, skewing results when discussions deviate from the original topic, suggesting the need for better methods or alternative data sources for accurate analysis.
[146]	2024	Spatial Federated Learning	The paper introduces a novel ensemble technique combining spatial federated learning with sentiment analysis, utilizing news stored on a blockchain for stock market predictions. Results show improved prediction accuracy, outperforming traditional models. A 5-bit pattern guides trading decisions, validated on Hong Kong Stock Exchange datasets through sentiment transfer learning.	The paper's limitations include heavy reliance on the quality and quantity of news data for sentiment analysis, making predictions vulnerable to biased or limited information. The ensemble and federated learning framework also increases implementation complexity, and its generalizability to other stock markets requires further validation across different regions and datasets.
[147]	2023	ChatGPT 3.5	This paper examines the capabilities of large language models, focusing on ChatGPT 3.5, for financial sentiment analysis in the foreign exchange market. ChatGPT surpassed FinBERT by 35% in sentiment classification accuracy and showed a 36% stronger correlation with market returns, demonstrating its effectiveness in interpreting market trends and informing trading strategies.	The paper acknowledges limitations, including the short duration of the dataset, which may not capture all factors influencing financial markets. Additionally, the models only partially aligned with market movements, suggesting that sentiment analysis alone may not fully explain price variations, requiring further studies with extended time frames for validation.
[148]	2022	Machine Learning	The paper presents a novel sentiment index that incorporates weighted textual content and financial anomalies, enhancing stock trend predictions by considering day-of-the-week and holiday effects. Experimental results show improved predictive ability across various machine learning models, contributing to better accuracy, risk management, and potential returns for investors.	The paper overlooks transaction fees, impacting the real-world applicability of trading strategies derived from the sentiment index. Additionally, it highlights challenges faced by retail investors in executing short trades, which may restrict the practical implementation of the proposed strategies in certain markets, limiting their overall effectiveness and accessibility.

raw and preprocessed price data from Yahoo Finance and tweet data from Twitter, enabling stock movement prediction using text and price signals. The dataset of stock market indices [188] tracks the performance of eight stock market indices (IPC, S&P 500, DAX, DJIA, FTSE, N225, NDX, CAC) from June 2006 to May 2023, including daily stock indices and various economic indicators sourced from Yahoo Finance and OECD.

The Stock-Market Sentiment Dataset [189] comprises tweets collected from multiple Twitter handles, categorizing economic news into positive and negative sentiments, serving as a valuable resource for sentiment analysis in trading strategies. The Stock Tweets for Sentiment Analysis and Prediction dataset [190] contains over 80,000 tweets related to the top 25 stock tickers on Yahoo Finance, collected between September 30, 2021, and September 30, 2022. It includes tweet texts, stock names, company names, and corresponding stock market price and volume data, facilitating sentiment analysis and stock price prediction.

The Dataset for Stock Market Prediction [191] consists of historical stock prices for three petroleum companies—Pakistan State Oil, Hascol, and Attock Petroleum Limited—extracted from the Pakistan Stock Exchange website over the last four years, including daily attributes and Twitter data for sentiment analysis. The United States Stock Market Index dataset [192] captures US stock market activity, detailing changes in major indices and sector performance, including information on oil price fluctuations following geopolitical events and significant stock movements. The CryptoBubbles dataset [193] encompasses around 404 cryptocurrencies from top exchanges, featuring daily price data and tweets for bubble detection, allowing analysis of market behaviors and trends despite inherent challenges.

These datasets serve as essential resources for researchers and practitioners in the field of algorithmic trading, enabling the development and testing of deep learning models that can effectively analyze market behavior and make informed trading decisions.

5.3. Performance metrics

In assessing the performance of deep learning (DL) models in algorithmic trading, a range of evaluation metrics is employed to capture different aspects of model effectiveness. These metrics are drawn from both the fields of machine learning and finance to measure predictive accuracy, profitability, and risk-adjusted returns.

5.3.1. Accuracy, precision, and recall

For classification tasks, such as predicting whether stock prices will rise or fall, metrics such as accuracy, precision, and recall are widely used [194,195]. These metrics evaluate how well the DL models are able to predict binary or multi-class outcomes based on historical data.

Table 11
Summary of selected studies on risk management.

Ref.	Year	Model	Contribution	Limitation
[156]	2024	–	The paper demonstrates how AI-driven predictive analytics enhances risk assessment, decision-making, and profitability in finance. It emphasizes AI's role in real-time risk detection, proactive decision-making, and regulatory compliance. Additionally, dynamic learning models continuously improve predictions, helping institutions mitigate risks and meet regulatory requirements efficiently.	The paper highlights limitations such as the dependence on high-quality data for accurate AI predictions and the complexity of integrating AI into existing financial systems. It also neglects possible ethical and regulatory issues, such as data privacy and algorithmic bias, which are vital considerations for the implementation of AI technologies in finance.
[157]	2024	–	The paper discusses the integration of AI in stock trading, highlighting its role in improving risk management and decision-making processes. AI technologies, including machine learning and neural networks, enhance trading efficiency while addressing regulatory and ethical concerns. It also explores real-world case studies and future AI trends in finance.	The paper identifies limitations, including the risk of overfitting in AI models, which may hinder their ability to generalize to future market conditions. Additionally, the reliance on historical data can lead to poor performance in changing markets. Ethical concerns, such as potential market manipulation, also require careful governance.
[158]	2023	LSTM	The paper contributes to predictive analysis and risk management in trading by integrating LSTM networks and collaborative filtering, enhancing stock market predictions. Tested on the Stock Price EOD Dataset, the model achieves over 95% accuracy, outperforming traditional benchmarks and highlighting the effectiveness of DL in real-world trading scenarios.	The paper points out the challenges of applying machine learning to stock market predictions, especially when dealing with time series data, as the outcomes may be unreliable. Although deep learning models have shown promise, additional research is necessary to investigate more algorithms and datasets to enhance the robustness and applicability of the proposed models.
[159]	2020	LSTM	The paper introduces an Automated Trading System (ATS) using LSTM networks for stock price prediction, integrated with risk management strategies. The LSTM-RMODV method achieved a 228.94% return on invested capital. Despite low prediction accuracy, robust risk management ensured consistent profitability, highlighting its significance in trading systems.	The paper highlights overfitting as a key limitation of Artificial Neural Networks (ANN), affecting real-world performance. It also raises concerns about model generalizability due to limited evaluation in actual market conditions. Additionally, while technical knowledge is useful, deeper market insights are necessary for improving model performance, especially with advanced techniques like VWAP.
[160]	2020	Decision Tree & ANN	The paper presents the Artificial Intelligent Risk Management System (AIRMS), employing machine learning for risk management in finance. It developed two systems, AIRMS-DT and AIRMS-ANN, which improved currency portfolio returns by 50% and 40%, respectively, effectively classifying trading signals and outperforming original portfolios.	A key limitation of the study is the complexity of calibrating artificial neural networks, which may delay their implementation in real-world scenarios. Additionally, the research emphasizes the need for further investigation into diverse strategies and feature extraction methods to enhance the model's overall effectiveness and performance.
[161]	2020	Neural Network	The paper enhances financial risk management by developing an AI system that integrates neural networks, digitized news fluctuations, and candlestick chart data to improve price forecasts for SiU9 US Dollar futures. Results show significant accuracy improvements and effective risk assessment, minimizing losses in speculative trading through a neural network algorithm.	The study's primary limitation is the complexity in calibrating artificial neural networks, which may hinder their practical implementation in real-world trading. Additionally, the research emphasizes the need for further investigation into diverse strategies and feature extraction methods to improve the model's overall effectiveness and performance in financial risk management.

- **Accuracy:** Accuracy measures the ratio of correctly predicted observations to the total observations:

$$\text{Acc} = \frac{T.Positive + T.Negative}{Total} \tag{9}$$

where $T.Positive$ is the number of true positives, $T.Negative$ is the number of true negatives, and Total means sum of all data.
- **Precision:** Precision focuses on the proportion of true positives among all positive predictions:

$$\text{Prec} = \frac{T.Positive}{T.Positive + F.Positive} \tag{10}$$

High precision indicates a low false positive rate, which is crucial for minimizing incorrect buy/sell decisions in algorithmic trading.
- **Recall:** Recall, or sensitivity, measures the proportion of actual positives that were correctly identified:

$$\text{Rec} = \frac{T.Positive}{T.Positive + F.Negative} \tag{11}$$

In trading, a high recall ensures that the model captures as many profitable trades (true positives) as possible.
- **F1-Score:** The F1-score balances precision and recall, providing a single measure of a model's accuracy when the class distribution is imbalanced:

$$\text{F1-Score} = 2 \times \frac{\text{Prec} \times \text{Rec}}{\text{Prec} + \text{Rec}} \tag{12}$$

The F1 score is especially useful in trading scenarios where false positives and false negatives have different costs.

5.3.2. Mean squared error (MSE) and root mean squared error (RMSE)

For regression tasks, such as predicting future stock prices, the MSE and RMSE are commonly used [196,197]. These metrics measure the mean squared distance between the predicted and actual values.

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2 \tag{13}$$

where x_i is the actual value, $\hat{x}_i$ is the predicted value, and N is the number of observations. MSE penalizes larger errors more than smaller ones, making it sensitive to outliers.

$$\text{RMSE} = \sqrt{MSE} \tag{14}$$

RMSE provides a more interpretable metric since it is on the same scale as the original data. It is widely used to evaluate stock price predictions or forecast error in financial markets.

5.3.3. Sharpe Ratio (SR)

In algorithmic trading, financial metrics such as the SR are essential for assessing the risk-adjusted performance of a trading strategy [198].

Table 12
Summary of selected studies on anomaly detection and fraud detection.

Ref.	Year	Model	Contribution	Limitation
[169]	2024	GNN	This paper introduces a novel fraud detection framework integrating Graph Neural Networks (GNNs) with anomaly detection. Applied to the imbalanced Credit Card Fraud Detection dataset, the model achieves a 95% detection rate with a 2% false positive rate, outperforming state-of-the-art methods by 10% and demonstrating robustness against complex fraud schemes.	The main limitation of this paper is its reliance on a specific dataset, which may not capture the full diversity of global fraud patterns. Additionally, while the model shows robustness against certain fraud schemes, its performance on emerging and highly complex fraud tactics remains unexplored, requiring further validation.
[170]	2024	Transformer-based autoencoder	The paper presents a novel Transformer-based autoencoder framework for detecting anomalies in limit order book (LOB) data. It introduces a dissimilarity function and a trade-based manipulation simulation methodology, achieving high performance on NASDAQ stock data, surpassing traditional models like LSTM in detecting fraudulent patterns.	The paper faces challenges with the curse of dimensionality due to multiple hidden states per feature, complicating the learning process. Additionally, the scarcity of relevant machine learning literature for financial market anomalies and concerns about addressing the sequential nature of trade-based manipulations limit the model's generalizability.
[171]	2024	GNN	This paper explores the use of GANs in fraud detection, demonstrating their ability to model complex data distributions and detect anomalies in transactions. The proposed GAN-based system enhances transaction security, outperforming traditional methods, and offers a foundational framework for future research on GAN applications across various domains.	The paper highlights technical challenges in GANs, such as pattern collapse, and limiting data diversity. It also raises privacy concerns, particularly in sensitive sectors like finance and healthcare, where synthetic data generation could expose private information. Additionally, ethical issues surrounding the misuse of GANs, such as identity forgery, are addressed.
[172]	2024	–	The paper presents a transformative framework for fraud detection in fintech, showcasing how advanced AI techniques, including deep learning and natural language processing, outperform traditional methods. It highlights AI's enhanced capabilities in real-time detection and unstructured data analysis, emphasizing the need for scalable, adaptive, and predictive solutions.	The paper highlights limitations including data privacy concerns due to the extensive personal data required for AI-driven fraud detection, risks of algorithmic bias from historical data, and the challenge of continuous learning. These systems must adapt to evolving fraud tactics, which can be resource-intensive and complex to maintain.
[173]	2024	LightGBM	The paper investigates anomaly detection (AD) methods for fraud detection in online credit card payments, comparing them to supervised learning approaches like LightGBM. While LightGBM performs better across metrics, AD methods show more robustness to distribution shifts. However, AD methods fall short in fraud detection effectiveness compared to LightGBM.	The paper's limitations include the lower fraud detection performance of AD methods compared to LightGBM and their reliance on normal samples, which limits adaptability to new anomalies. Additionally, the results are based on a specific dataset, potentially limiting their applicability to other datasets or contexts with different characteristics.
[174]	2023	Random Forests and Gradient Boosting Machines	The paper emphasizes the need for real-time machine learning in fraud detection to improve financial security by moving beyond static systems. Results show that machine learning models enhance fraud detection by reducing false positives and increasing detection speed, with fine-tuning improving the balance between precision and recall.	The paper highlights challenges such as potential bias in machine learning models, leading to unfair targeting of demographics. It also addresses the lack of transparency in models, which can undermine trust and complicate regulatory compliance. Additionally, current systems still face inherent challenges for effective fraud detection.
[175]	2020	SADE	The paper introduces the SADE framework, which detects anomalies in financial transaction networks by focusing on subgraph-level patterns using role-guided embeddings. Extensive experiments show that SADE outperforms existing methods in detecting anomalous subgraphs, demonstrating its effectiveness in fraud detection and risk modeling without requiring prior knowledge.	The paper does not explicitly address limitations, but potential challenges include the complexity of selecting parameters for role-guided embeddings, which could affect performance. Additionally, the framework's reliance on the quality of financial transaction data may hinder effectiveness, as noisy or incomplete data could lead to inaccurate anomaly detection results.

The SR measures the excess return (the return above a risk-free rate) per unit of volatility (risk):

$$\mathrm{SR} = \frac{\mathbb{E}[C_x - C_y]}{\sigma_x} \tag{15}$$

where C_x is the return of the portfolio, C_y is the risk-free rate, and σ_x is the standard deviation of the portfolio's return (volatility). A higher SR indicates a better risk-adjusted return. In DL-based trading, the Sharpe Ratio is often used to evaluate the profitability of models while accounting for the risks associated with market volatility.

5.3.4. Return on investment (ROI)

ROI is another financial metric used to assess the profitability of DL-based trading models [199]. It is calculated as:

$$\mathrm{ROI} = \frac{\text{Net Profit}}{\text{Investment Cost}} \times 100 \tag{16}$$

where the net profit is the total gain from the investment and the investment cost is the amount initially invested. ROI measures the efficiency of the investment and is often used to compare the performance of different trading strategies implemented using DL models.

5.3.5. Sharpe ratio vs. ROI

While ROI focuses purely on profitability, the Sharpe Ratio also considers the risk (volatility) taken to achieve that profit. In financial markets, a high ROI might not always be desirable if it comes with excessive risk, which is why the Sharpe Ratio is often preferred for evaluating DL-based trading strategies [200,201].

5.4. Effectiveness of performance metrics

The effectiveness of these metrics varies depending on the application. For example:

- **Accuracy, Precision, and Recall** are effective in binary classification tasks like predicting price movements (up/down). They help ensure that DL models minimize incorrect buy/sell signals. Higher values are generally better for these metrics, as they indicate fewer errors in classification, while lower values suggest more misclassifications and less reliable predictions.

Table 13
Summary of selected studies on supply chain forecasting.

Ref.	Year	Model	Contribution	Limitation
[180]	2021	LSTM	This paper proposes an LSTM-based method for multivariate time series forecasting and an LSTM Autoencoder combined with OCSVM for anomaly detection. The model demonstrates superior performance in fashion retail and NASA datasets, optimizing hyperparameters and integrating data sources to improve prediction accuracy.	This anomaly detection model primarily identifies anomalies from historical data without predicting future anomalies. Data access restrictions from companies limited the study's scope. Additionally, the LSTM-based method produces a single value for multivariate data, potentially constraining its effectiveness in more complex scenarios.
[181]	2021	Ensemble Model	This study introduces a hybrid RotF-LB ensemble approach to forecast credit risk in agriculture 4.0 investments. It identifies 22 key variables and provides practical guidelines for SMEs and FSPs. The model outperforms others in forecasting accuracy, utilizing data from 216 SMEs, 195 enterprises, and 104 FSPs.	This study acknowledges potential sample selection bias and the need for larger datasets for validation. Dimensionality challenges persist despite the LB algorithm, and further exploration of non-linear methods like autoencoders is suggested. Additionally, the study recommends comparing the RotF-LB approach with more advanced EML techniques.
[183]	2020	LSTM	This paper presents a cross-temporal forecasting framework (CTFF) using LSTM networks to ensure forecast coherency across retail supply chain levels. It demonstrates lower MAE, MSE, and MAPE compared to cross-sectional methods, with statistically significant improvements validated by t-tests and p-values at confidence levels above 95%.	The CTFF relies heavily on high-quality point-of-sales data, limiting performance with poor data. Its applicability to industries beyond large retail supply chains remains uncertain. The computational complexity of LSTM-based integration may hinder adoption by smaller organizations, while external market factors and disruptions are not comprehensively addressed.
[182]	2020	LightGBM and LSTM	This paper presents a hybrid model combining LightGBM and LSTM for supply chain sales forecasting. It offers high accuracy, efficiency, and interpretability, improving inventory management and demand planning. The model outperforms traditional methods in prediction speed and provides valuable insights into sales influences.	This hybrid model's complexity requires more computational resources and may be harder to implement. Its effectiveness depends on data quality, and poor data can lead to inaccurate forecasts. Additionally, its performance may vary across industries, limiting its broader applicability beyond the tested datasets.

- **MSE and RMSE** are valuable for regression tasks, such as predicting future stock prices or financial indices. These metrics provide insights into the precision of the model's predictions. Lower values are better for MSE and RMSE, as they indicate less deviation from the actual values. Higher values indicate greater deviation from the actual values, suggesting less accurate predictions.
- **Sharpe Ratio** is critical for evaluating the overall performance of DL-based trading strategies by accounting for both return and risk. It helps in selecting strategies that provide the best risk-adjusted returns. Higher values are better for the Sharpe Ratio, as they indicate higher returns relative to risk, while lower values indicate less favorable returns for the amount of risk taken.
- **ROI** is useful for measuring the raw profitability of a trading strategy, though it should be paired with other metrics like the Sharpe Ratio to provide a complete picture of performance. Higher values are better for ROI, as they indicate greater profitability, while lower values suggest less profitability or potential losses.

5.5. Comparison of some recent studies

In recent years, deep learning techniques have gained significant attention in the field of algorithmic trading [100,202]. These studies explore various methods for improving trading strategies by leveraging advanced algorithms like neural networks, decision trees, and reinforcement learning. Researchers have focused on applying deep learning models to predict stock prices, identify trading signals, and optimize trading decisions. While these studies show promising results, they also face challenges such as model overfitting, data quality issues, and the adaptability of models to different market conditions.

Table 15 provides a comprehensive comparison of several studies related to deep learning for algorithmic trading, summarizing key aspects such as datasets used, models employed, results achieved, contributions made, and limitations identified.

6. Challenges identified

Despite the considerable advancements in deep learning for financial applications, these challenges underscore the complexities involved in developing robust models for algorithmic trading [206,207]. Addressing these issues is crucial for improving model performance and reliability, ultimately fostering greater trust and adoption among traders and financial institutions. Continued research and innovation in this domain will be essential for overcoming these obstacles and unlocking the full potential of deep learning in finance.

6.1. Data quality

One of the most frequently cited challenges in the literature is the quality of financial data. Financial markets are notoriously noisy, and this presents significant difficulties for deep learning (DL) models [208,209]. Financial data is often influenced by a wide range of factors such as market sentiment, macroeconomic news, and geopolitical events, which introduce a high degree of variability and randomness.

6.1.1. Noise in financial data

Noise in financial data refers to random price fluctuations that do not represent genuine market signals. Noise is particularly problematic for DL models that aim to extract patterns from historical data [208,210]. Models trained on noisy data are more likely to capture irrelevant patterns, leading to poor predictive performance [211]. For instance, stock prices are influenced by short-term market fluctuations that may not follow any predictable pattern, but DL models may incorrectly interpret these fluctuations as meaningful trends.

DL models tend to fit the noise in financial time-series data, which can lead to overfitting [212]. The literature highlights that despite the use of advanced regularization techniques such as dropout and weight decay, overfitting remains a persistent issue when models are trained on noisy or non-stationary data.

6.1.2. Missing data

Missing data is another critical issue, especially in high-frequency trading, where gaps in data can arise due to network latency, exchange outages, or reporting delays [213,214]. DL models often require complete datasets for accurate predictions, and missing data points can significantly degrade model performance. Imputation techniques are commonly used to address this issue, but they introduce their own

Table 14
Summary of datasets used in deep learning for algorithmic trading.

Name	Description
Astock [184]	The Astock dataset, focused on the China A-shares market, contains 40,963 stock-specific news items (July 2018–November 2021) annotated with trading actions. It features 24 stock factors, is divided into in-distribution and out-of-distribution splits, and supports stock movement classification and simulated trading, using relevant financial evaluation metrics.
Stock Market Dataset [185]	The dataset contains historical daily prices of NASDAQ-traded stocks and ETFs, retrieved via Yahoo Finance using the yfinance Python package, up to April 1, 2020. Each ticker's data is stored in CSV format with fields like date, open, high, low, close, adjusted close, and volume, organized into ETFs and stock folders.
NIFTY-50 Stock Market Data [186]	The NIFTY-50 dataset contains daily stock price history and trading volumes for fifty stocks in India's NIFTY-50 index from January 1, 2000, to April 30, 2021. It includes individual CSV files for each stock and metadata with macro-level information, updated monthly for ongoing analysis.
StockNet Dataset [187]	The Stocknet dataset includes two years (2014–2016) of stock price movements for 88 stocks across 9 sectors, along with Twitter data. It features both raw and preprocessed price data from Yahoo Finance and tweet data from Twitter, enabling stock movement prediction using text and price signals.
datasets of stock market indices [188]	The dataset tracks the performance of eight stock market indices (IPC, S&P 500, DAX, DJIA, FTSE, N225, NDX, CAC) from June 2006 to May 2023. It includes daily stock indices and FX rates, quarterly GDP, and monthly CPI, RFR, UR, BOP, and GFCF data, sourced from Yahoo Finance and OECD.
Stock-Market Sentiment Dataset [189]	The Stock-Market Sentiment Dataset comprises tweets collected from multiple Twitter handles, categorizing economic news into positive (1) and negative (−1) sentiments. It contains 3,685 positive and 2,106 negative entries, organized into two columns: Text and Sentiment. This dataset serves as an insightful resource for sentiment analysis in stock trading.
Stock Tweets for Sentiment Analysis and Prediction [190]	The dataset comprises over 80,000 tweets related to the top 25 stock tickers on Yahoo Finance, collected between September 30, 2021, and September 30, 2022. It includes tweet texts, stock names, company names, and corresponding stock market price and volume data, facilitating sentiment analysis and stock price prediction.
Dataset for Stock Market Prediction [191]	The dataset comprises historical stock prices for three petroleum companies: Pakistan State Oil (PSO), Hascol, and Attock Petroleum Limited (APL), extracted from the Pakistan Stock Exchange (PSX) website over the last four years. It includes daily attributes like total trade volume, high, low, open, and close prices. Additionally, Twitter data for sentiment analysis was collected using Twint and Tweepy, capturing user-profiles and tweet attributes to calculate a composite influence score.
United States Stock Market Index [192]	The dataset captures US stock market activity, detailing changes in major indices (Dow, S&P 500, Nasdaq) and sector performance. It includes information on oil price fluctuations following geopolitical events, US services sector expansion, labor market indicators, and significant stock movements, such as Spirit Airlines' plunge amid bankruptcy talks.
CryptoBubbles dataset [193]	The CryptoBubbles dataset includes around 404 cryptocurrencies from top exchanges, covering daily price data from March 1, 2016, to April 7, 2021. It features essential price metrics and 2.4 million tweets for bubble detection using the PSY model, allowing analysis of market behaviors and trends, despite inherent challenges.

challenges, particularly in terms of preserving the temporal dynamics of financial data [215].

$$\hat{x}_t = \frac{1}{N}\sum_{i=1}^{N} x_{t-i} \tag{17}$$

Here, $\hat{x}_t$ represents the imputed value for time t based on the mean of the previous N observations. While simple imputation methods such as this can address missing values, they may fail to capture the intricate market dynamics and dependencies, leading to inaccurate predictions.

6.2. Overfitting

Overfitting happens when a model excels at the training data but struggles to apply what it learned to new, unseen data [216,217]. This is a major challenge in the application of DL to algorithmic trading. The inherent complexity of DL models, such as RNN and LSTM networks, often leads to overfitting, particularly in financial markets characterized by high volatility and unpredictability [218,219].

6.2.1. Impact of overfitting in trading

Overfitting can result in models that are highly sensitive to historical market conditions but ineffective in capturing future trends [220,221]. In algorithmic trading, this can manifest as poor real-time performance, where models perform exceptionally well on backtested historical data but fail to maintain profitability in live trading. This challenge is intensified by the ever-changing nature of financial markets, where historical performance does not guarantee future results.

Various methods have been suggested in the literature to address overfitting, including:

- **Dropout:** A regularization technique where random neurons are dropped during training to prevent the model from becoming too reliant on specific features. The dropout rate γ is set between 0 and 1, controlling the proportion of neurons to drop:

$$h_i^{(l)} = \begin{cases} 0, & \text{with probability } \gamma \\ h_i^{(l)}, & \text{with probability } 1-\gamma \end{cases} \tag{18}$$

  where $h_i^{(l)}$ is the activation of neuron i at layer l.
- **Cross-Validation:** K-fold cross-validation is commonly used to assess a model's generalization capabilities. This method involves dividing the dataset into k subsets, where the model is trained on $k-1$ subsets and evaluated on the remaining subset. This procedure is repeated k times, and the model's performance is averaged across all folds.

$$\mathrm{MSE}_{\mathrm{CV}} = \frac{1}{k}\sum_{i=1}^{k} \mathrm{MSE}_i \tag{19}$$

Despite the use of such techniques, overfitting remains a critical issue, particularly in high-frequency and short-term trading strategies, where the noise in the data often dominates the underlying market patterns.

6.3. Model interpretability

Another major challenge identified in the literature is the interpretability of DL models. DL models, particularly DNNs, are often referred to as "black boxes" due to their complexity and the difficulty in understanding how they arrive at specific predictions [222,223]. This lack of transparency can be problematic in algorithmic trading, where understanding the rationale behind a model's decisions is important for gaining trust from traders and regulators [224,225].

6.3.1. Black-box nature of DL models

In traditional ML models such as decision trees or linear regression, the decision-making process is more transparent because the model structure can be easily interpreted [226,227]. However, in deep learning models, particularly those with multiple layers and a high number of parameters, it is challenging to discern which features are driving the model's predictions.

The literature proposes several methods for improving interpretability, including:

Table 15
Comparison of recent studies on deep learning for algorithmic trading.

Ref	Year	Model	Dataset	Result	Contribution	Limitation
[144]	2024	CNN	Turkish tweet dataset [203]	Accuracy 83.02% (Binary) & 72.73% (Multi-Class)	This paper presents a sentiment analysis framework for Turkish financial tweets utilizing deep learning models such as CNN, LSTM, and GRU-CNN. The CNN model, enhanced with pre-trained word embeddings, achieved the best performance, with an accuracy of 83.02% for binary classification and 72.73% for multi-class classification, demonstrating the effectiveness of deep learning in sentiment analysis for resource-constrained languages.	The paper points out the potential bias in data collection caused by the use of specific keywords, which could distort sentiment representation. It also highlights the challenges posed by the ambiguity of Turkish tweets, which complicates preprocessing and affects model performance. Furthermore, the research mentions the limited amount of sentiment analysis conducted in Turkish compared to English, suggesting this is an area for future exploration.
[158]	2023	LSTM	Stock Price Dataset EOD [204]	Accuracy 95%	This paper enhances predictive analysis and risk management in trading by combining LSTM networks with collaborative filtering, improving stock market forecasts. Evaluated on the Stock Price EOD Dataset, the model achieves an accuracy of over 95%, surpassing traditional benchmarks and demonstrating the effectiveness of deep learning in practical trading applications.	This paper highlights the difficulties of using machine learning for stock market predictions, particularly when working with time series data, as the results may lack reliability. While deep learning models have shown potential, further research is needed to explore additional algorithms and datasets to improve the robustness and applicability of the proposed models.
[57]	2024	LSTM	BEXIMCO Pharmaceutical [205]	RMSE 12.312 & MAPE 2.06%	This paper evaluates the performance of SMA, EMA, and LSTM models for stock price prediction. It shows that LSTM outperforms the other models in short-term forecasting, achieving an RMSE of 12.312 and a MAPE of 2.06%, whereas SMA and EMA provide better results for long-term predictions.	The paper emphasizes LSTM's limitations in long-term stock price prediction, where SMA and EMA yield better results. It also acknowledges the intrinsic complexity of the stock market, which impacts the reliability of predictions, and highlights the limited applicability of the findings due to the use of datasets from only six companies.
[125]	2024	GRA-WD-BiLSTM	Own Dataset	Accuracy 95.93% (SSEC), 93.02% (SZI) & 97.07% (HSI)	This paper presents a GRA-WD-BiLSTM hybrid model for forecasting stock prices based on environmental factors such as air quality and weather. The model demonstrated strong prediction accuracies of 95.93% for the SSEC, 93.02% for the SZI, and 97.07% for the HSI, highlighting its effectiveness across different stock indices.	This study's limitations include restrictions in selecting environmental data due to equipment and data availability, which limited the range of influencing factors considered. Furthermore, it did not incorporate seasonal variations in environmental factors, which could impact the accuracy of stock price predictions.
[118]	2024	LLM	Own Dataset	Accuracy 74.4%	This paper investigates the application of large language models (LLMs) such as OPT, BERT, and FinBERT for financial sentiment analysis, showing their enhanced effectiveness in predicting market trends. The OPT model, in particular, reached a 74.4% accuracy in forecasting stock returns and yielded a 355% return using a long-short strategy between 2021 and 2023.	This paper discusses the difficulties in using LLMs for financial analysis, emphasizing the necessity for technical skills, computational power, and funding. It also recognizes the challenges in interpreting textual data and proposes that further research is required to investigate alternative models and improve methods for analyzing financial texts.
[126]	2023	BiLSTM-MTRAN- TCN	Shanghai and Shenzhen stock markets Dataset	MAE 0.087, MSE 0.014, RMSE 0.118, & R^2 0.986	This paper introduces an innovative BiLSTM-MTRAN-TCN model for stock price forecasting, enhancing prediction accuracy and stability compared to conventional approaches. It achieves an increase in R^2 ranging from 0.3% to 15.6% and a reduction in RMSE between 24.3% and 93.5%, showing excellent generalization across various stock indices and time frames.	Although the model improves prediction accuracy, it may face difficulties in fully capturing the complexities of market dynamics due to the inherent unpredictability of financial markets. Furthermore, the paper does not provide an in-depth analysis of the computational costs and scalability of the proposed approach, which raises concerns about its practicality in real-time applications.

- **Feature Importance:** Techniques such as SHAP (SHapley Additive exPlanations) [228] values and LIME (Local Interpretable Model-agnostic Explanations) [229] can be used to assign importance scores to features, providing insight into how the model uses input data to make predictions. SHAP values are computed as:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \tag{20}$$

where ϕ_i is the Shapley value for feature i, S is a subset of features, and N is the total set of features. This approach offers a way to decompose the model's output into contributions from each feature.
- **Attention Mechanisms:** Attention mechanisms, commonly used in NLP tasks, have been adapted for use in time-series financial data to improve model interpretability [230]. Attention weights highlight the importance of different time steps in contributing to a prediction:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{t=1}^{T} \exp(e_t)} \tag{21}$$

where α_t is the attention weight assigned to time step t, and e_t is the attention score. These mechanisms help to identify which market events or time periods are most relevant to the model's predictions.

However, despite advances in interpretability techniques, the challenge of making complex DL models transparent to traders and regulators remains a significant barrier to their broader adoption in algorithmic trading.

6.4. Computational complexity

Deep learning models are computationally intensive, particularly when applied to high-frequency trading or large-scale financial datasets [231,232]. The training process for deep neural networks can take considerable time and resources, especially for architectures such as LSTMs and CNNs, which are often used in financial markets.

6.4.1. Training time and resources

Training deep models on financial data often requires substantial computational resources, including high-performance GPUs or distributed computing environments [233,234]. This can be a limiting factor for smaller institutions or individual traders who may not have access to such infrastructure. In addition to the cost, long training times can also delay the deployment of models in live trading environments, where the ability to quickly adapt to market conditions is critical.

$$T_{\text{train}} = \frac{n \times d}{r} \tag{22}$$

In this equation, T_{train} represents the total training time, n is the number of samples in the dataset, d is the model complexity (e.g., the number of layers and parameters), and r is the computational resources available (e.g., GPU speed). As n and d increase, the training time grows, requiring more powerful computational setups.

6.4.2. Real-time trading and latency

In high-frequency trading, real-time performance is crucial, and even small delays in executing trades can lead to missed opportunities and financial losses. The computational complexity of DL models, particularly those that involve deep architectures or ensemble methods, can introduce latency in decision-making [235]. This latency is problematic in environments where trades need to be executed within milliseconds.

Efforts to reduce latency often involve simplifying the model architecture or using techniques such as model pruning and quantization to reduce the computational demands of DL models. However, there is often a trade-off between model complexity (and accuracy) and the speed of execution [236].

6.5. Market complexity

Financial markets are shaped by a wide range of factors, such as macroeconomic trends, geopolitical developments, and market sentiment, which contribute to their complexity and dynamism. Capturing these interactions in DL models is challenging, as markets are not governed by fixed rules but by a multitude of interacting variables, many of which are difficult to quantify [237,238].

6.5.1. Non-stationarity of financial data

The main challenge in modeling financial markets is the non-stationarity of financial data. Unlike static datasets, financial markets evolve over time, with changes in market structure, trading behavior, and external factors [239,240]. This makes it difficult for DL models trained on historical data to generalize to future market conditions. Traditional statistical models often assume stationarity, but this assumption is frequently violated in financial markets, leading to poor model performance [241].

To address this issue, some studies have proposed adaptive learning methods, where the model parameters are updated as new market data becomes available. Reinforcement learning, in particular, has shown promise in this area, as it allows models to continuously learn from new market data and adjust their strategies in real-time [165].

6.5.2. High dimensionality of financial data

Financial markets generate massive amounts of data, including price data, order book information, economic indicators, and social media sentiment. The high dimensionality of this data poses a challenge for DL models, which must learn to filter out irrelevant features while capturing the most important ones [242,243]. Dimensionality reduction techniques, such as autoencoders and principal component analysis (PCA), are commonly used to address this issue, but they can also result in the loss of important information [244,245].

$$\hat{X} = W \cdot X \tag{23}$$

In the equation above, $\hat{X}$ represents the lower-dimensional representation of the original data X, and W is the transformation matrix used for dimensionality reduction. While this approach helps to simplify the model and reduce computational complexity, it also introduces the risk of discarding valuable information that could improve the model's performance.

7. Discussion and future research directions

This review highlights the transformative potential of deep learning models in algorithmic trading and sets the stage for future exploration in this dynamic field. As researchers and practitioners continue to refine these methodologies, ongoing collaboration between academia and industry will be essential to address practical challenges and drive innovation.

7.1. Interpretation of findings

This review has synthesized the use of DL models in algorithmic trading, revealing several important trends and gaps. First, DL models such as LSTM, CNN, and RL agents dominate the landscape of financial predictions due to their ability to handle non-linear patterns and high-dimensional data. LSTMs, in particular, have demonstrated strong capabilities in time-series forecasting, a crucial task in financial markets. Reinforcement Learning has also gained traction, particularly in autonomous trading strategies, where its ability to adapt and optimize in dynamic environments has shown promise [246].

However, this synthesis also highlights some significant gaps in the literature. One key issue is the over-reliance on historical data, which may not always capture future market dynamics due to the non-stationary nature of financial markets [247]. The lack of attention to market complexity, including the influence of geopolitical events, social sentiment, and macroeconomic indicators, suggests that current models are often too narrowly focused [248]. Furthermore, while many studies report impressive results in back-testing, real-world performance often falls short due to challenges such as data noise, overfitting, and model interpretability.

7.2. Theoretical and practical implications

Theoretically, the findings of this review contribute to a deeper understanding of the potential of DL models in financial markets. DL architectures like LSTMs and CNNs offer substantial theoretical advantages over traditional machine learning (ML) models by capturing complex dependencies and providing more accurate predictions [48]. However, the black-box nature of these models raises significant concerns regarding their interpretability, particularly in regulated financial environments where transparency is critical [249].

From a practical standpoint, the integration of DL in algorithmic trading offers traders and financial institutions powerful tools to enhance decision-making, optimize trading strategies, and reduce human error [31]. Traders and developers of trading algorithms can benefit from DL models' ability to automate complex trading strategies and continuously learn from new data. However, the practical adoption of these models is limited by challenges such as high computational costs, data quality issues, and the need for model explainability. Moreover, financial institutions must also navigate regulatory challenges when deploying such advanced models in real-world trading environments.

7.3. Limitations of the study

Several limitations in this review must be acknowledged. First, while an extensive search strategy was employed, the review may still suffer from publication bias, as studies with negative results are often underreported. Furthermore, this review mainly concentrated on studies published in English, which may have led to the exclusion of important research published in other languages. Another limitation is the varying quality of the selected studies; while most studies applied rigorous methodologies, some lacked transparency regarding their model training and evaluation processes. Finally, this review was constrained by the available literature between 2018–2024, which may omit other advancements in deep learning and algorithmic trading.

7.4. Emerging trends in DL for financial prediction

Recent advancements in deep learning are opening new avenues for improving financial predictions. One of the most promising developments is the rise of attention mechanisms and transformer architectures, which have shown remarkable success in NLP and are now being adapted for financial time-series forecasting [250]. Attention mechanisms allow models to focus on the most relevant parts of the input data, enabling them to better capture important market trends and events. Transformers, with their self-attention capabilities, offer significant advantages in modeling long-term dependencies without the need for sequential processing, as seen in recurrent architectures [63,251].

Another emerging trend is the use of hybrid models that combine multiple DL techniques. For example, hybrid models that integrate LSTMs with CNNs or Reinforcement Learning have demonstrated superior performance by leveraging the strengths of each architecture [178]. These models can capture both short-term and long-term market trends, providing more robust predictions and trading strategies.

Moreover, there is a growing interest in integrating external data sources such as social media sentiment, news articles, and macroeconomic indicators into DL models. This approach, often referred to as "alternative data", has the potential to improve prediction accuracy by providing a more holistic view of market dynamics [252]. These data sources can be processed using NLP techniques such as BERT (Bidirectional Encoder Representations from Transformers) [253] to gauge market sentiment and anticipate the impact of news on asset prices.

7.5. Addressing current challenges

Several challenges discussed in this review require attention in future research. One of the most pressing issues is the need for improved data preprocessing techniques to handle noise and missing data more effectively [254]. Advanced data imputation methods, such as generative models like Variational Autoencoders (VAEs), can help in reconstructing missing data without introducing bias. Additionally, techniques like data augmentation and denoising can be further explored to improve the robustness of DL models against noisy financial data [255,256].

Overfitting remains a persistent challenge in DL-based algorithmic trading, particularly when models are trained on limited or historical data [30]. Future research should explore the use of more advanced regularization techniques, such as adversarial training and ensemble methods, to improve model generalization. Moreover, developing adaptive learning methods, where models continuously update based on new market data, could help address the problem of non-stationarity in financial markets.

Model interpretability is another critical area for future research. While techniques like SHAP [228] values and LIME [229] have been proposed, there is still a need for more sophisticated tools that can explain the decisions of complex DL models in a manner that is accessible to traders, regulators, and other stakeholders. The development of interpretable DL architectures, such as explainable reinforcement learning models, could also help address regulatory concerns about black-box models.

Finally, addressing the computational demands of deep learning in financial markets will be essential for broader adoption. Research into model compression techniques, such as pruning and quantization, could reduce the computational cost of deploying DL models in real-time trading systems. Additionally, advances in distributed computing and cloud-based infrastructure could provide more accessible resources for training and deploying DL models at scale.

8. Conclusion

This review has highlighted the transformative potential of deep learning in algorithmic trading, where models such as LSTM, CNN, and Reinforcement Learning have shown substantial improvements in predicting financial markets and optimizing trading strategies. However, significant challenges remain, particularly related to data quality, overfitting, and the interpretability of complex DL models. Financial markets are noisy, volatile, and influenced by a multitude of factors, making it difficult for models to generalize well. Additionally, the black-box nature of DL models raises concerns for traders and regulators who require transparency in decision-making. Emerging trends such as attention mechanisms, transformer architectures, and hybrid models offer promising solutions to these challenges, alongside integrating alternative data sources like social media sentiment and news. Future research must focus on improving model robustness, developing explainable AI techniques, and addressing computational efficiency to unlock the full potential of DL in real-world trading environments. By overcoming these hurdles, DL can significantly enhance the accuracy and effectiveness of algorithmic trading, providing traders with more powerful tools for navigating complex financial markets.

CRediT authorship contribution statement

MD Shahriar Mahmud Bhuiyan: Writing – original draft, Methodology, Formal analysis, Conceptualization. **MD AL Rafi:** Writing – original draft, Methodology, Formal analysis, Conceptualization. **Gourab Nicholas Rodrigues:** Writing – original draft, Investigation, Formal analysis, Conceptualization. **MD Nazmul Hossain Mir:** Visualization, Validation, Resources, Methodology, Formal analysis, Conceptualization. **Adit Ishraq:** Writing – review & editing, Visualization, Validation, Methodology, Investigation. **M.F. Mridha:** Writing – review & editing, Supervision, Methodology. **Jungpil Shin:** Writing – review & editing, Visualization, Validation, Methodology.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: M. F. Mridha reports was provided by American International University Bangladesh. M. F. Mridha reports a relationship with American International University Bangladesh that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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