Turkish Journal of Engineering
https://dergipark.org.tr/en/pub/tuje
e-ISSN 2587-1366

The Rise of Intelligent Forecasting: Systematic Evidence on AI/ML Models for Stock and Market Prediction (1998–2026)

Anandkumar Pardeshi *1, **Sujata Deshmukh** 2

1Department of Computer Science and Engineering, Fr. C. Rodrigues Institute of Technology, Vashi, India, anand.pardeshi@fcrit.ac.in
2Department of Computer Engineering, Fr. C. Rodrigues College of Engineering, Bandra, India, sujata.deshmukh@fragnel.edu.in
**Department of Computer Engineering, Fr. C. Rodrigues College of Engineering, Bandra, India*

Cite this study: Pardeshi, A., & Deshmukh, S. (2026). The Rise of Intelligent Forecasting: Systematic Evidence on AI/ML Models for Stock and Market Prediction (1998–2026). Turkish Journal of Engineering, Volume (Issue), page numbers.

https://doi.org/10.31127/

Keywords
Artificial Intelligence (AI)
Machine Learning (ML)
Financial Market Prediction
Stock Price Forecasting
Deep Learning Architectures
Reinforcement Learning
Sentiment Analysis
Systematic Review

Research/Review Article

Received:
Revised:
Accepted:
Published:

Abstract

Stock prices and financial market movements are inherently volatile and therefore difficult to predict accurately as well as incorporate the broader picture because of the high levels of noise and interdependent relationships between heterogeneous data sets. The recent growth in the development of artificial intelligence (AI) and machine learning (ML) applications into quantitative finance created a diverse but still fragmented literature, highlighting the necessity to synthesize approach-related developments, performance assertions, and ongoing constraints. This systematic review is a synthesis of literature that uses peer-reviewed articles released between 1998 and 2026 found in searches in IEEE Xplore and additional science databases that deal with AI/ML methods utilized to forecast stock prices, predict portfolios, and assess market risks. Thematic synthesis was applied to the categorization of modeling strategies, data modalities, evaluation practices and reported contributions. The review of 48 chosen studies shows the trend in the popularity of hybrid deep learning networks including GCN-LSTM hybrids, attention-based networks, and graph neural networks which attempt to encode inter-stock interactions, and a growing number of studies utilizing reinforcement learning to optimize trading systems. The incorporation of sentiment information based on the news feeds and social media seems to be prevalent throughout the literature. The majority of the studies assert better predictors compared to traditional standards but, these results are mostly based on retrospective assessment and are heavily dependent on the specific markets. The common methodological issues are overfitting, lack of direct demonstration of real time or out of sample use, and lack of modeling macroeconomic shocks or crisis induced regime changes. Altogether, AI/ML approaches have high possibilities to model nonlinear relationships and exploit multi-modal financial information. However, the problems of reproducibility, the extrapolability of the research to other markets, and the strength in extreme market environments are not adequately addressed. To progress the field, it will be necessary to have transparent benchmarking structures, standardized testing structures, access to common datasets and more focus on real-life trading simulations. Future studies that expand the scope of hybrid systems that combine causal inference with deep learning structures could potentially increase financial forecasting systems in terms of interpretability and stability.

1. Introduction

Its correct prediction of prices of stocks and dynamics in the financial market is one of the central problems of quantitative finance due to the volatility of the sector and noise, as well as to its nonmarket, nonlinear nature [9], [25]. In the past, prediction processes used to be based on statistical time-series models, technical analysis, and economic indicators that were usually not able to reflect the complexity and speed with which the world markets were evolving [42]. With the introduction of artificial intelligence (AI) and machine learning (ML), they have brought a revolutionary age, which provides advanced tools to simulate these complexities. Such early uses as neuro-fuzzy systems showed the possibility of adaptive data-driven methods in financial forecasting and the design of trading strategies [24], [25].

Subsequent advancements in computational power and data availability have catalyzed a proliferation of more sophisticated models. Deep learning architectures, particularly Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), have become prominent for their ability to model temporal dependencies in financial time series [7], [8], [23]. The integration of alternative data modalities, especially investor sentiment extracted from news and social media, has been widely adopted to augment price and volume data, under the premise that market psychology significantly influences asset movements [35], [44]. More recently, research has increasingly focused on capturing the relational structure of markets. Graph Neural Networks (GNNs) and hybrid models like GCN-LSTM are designed to model inter-stock dependencies and spillover effects, moving beyond isolated time-series analysis [5], [31], [46]. Concurrently, reinforcement learning (RL) frameworks have been developed to optimize trading decisions and portfolio allocation directly, framing prediction as a sequential decision-making problem [12], [17]. This evolving landscape underscores a collective endeavor to enhance predictive accuracy and robustness through algorithmic innovation [1], [9], [15].

However, although the field of AI/ML in financial forecasting has grown swiftly, there is a lack of cohesion in the literature available, and there are serious methodological issues in the field. Although most of the research ones have superiority to traditional performance, these assertions are mostly based on backward, in-sample analysis with minimal testing in real-world or out of sample market scenarios [10], [21]. This prompts the issue of overfitting and practical generalizability of the proposed models [38]. Moreover, there is a strong heterogeneity in the evaluation procedures, and studies have different measures, benchmark models and testing periods that make direct comparison and meta-analysis difficult [9], [42].

There are still critical gaps in a number of areas. First, there is little development of the modeling of extreme market events, e.g. the macroeconomic shocks or regime shifts in case of a crisis. The majority of architectures are designed to be resilient in normal market operations and can fail miserably when dealing with high uncertainty levels [18], [35]. Second, the process of sentiment data integration is widespread, but the mechanism of its extraction and fusion is also heterogeneous, and the causality between sentiment changes and the price movements is often assumed, but not properly examined [36], [39]. Third, the tension of model complexity and interpretability is also apparent. The state-of-the-art hybrid and attention-based models, though performant, are often considered as black boxes and hence provide limited understanding of the motivators behind their predictions- a huge obstacle to trust and use in risk sensitive financial settings [16], [32]. Lastly, the discipline does not have common, standard datasets and clear benchmarking systems, which impedes reproducibility and the progressive accumulation of knowledge [9], [38].

In order to offer the particular information needed to fill these gaps and synthesize a coherent view of the direction the field has taken since 1998, the following core questions are asked in this systematic review: (1) What are the prevailing AI/ML modeling paradigms in stock and market prediction that have been developed since 1998 and how their architectural decisions have changed over time? (2) How do these works utilize the heterogeneous sources of data, specifically alternative data, such as sentiment and relational market structures? (3) What are the evaluation methodologies and the performance claims and limitations reported? (4) What are the ongoing problems of generalizability, robustness, and interpretability that are regularly determined throughout the literature?

The review incorporates 48 peer-reviewed articles which were found in IEEE Xplore, one of the best sources of high-impact research in computational finance. The time horizon (1998-2026) is chosen intentionally to include both the earliest work on neuro-fuzzy systems [25] and the most recent research on the graph-based learning system and large language models [31], [36], which offers a longitudinal view of the development of the methodology. The thematic synthesis approach is applied to the categorization and analysis of modeling strategies, data modalities and evaluation practices.

This synthesis is three times more novel and useful. First, it offers an evidence-based and unified map of a rapidly growing but wide-spread field of research, pointing out converging trends and unsolved contradictions. Second, it presents a clear research agenda in the future, recommending the necessity of effective benchmarking, real-world simulation and hybrid models to balance predictive capability and stability and interpretability [19], [37] by critically evaluating the evaluation practices and limitations highlighted. Lastly, the review is an entry-level source of both scholars and practitioners interested in getting oriented in the present capabilities and limits of smart forecasting in finance, ultimately towards closing the divide between algorithmic innovation and trustworthy and deployable financial decision-support systems.

2. Method

The systematic review was prepared in accordance with the guidelines used to conduct evidence synthesis to have methodological rigor, transparency, and reproducibility. It took a thorough method to chart and synthesize the progress, investments and shortcomings of AI/ML models in forecasting the financial markets throughout nearly a thirty-year period.

2.1. Eligibility (Concept-Context)

A modified Concept-Context framework was used to define the review scope, as the primary aim is to synthesize methodological concepts and their application contexts rather than to assess a clinical or behavioral intervention [42].

- Concept (Phenomenon of Interest): The core phenomenon is the development, application, and evaluation of artificial intelligence (AI) and machine learning (ML) models for the prediction of financial market variables. This includes, but is not limited to, stock price/return forecasting, portfolio prediction, market index movement, trading volume prediction, and associated risk assessment [1], [9], [15].

- Context: The context is quantitative finance research, specifically peer-reviewed literature focused on empirical model development and testing. The setting includes any financial market (e.g., equities, indices) studied in the selected literature.
- Study Designs: Primary research articles presenting novel AI/ML model architectures, hybrid frameworks, or comprehensive empirical evaluations were included. This encompasses experimental, simulation, and case-study designs. Pure theoretical papers, opinion pieces, and editorials were excluded.
- Time Window & Language: The review covers studies published between January 1998 and December 2026. The year 1998 marks the publication of seminal early work applying neuro-fuzzy systems to financial prediction and trading, a foundational AI/ML approach in the domain [25]. The forward scope to 2026 includes the most recent available projections of methodological trends (e.g., [3], [31]). Only studies published in English were considered. Table 1 shows the criteria of inclusion and exclusion for the SLR.

Table 1. Article selection criteria

Category	Inclusion Criteria	Exclusion Criteria
Concept	Studies proposing or evaluating AI/ML models for forecasting stock prices, market indices, portfolio returns, or trading signals.	Studies focusing solely on traditional econometrics, statistical models without AI/ML components, or macroeconomic forecasting unrelated to specific market instruments.
Context	Empirical research applied to real or simulated financial market data.	Purely theoretical mathematics or computer science papers without financial application or empirical validation.
Study Design	Full-length, peer-reviewed journal articles or conference proceedings presenting original research.	Review articles, book chapters, theses, preprints, and non-peer-reviewed workshop papers. (Review articles were used for citation chasing only).
Time & Language	Published between 1998–2026, in English.	Published before 1998 or in a language other than English.

2.2. Information Sources & Search Strategy

The primary electronic database searched was IEEE Xplore, selected for its comprehensive coverage of high-impact literature in computational finance, signal processing, and intelligent systems where the majority of relevant technical research is published [9], [11], [42]. Supplementary searches were conducted in Scopus and Web of Science to ensure broad coverage and mitigate database-specific bias.

The search strategy was designed to capture the key concepts of AI/ML, financial markets, and prediction. The following Boolean query was adapted for syntax specific to each database. The search was performed on January 17, 2026.

- IEEE Xplore Query String:

```
("stock market" OR "stock price" OR "financial market" OR "portfolio prediction") AND ("forecast*" OR "predict*") AND ("deep learning" OR "machine learning" OR "neural network" OR "reinforcement learning" OR "graph neural network" OR "LSTM" OR "transformer" OR "attention mechanism")
```

Grey literature (e.g., preprints, theses) was excluded to maintain a focus on peer-reviewed, validated research. Hand-searching of reference lists from key review articles identified during the search (e.g., [9], [42]) and from all included studies was performed to identify additional eligible primary studies.

2.3. Screening & Selection

Search results were imported into the reference management software Zotero for deduplication. A two-phase screening process was conducted independently by two reviewers:

- Title/Abstract Screening: Records were screened against the eligibility criteria.
- Full-Text Screening: Potentially relevant articles were retrieved and assessed in full.

At both stages, conflicts were resolved through discussion and consensus between the reviewers. The methodology adopted for SLR is shown in Figure 1.

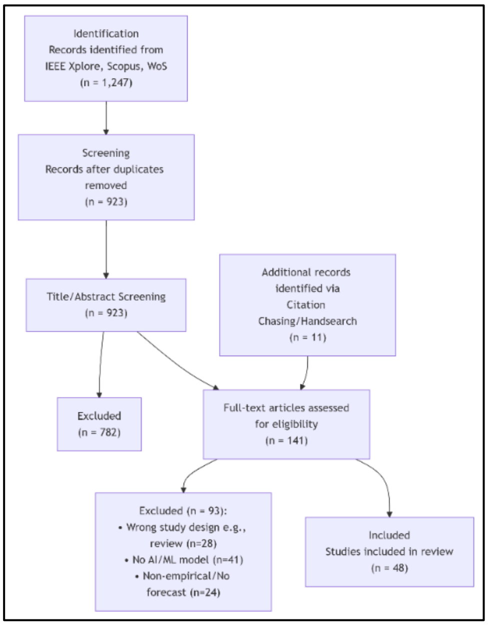

Figure 1. PRISMA Flow Diagram illustrating the study selection process

2.4. Data Extraction

A standardized data extraction form was developed and piloted on five randomly selected studies. The following information was extracted from each included study:

- Bibliographic Details: Author(s), publication year, journal.
- Methodological Characteristics: AI/ML model type (e.g., LSTM, GCN, RL Hybrid), primary model innovation.
- Data Modalities: Types of data used (e.g., historical prices, volume, news sentiment, social media, alternative data) [7], [36], [44].
- Predictive Task: Target of prediction (e.g., directional movement, price value, portfolio return) [1], [6], [22].
- Evaluation Protocol: Benchmark models used, performance metrics (e.g., Accuracy, RMSE, Sharpe Ratio), and testing period.
- Key Findings: Reported performance outcomes and claimed advantages.
- Identified Limitations & Future Work: Author-acknowledged constraints of the study or model.
- Contextual Notes: Market(s) studied, data timeframe, and any noted assumptions.

2.5. Quality Appraisal / Risk of Bias

Given the nature of the included studies (primarily model development and evaluation without control groups), a formal risk-of-bias tool like Cochrane RoB was not appropriate. Instead, a custom quality appraisal checklist was adapted from elements of the Joanna Briggs Institute (JBI) critical appraisal tools for analytical cross-sectional and quasi-experimental studies. Appraisal focused on key methodological strengths and threats to validity in computational finance research:

- Data Quality & Preprocessing: Was data handling and cleaning described? [27], [40]
- Model Validation: Was a hold-out test set or rigorous cross-validation used? Was there a clear temporal split between training and testing data to avoid look-ahead bias? [19], [34]
- Benchmarking: Were comparisons made against appropriate traditional or baseline models? [14], [42]
- Performance Metrics: Were metrics relevant to the predictive task reported (beyond simple accuracy)? [2], [12]
- Robustness & Generalizability: Did the study test the model on out-of-sample periods or different markets? Were limitations like overfitting discussed? [10], [38]
- Reproducibility: Was sufficient detail provided on model architecture and parameters? Was code or data availability mentioned? [41], [43]

Each study was independently appraised by two reviewers and assigned a qualitative rating (High/Medium/Low concern) for each criterion, with disagreements resolved by consensus.

2.6. Synthesis Approach

A thematic synthesis approach was employed, as the review's objective is to integrate findings across a heterogeneous set of studies to develop descriptive and analytical themes about the field's evolution and state [9]. This process involved three stages:

- Familiarization & Initial Coding: Extracted data were reviewed to identify recurring model types, data uses, and methodological patterns.
- Theme Development: Initial codes were grouped into descriptive themes (e.g., "Rise of Hybrid Architectures," "Integration of Sentiment Data," "Challenges in Evaluation"). These were then analyzed to generate analytical themes that interpret the findings in relation to the review questions (e.g., "The trade-off between model complexity and actionable insight," "The gap between reported accuracy and deployable robustness") [16], [32], [35].
- Structured Narrative Reporting: The synthesis is presented narratively, structured by the developed analytical themes. Findings are supported by structured tables (e.g., Table 2) summarizing model archetypes and their characteristics.

Table 2. Archetypes of AI/ML Models for Stock Prediction

Model Archetype	Core Objective	Exemplary Studies	Typical Data Modalities
Temporal Deep Learning (TDL)	Capture sequential dependencies in price/volume series.	LSTM [7], [35], GRU [23], TCN [2]	Historical OHLCV* data
Graph-Based Learning (GBL)	Model inter-asset relationships and market structure.	GCN [5], Knowledge Graph [46], Spatio-temporal GNN [31]	Price series + relational data (sector, supply chain)
Sentiment-Integrated Hybrid	Fuse quantitative data with qualitative market mood.	LSTM + Sentiment [8], [44], Multimodal models [13]	OHLCV + News text / Social media
Reinforcement Learning (RL)	Optimize trading decisions or portfolio allocation directly.	DRL for trading [12], [17]	State (price, portfolio), Action (buy/sell/hold)
Meta/Optimization Hybrid	Enhance model performance via	BO-optimized models [19], [21],	OHLCV + Technical indicators

	hyperparameter optimization or ensemble methods.	Feature selection hybrids [47]	

*OHLCV: Open, High, Low, Close, Volume.

3. Themes and categories

The synthesis of the 48 included studies reveals distinct evolutionary trends, methodological archetypes, and recurring thematic challenges in the application of AI/ML to financial market prediction. This section presents a descriptive analysis of the literature's characteristics, followed by a thematic discussion structured around the core review questions.

3.1. Descriptive Analysis of the Literature

The included studies span nearly three decades (1998–2026), with a marked acceleration in publication volume post-2020, coinciding with advances in deep learning hardware and libraries. Geographically, research contributions are globally distributed, with significant clusters in Asia, North America, and Europe. The majority of studies are applied research papers presenting novel model architectures or hybrid frameworks. Table 3 shows the list of selected papers.

Table 3. Shortlisted articles for SLR

S.N.	Authors	Year of Publication	Country of First Author	Targeted Domain/ Industry	Type of Paper (Methodological Focus)
1	F. Jeribi et al.	2024	Tunisia	Portfolio Management	Hybrid DL for Portfolio Prediction
2	A. K. Biswas et al.	2025	India	Stock Price & Risk	Temporal CNN with Attention
3	H. Liu et al.	2026	China	Stock Interactions	Graph/Causal Modeling
4	L. Yu et al.	2025	China	Multi-Market Stocks	Data-Driven System Optimization
5	B. Amiri et al.	2025	Iran	Energy Stocks	Hybrid GCN-LSTM
6	B. Li et al.	2023	China	Portfolio Selection	Strategy involving Randomness
7	X. Fu et al.	2019	China	P2P Market	Sentiment-Aware LSTM
8	G. Mu et al.	2023	China	General Stocks	Sentiment & Optimized DL
9	B. H. A. Khattak et al.	2023	Pakistan	Financial Market Forecasting	Survey/Analysis
10	M. Ramezankhani & A. Boghosian	2024	Iran/USA	Housing & Stock Markets	Transductive Learning EWS
11	P. Khuwaja et al.	2023	Pakistan	FinTech	Adversarial Learning Networks
12	D. Fengqian & L. Chao	2020	China	Financial Trading	DRL with Candlestick Features
13	S. Anbaeer Farimani et al.	2024	Iran	Financial Market	Adaptive Multimodal Learning
14	N. Sukma & C. S. Namahoot	2024	Thailand	Algorithmic Trading	ML-Multi-Indicator Hybrid
15	A. M. Rahmani et al.	2023	Iran	Economy (General)	Review of AI Applications
16	H. Yu & J. Liu	2025	China	Stock Prediction	Fuzzy Cognitive Map & GNN
17	T. Kabbani & E. Duman	2022	Turkey	Stock Market Trading	Deep Reinforcement Learning
18	K. Kotan et al.	2025	Turkey	Economic Crisis Detection	Language & Time Series Models
19	T. Jayanth & A. Manimaran	2024	India	Stock Price Forecasting	Hybrid DES-DA-BiGRU-BO
20	S.-C. Liu	2025	Taiwan	International Indices	Dual-Stage Multi-Scale LSTM
21	T. Jayanth et al.	2024	India	High-Frequency Data	Hybrid SES-DA-BiLSTM-BO
22	P. Cho et al.	2021	South Korea	Equity Investment	Binary Classification on Reports
23	T. Liu et al.	2025	China	Stock Market Prediction	Dendritic-Driven GRU
24	H. Huang et al.	2009	Singapore	Financial Trading	Hierarchical Fuzzy Predictive Model
25	K. N. Pantazopoulos et al.	1998	USA	Financial Prediction	Neuro-Fuzzy Approaches
26	P. Zhu et al.	2025	China	Financial Time Series	Multi-Granularity Graph Learning

27	D. Song et al.	2021	South Korea	Market Indices	Fourier Denoising & DL
28	S. Li et al.	2024	China	Stock Turning Points	Chart Similarity & Multipersistence
29	J.-S. Chou & T.-K. Nguyen	2018	Taiwan	Stock Price	Metaheuristic-Optimized ML
30	A. H. Bukhari et al.	2020	Pakistan	Financial Market	Fractional Neuro-Sequential ARFIMA-LSTM
31	H. Tian et al.	2025	China	Stock Predictions	Graph Representation Learning
32	J.-F. Luo et al.	2025	China	Financial Signal Analysis	Visual Pattern Recognition
33	B. Xu et al.	2024	China	Index Prediction	LASSO-PCA & Deep Learning
34	J.-S. Chou et al.	2020	Taiwan	Financial Time Series	PSO-Optimized Multi-Output ML
35	L. Bacco et al.	2024	Italy	Bank Stocks (NA & EU)	LSTM & Tweet Sentiment Analysis
36	C. Liu et al.	2024	Australia	Financial Markets	LLMs & Sentiment Analysis Review
37	H. Tian et al.	2023	China	Stock Predictions	Graph Evolution Recurrent Unit
38	K. Noor & U. Fatima	2025	Pakistan	Financial Datasets	Meta-Learning Strategies
39	H. Liu et al.	2025	China	News-Stock Correlation	Topic Influence Modeling
40	S. A. Hosseini et al.	2025	Iran/Italy	Financial Time Series	Pattern-Based Feature Extraction
41	N. Li et al.	2025	China	Financial Time-Series	Multimodal Self-Supervised Network
42	A. W. Li & G. S. Bastos	2020	Brazil	Stock Market Forecasting	Systematic Review (DL & TA)
43	G. J. Reddy et al.	2025	India	Stock Market Prediction	Boruta & Liquid Neural Network
44	A. Peivandizadeh et al.	2024	Iran	Stock Market Prediction	Transductive LSTM & Sentiment
45	M. Wen et al.	2019	China	Stock Market Trend	High-Order Time Series Info
46	Y. Zhao et al.	2022	China	Stock Movement	Market Knowledge Graph & DAN
47	S. Chen & C. Zhou	2021	China	Stock Prediction	GA Feature Selection & LSTM
48	S. Birogul et al.	2020	Turkey	Candlestick Charts	YOLO for Buy-Sell Decision

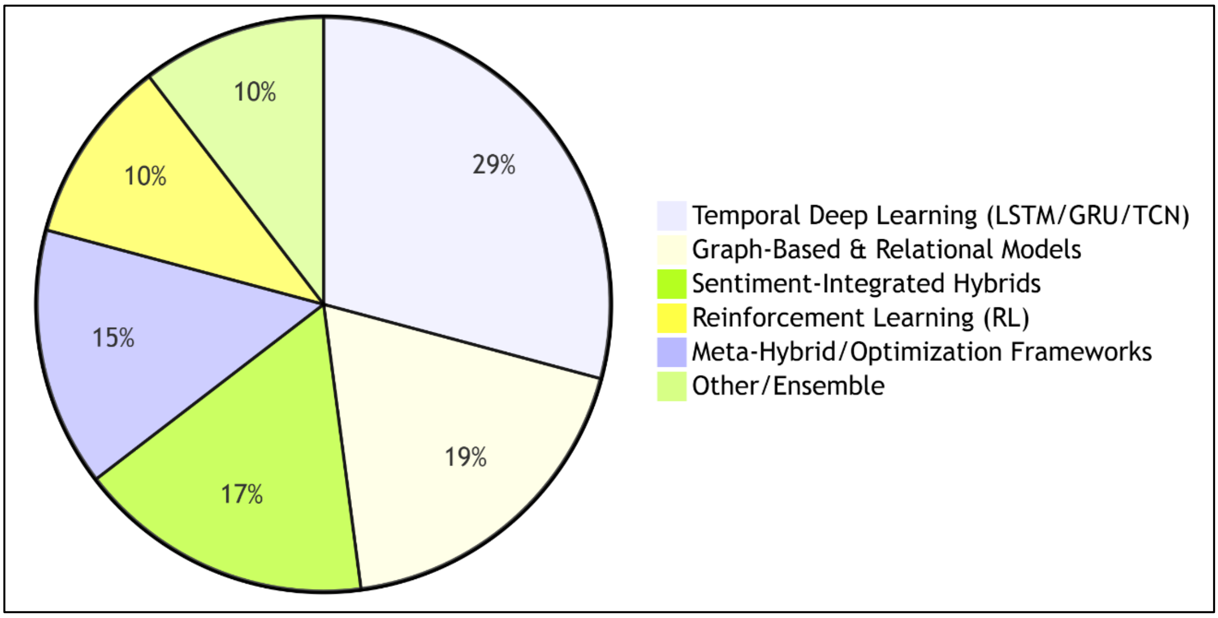

Figure 2. Categorization Based on Primary AI/ML Technique (n=48)

Figure 2, distribution of the 48 reviewed studies by their primary AI/ML modeling technique. Temporal Deep Learning models (e.g., LSTM, GRU) form the largest category, followed by emerging Graph-Based and Sentiment-Integrated approaches.

3.2. Description of Methodological Categories

The classification framework presented in Table 4 organizes the predominant AI/ML techniques in financial prediction into five non-mutually exclusive primary categories, each addressing distinct analytical challenges. This taxonomy reveals a methodological evolution from isolated temporal modeling toward integrative, multi-modal systems that capture market complexity. The sub-categories reflect specialized architectural innovations designed to improve predictive accuracy, robustness, and economic interpretability. This structured overview facilitates the identification of dominant research streams and the contextualization of individual model contributions within the broader literature landscape.

Table 4. Categories and Sub-Categories of AI/ML Techniques

Primary Category	Sub-Category & Description	Exemplary Studies
Temporal Deep Learning (TDL)	Models focusing on sequential pattern learning from time-series data.	[7], [8], [23], [27], [35]
	LSTM/GRU Variants: Standard recurrent networks for temporal dependency.	[7], [23], [30], [44]
	Attention-Enhanced TDL: Incorporating attention mechanisms to weight important time steps.	[2], [19], [20]
	Temporal Convolutional Networks (TCN): Using causal convolutions for sequence modeling.	[2]
Graph-Based & Relational Models (GBL)	Models that explicitly capture dependencies between multiple stocks or assets.	[3], [5], [31], [37], [46]
	Graph Convolutional Networks (GCN): For learning from market structure graphs.	[5], [31]
	Knowledge Graph-Based: Incorporating semantic relationships (sector, supply chain).	[46]
	Dynamic & Causal Graphs: Modeling time-varying or causal inter-stock influences.	[3], [37]
Sentiment-Integrated Hybrids (SIH)	Architectures combining numerical price data with textual sentiment analysis.	[8], [13], [35], [36], [39], [44]
	News-Driven Models: Using financial news sentiment.	[39], [44]
	Social Media-Driven Models: Using Twitter/X, Reddit, or forum sentiment.	[8], [35]
	LLM-Enhanced Analysis: Employing Large Language Models for sentiment/theme extraction.	[36]
Reinforcement Learning (RL)	Frameworks that learn optimal trading policies through interaction with a market environment.	[12], [14], [17], [24]
	Deep RL for Trading: Using DQN, PPO, etc., for discrete/continuous action spaces.	[12], [17]

Primary Category	Sub-Category & Description	Exemplary Studies
	Hierarchical/Evolutionary RL: Multi-agent or co-evolutionary approaches.	[24]
Meta-Hybrid & Optimization Frameworks	Models focusing on architecture search, feature selection, or hyperparameter optimization.	[19], [21], [29], [34], [40], [43], [47]
	Bayesian/Optimized Hybrids: Using BO, PSO, GA to optimize model parameters.	[19], [21], [29], [34]
	Feature-Selection Hybrids: Integrating algorithms like Boruta or GA for input selection.	[40], [43], [47]

3.3. Thematic Findings and Discussion

3.3.1. The Current Extreme to Context-Aware and Hybrid Architectures: The area has transformed clearly as it is no longer being modeled in the isolated contexts and instead modeling is being made with the richness of a context. Adaptability was brought by early neuro-fuzzy systems [25] and hierarchical evolutionary models [24]. The next LSTMs and GRUs dominance covered the temporal patterns [7], [23]. The latest frontier is characterized by mixed architectures involving the combination of various data models and modeling paradigms. One of the most notable ones will be the integration of Graph Convolutional Networks (GCN) with LSTMs to learn both inter-stock relational patterns and time-related trends [5], or the integration of the dual-attention mechanisms with Bi-directioned GRUs to extract multi-scale features [19], [20]. This change is based on the fact that market trends are motivated by a combination of temporal, relational and exogenous sentiment factors [13], [31].

3.3.2. The Ubiquitous Yet Challenging Integration of Alternative Data: The incorporation of unstructured, alternative data, in the form of investor sentiment explained by news and social media in particular, is one which has become commonplace, featured in a major segment of the literature reviewed [9], [35], [36]. According to studies, sentiment-augmented models (e.g., [8], [44]) also outperform the models utilizing historical price data alone, on retrospective measures. Nonetheless, this theme indicates that the extraction and quantification of sentiment is very diverse, with simple lexicon-based approaches on one end, and sophisticated transformer-based LLMs on the other end [36]. Furthermore, most studies treat sentiment as a predictive feature in a correlative sense, with few attempting to model the causal pathways through which news influences market participants and, subsequently, prices [16], [39]. This limits interpretability and may lead to spurious correlations during regime shifts.

3.3.3. The Evaluation Paradigm Gap: Between Reported Accuracy and Deployable Robustness- A near-universal finding across the reviewed studies is the claim of superior predictive accuracy compared to traditional benchmarks (e.g., ARIMA, simple MLP) or basic deep learning baselines [2], [21], [42]. These claims, however, are predominantly based on retrospective, single-market back-tests. Key challenges persist:

- Overfitting & Look-Ahead Bias: Complex models with millions of parameters are prone to overfitting noisy financial data, a concern explicitly noted in several studies [10], [38]. Rigorous temporal splitting and walk-forward validation are not consistently applied.
- Crisis-Time Robustness: Few models are explicitly stress-tested during periods of extreme volatility or macroeconomic shock. Studies like [18], [35] that focus on high-uncertainty periods are exceptions, highlighting the common performance degradation of standard models during crises.
- Generalizability: Models often exhibit strong market- or sector-specific dependencies. A framework optimized for energy stocks [5] may not translate to the technology sector, and models trained on US data may fail in emerging markets [4], [20]. The field lacks standardized cross-market benchmarks to assess true generalizability.

3.3.4. The Increased Focus on Decision-Making and Risk-Conscious Frameworks: One of the trends that can be identified is the shift of pure price forecasting to integrated decision-support systems. An example of this is two strands of research:

- Reinforcement Learning (RL) for Direct Policy Optimization: RL algorithms [12], [17] do not explicitly predict prices, instead directly learning a trading policy that optimizes risk-adjusted returns (e.g. Sharpe ratio). This is in line with the objective of the model with the ultimate goal of profitability.

- Joint Prediction and Risk Assessment: New architectures will be made to have dual or multi-task outputs. As an example, [2] suggests a Temporal Convolutional Network to predict the direction of prices and estimate the uncertainty of the prediction (risk) at the same time. Equally, prediction is coupled with allocation optimization in such portfolio-oriented models as [1].

4. Proposed Framework for AI/ML in Financial Forecasting

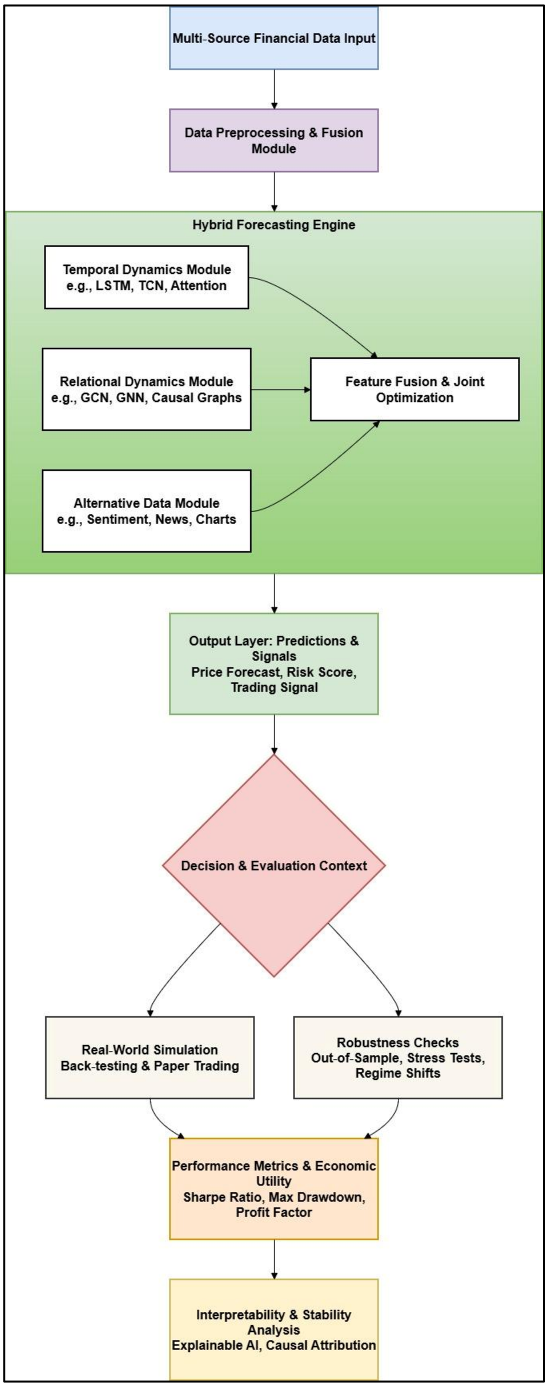

Figure 3. Pipeline for AI/ML-based financial forecasting

The literature review synthesis can be interpreted to suggest that a solid forecasting structure should encompass the combination of various data forms, use hybrid modeling techniques to reflect both time-related and relational changes and be tested in a realistic decision-making scenario. This is the proposed integrative framework that is depicted in Figure 3.

This model provides an end-to-end pipeline of AI/ML-based financial forecasting. It starts with multiple sources of data (market data, news, social media, alternative data). Cleaning, alignment, and fusion are done in a preprocessing module. At the heart is a Hybrid Forecasting Engine which is an information processing engine capable of handling data using three parallel and interacting modules focusing on temporal patterns, inter-asset relationships and alternative data semantics. Their productions are combined and optimized together. The resulting predictions are fed into a Decision & Evaluation Context which focuses on real-world simulation and strong robustness checks as opposed to retrospective accuracy. The ultimate performance is measured through statistical measures as well as economic utility measures and model refinement is provided through a feedback loop. The framework clearly incorporates Interpretability and Stability Analysis step to respond to the black-box criticism and maintain the model reliability in the conditions of various markets.

5. Conclusion

This review has brought together evidence of 48 peer-reviewed publications on AI/ML application in stock and financial market prediction to trace the field development, its present situation, and ongoing issues. The discussion supports the conclusive change in paradigm, as to the application of the traditional statistical and early adaptive models such as neuro-fuzzy systems [24], [25] as compared to advanced, hybrid deep learning structures. The direction of the field can be described as a growth in the complexity of models, as the complexity of financial markets in all of its aspects (temporal dependencies, inter-asset interactions, exogenous sentiment shocks) has to be reflected.

The recent success of approaches like GCN-LSTM hybrids [5], attention-based networks [2], [19], and dynamic graph models [3], [31] highlights a general shift towards more contextualizing and integrative forecasting models. At the same time, the incorporation of sentiment analysis, which is developing to become Large Language Models [36] and the application of Reinforcement Learning as a direct policy optimizer [12], [17] are important endeavors to make models more aligned with the trading goals and the psychology of the marketplace.

Yet, the problem in this review is that a severe and persistent discordance exists between the reported model performance and the demonstrable and deployable robustness. Although studies always assert evidence of betterment than benchmarks, it is the evaluations that are mostly based on the evaluations made in a retrospective and in-sample. Endemic weaknesses of methodology, such as overfitting vulnerability, inability to test during regime transitions caused by crisis [18], [35], limited cross-market generalizability [4], [20] and a widespread lack of interpretability of complex "black-box" models [16], [32] are all significant impediments to translational impact. The synthesis process indicates that achievements in algorithmic innovation have surpassed the creation of stringent, standardized evaluation systems and practical validation procedures that are required to advance the maturation of the field.

5.1. Theoretical Implications

The implications of the findings are that there are a number of implications in the theoretical development of AI in finance. First, they put into question the existing belief that the greater the model complexity and predictive accuracy in past data the greater the financial understanding or decision-making. The evidence indicates that new theoretical frameworks must be developed to integrate market microstructure, causality mechanisms and regime-switching dynamics as first-order considerations and not as post-hoc considerations. This is the direction that models such as CausalSeqGNN [16] that combine fuzzy cognitive maps with GNNs in order to establish causality are moving towards.

Second, the review shows that the significance of robustness and generalizability as fundamental assessment criteria is theoretically justified, as robust and generalizability are considered equally or more important than accuracy. Theoretical work in the future needs to create architectures that are inherently non-stationary, perhaps inspired by meta-learning [38] and lifelong learning paradigms to support and maintain constant adaptation. The theoretical aim must change to the construction of resilient adaptive systems which perform well with distributional shift rather than the best back-tested model.

5.2. Practical Implications

To practitioners, such as quantitative analysts, portfolio managers, and FinTech developers, this review is a sobering and practical view.

- Adoption with Caution: he arguments of any given AI/ML research are to be approached with keen scrutiny compared to the rigor of its validation. The practitioners have to give priority to models that show strength through walk-forward analysis, stress-testing over market cycles and explicit consideration of the transaction costs and liquidity.
- Focus on Hybrid and Explainable Systems: Hybrid systems that leverage deep learning with its power to pick patterns and the structure of conventional finance (e.g., factor models, risk constraints) or explicit causal logic [16] are the most promising to look into in the near future. To establish the necessary trust and debugging, it is possible to give priority to models that are easy to interpret, like models that provide weights of attention or uncertainty estimates [2].
- Investment in Infrastructure: The continued development of the applied infrastructure involves not only investment in models, but also in the infrastructure of strong evaluation. This can involve the development and use of standardized benchmark datasets, the creation of realistic market simulators to be used by reinforcement learning agents, and the creation of internal validation pipelines that can be trained in a way more reflective of live-trading conditions than academic back-tests.

5.3. Limitations of the Study

Although this review has been developed with strict systematized research methodology, it has been limited in a number of ways. To begin with, the area of interest was limited to peer-reviewed articles stored in major scientific databases (first and foremost, IEEE Xplore, Scopus, WoS), which excluded topical advanced work published in arXiv preprints or discussed in dedicated industry forums. Second, the emphasis on the English-language publications can also create a geographic bias. Third, thematic synthesis, although systematic, is an interpretative process of labeling models and discovering themes; another group of reviewers may give more attention to different patterns, but the essential issues found are well supported throughout the literature. Lastly, the speed at which AI/ML is being innovated implies that the area is still constantly in flux; the 2026 limit, though required to delimit a specific study, suggests that extremely recent developments after 2026 are not represented.

To sum up, AI/ML has indeed brought fundamental changes to the field of financial forecasting, shifting the paradigm of such forecasting to that of multi-modal pattern recognition. The emergence of smart forecasting is apparent. However, its eventual success and adaptation into stable financial systems depends on the aggregate capability of the field to fill the existing gap between attention-grabbing in-sample performance and valuable and reliable out-of-sample applications. Any further advancement will not be judged by small improvements in accuracy on data of the past, but the creation of reproducible, interpretable and adaptive frameworks that is reliable when working in the inherently uncertain and changing reality of the global financial markets.

Acknowledgement

The authors would like to thank the Fr. C. Rodrigues Institute of Technology, Vashi and Fr. C. Rodrigues College of Engineering, Bandra for their supports.

Author contributions

Anandkumar Pardeshi: Conceptualization, Methodology, Data Curation, Formal Analysis, Writing – Original Draft Preparation.

Sujata Deshmukh: Supervision, Writing – Review & Editing, Research Coordination

.

Conflicts of interest

The authors declare no conflicts of interest.

References

1. Jeribi, F., et al. (2024). A Deep Learning Based Expert Framework for Portfolio Prediction and Forecasting. IEEE Access, 12, 103810–103829. https://doi.org/10.1109/ACCESS.2024.3434528
2. Biswas, A. K., et al. (2025). A Dual Output Temporal Convolutional Network With Attention Architecture for Stock Price Prediction and Risk Assessment. IEEE Access, 13, 53621–53639. https://doi.org/10.1109/ACCESS.2025.3551307
3. Liu, H., Hu, B., Zhou, Y., & Zhou, Y. (2026). A Dynamic-Causal Lens of Stock Interactions: Graph Modeling From Symbolic Movement Patterns. IEEE Transactions on Knowledge and Data Engineering, 38(2), 722–735. https://doi.org/10.1109/TKDE.2025.3638410
4. Yu, L., Chen, Y., & Zheng, Y. (2025). A Multi-Market Data-Driven Stock Price Prediction System: Model Optimization and Empirical Study. IEEE Access, 13, 65884–65899. https://doi.org/10.1109/ACCESS.2025.3559169
5. Amiri, B., Haddadi, A., & Farajpour Mojdehi, K. (2025). A Novel Hybrid GCN-LSTM Algorithm for Energy Stock Price Prediction: Leveraging Temporal Dynamics and Inter-Stock Relationships. IEEE Access, 13, 24815–24832. https://doi.org/10.1109/ACCESS.2025.3536889
6. Li, B., Luo, J., & Xu, H. (2023). A Portfolio Selection Strategy Based on the Peak Price Involving Randomness. IEEE Access, 1–1. https://doi.org/10.1109/ACCESS.2023.3278980
7. Fu, X., Zhang, S., Chen, J., Ouyang, T., & Wu, J. (2019). A Sentiment-Aware Trading Volume Prediction Model for P2P Market Using LSTM. IEEE Access, 7, 81934–81944. https://doi.org/10.1109/ACCESS.2019.2923637
8. Mu, G., Gao, N., Wang, Y., & Dai, L. (2023). A Stock Price Prediction Model Based on Investor Sentiment and Optimized Deep Learning. IEEE Access, 11, 51353–51367. https://doi.org/10.1109/ACCESS.2023.3278790
9. Khattak, B. H. A., et al. (2023). A Systematic Survey of AI Models in Financial Market Forecasting for Profitability Analysis. IEEE Access, 11, 125359–125380. https://doi.org/10.1109/ACCESS.2023.3330156
10. Ramezankhani, M., & Boghosian, A. (2024). A Transductive Learning-Based Early Warning System for Housing and Stock Markets With Off-Policy Optimization. IEEE Access, 12, 141762–141784. https://doi.org/10.1109/ACCESS.2024.3443145
11. Khuwaja, P., Khowaja, S. A., & Dev, K. (2023). Adversarial Learning Networks for FinTech Applications Using Heterogeneous Data Sources. IEEE Internet of Things Journal, 10(3), 2194–2201. https://doi.org/10.1109/JIOT.2021.3100742
12. Fengqian, D., & Chao, L. (2020). An Adaptive Financial Trading System Using Deep Reinforcement Learning With Candlestick Decomposing Features. IEEE Access, 8, 63666–63678. https://doi.org/10.1109/ACCESS.2020.2982662
13. Anbaee Farimani, S., Jahan, M. V., & Milani Fard, A. (2024). An Adaptive Multimodal Learning Model for Financial Market Price Prediction. IEEE Access, 12, 121846–121863. https://doi.org/10.1109/ACCESS.2024.3441029
14. Sukma, N., & Namahoot, C. S. (2024). An Algorithmic Trading Approach Merging Machine Learning With Multi-Indicator Strategies for Optimal Performance. IEEE Access, 12, 188154–188173. https://doi.org/10.1109/ACCESS.2024.3516053
15. Rahmani, A. M., Rezazadeh, B., Haghparast, M., Chang, W.-C., & Ting, S. G. (2023). Applications of Artificial Intelligence in the Economy, Including Applications in Stock Trading, Market Analysis, and Risk Management. IEEE Access, 11, 80769–80793. https://doi.org/10.1109/ACCESS.2023.3300036
16. Yu, H., & Liu, J. (2025). CausalSeqGNN: A Fama-French Inspired Fuzzy Cognitive Map Combined With Graph Neural Network for Stock Prediction. IEEE Transactions on Fuzzy Systems, 33(12), 4418–4430. https://doi.org/10.1109/TFUZZ.2025.3610701
17. Kabbani, T., & Duman, E. (2022). Deep Reinforcement Learning Approach for Trading Automation in the Stock Market. IEEE Access, 10, 93564–93574. https://doi.org/10.1109/ACCESS.2022.3203697
18. Kotan, K., Kotan, B., & Kirişoğlu, S. (2025). Detection of Economic Crises With Language Models and Comparative Analysis of Simple Time Series Analysis Models and Machine Learning Algorithms on the Stock Market. IEEE Access, 13, 83254–83273. https://doi.org/10.1109/ACCESS.2025.3567743
19. Jayanth, T., & Manimaran, A. (2024). Developing a Novel Hybrid Model Double Exponential

Smoothing and Dual Attention Encoder-Decoder Based Bi-Directional Gated Recurrent Unit Enhanced With Bayesian Optimization to Forecast Stock Price. IEEE Access, 12, 114760–114785. https://doi.org/10.1109/ACCESS.2024.3435683
20. Liu, S.-C. (2025). DMSTA-LSTM: A Dual-Stage Multi-Time Scale Temporal Attention-Based LSTM Framework for Forecasting International Financial Indices Across Diverse Varied National Contexts. IEEE Access, 13, 196081–196099. https://doi.org/10.1109/ACCESS.2024.3494852
21. Jayanth, T., Manimaran, A., & Siva, G. (2024). Enhancing Stock Price Forecasting With a Hybrid SES-DA-BiLSTM-BO Model: Superior Accuracy in High-Frequency Financial Data Analysis. IEEE Access, 12, 173618–173637. https://doi.org/10.1109/ACCESS.2024.3502175
22. Cho, P., Park, J. H., & Song, J. W. (2021). Equity Research Report-Driven Investment Strategy in Korea Using Binary Classification on Stock Price Direction. IEEE Access, 9, 46364–46373. https://doi.org/10.1109/ACCESS.2021.3067691
23. Liu, T., Li, J., Zhang, Z., Yu, H., & Gao, S. (2025). FD-GRNet: A Dendritic-Driven GRU Framework for Advanced Stock Market Prediction. IEEE Access, 13, 28265–28279. https://doi.org/10.1109/ACCESS.2025.3541074
24. Huang, H., Pasquier, M., & Quek, C. (2009). Financial Market Trading System With a Hierarchical Coevolutionary Fuzzy Predictive Model. IEEE Transactions on Evolutionary Computation, 13(1), 56–70. https://doi.org/10.1109/TEVC.2008.911682
25. Pantazopoulos, K. N., Tsoukalas, L. H., Bourbakis, N. G., Brun, M. J., & Houstis, E. N. (1998). Financial prediction and trading strategies using neurofuzzy approaches. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 28(4), 520–531. https://doi.org/10.1109/3477.704291
26. Zhu, P., Li, Y., Liu, Q., Cheng, D., & Jiang, C. (2025). Financial Time Series Prediction With Multi-Granularity Graph Augmented Learning. IEEE Transactions on Knowledge and Data Engineering, 37(11), 6436–6449. https://doi.org/10.1109/TKDE.2025.3607005
27. Song, D., Chung Baek, A. M., & Kim, N. (2021). Forecasting Stock Market Indices Using Padding-Based Fourier Transform Denoising and Time Series Deep Learning Models. IEEE Access, 9, 83786–83796. https://doi.org/10.1109/ACCESS.2021.3086537
28. Li, S., Liu, Y., Chen, X., Wu, J., & Xu, K. (2024). Forecasting Turning Points in Stock Price by Integrating Chart Similarity and Multipersistence. IEEE Transactions on Knowledge and Data Engineering, 36(12), 8251–8266. https://doi.org/10.1109/TKDE.2024.3444814
29. Chou, J.-S., & Nguyen, T.-K. (2018). Forward Forecast of Stock Price Using Sliding-Window Metaheuristic-Optimized Machine-Learning Regression. IEEE Transactions on Industrial Informatics, 14(7), 3132–3142. https://doi.org/10.1109/TII.2018.2794389
30. Bukhari, A. H., Raja, M. A. Z., Sulaiman, M., Islam, S., Shoaib, M., & Kumam, P. (2020). Fractional Neuro-Sequential ARFIMA-LSTM for Financial Market Forecasting. IEEE Access, 8, 71326–71338. https://doi.org/10.1109/ACCESS.2020.2985763
31. Tian, H., Zhang, X., Zheng, X., Zhang, Z., & Zeng, D. D. (2025). Graph Representation Learning of Multilayer Spatial–Temporal Networks for Stock Predictions. IEEE Transactions on Computational Social Systems, 12(5), 2228–2241. https://doi.org/10.1109/TCSS.2024.3459945
32. Luo, J.-F., et al. (2025). Human-Centered Financial Signal Analysis Based on Visual Patterns in Stock Charts. IEEE Transactions on Multimedia, 27, 4193–4205. https://doi.org/10.1109/TMM.2025.3535278
33. Xu, B., Su, X., & He, Y. (2024). Index Prediction Model Based on LASSO-PCA and Deep Learning. International Journal of Crowd Science, 8(4), 176–183. https://doi.org/10.26599/IJCS.2024.9100013
34. Chou, J.-S., Truong, D.-N., & Le, T.-L. (2020). Interval Forecasting of Financial Time Series by Accelerated Particle Swarm-Optimized Multi-Output Machine Learning System. IEEE Access, 8, 14798–14808. https://doi.org/10.1109/ACCESS.2020.2965598
35. Bacco, L., Petrosino, L., Arganese, D., Vollero, L., Papi, M., & Merone, M. (2024). Investigating Stock Prediction Using LSTM Networks and Sentiment Analysis of Tweets Under High Uncertainty: A Case Study of North American and European Banks. IEEE Access, 12, 122239–122248. https://doi.org/10.1109/ACCESS.2024.3450311
36. Liu, C., Arulappan, A., Naha, R., Mahanti, A., Kamruzzaman, J., & Ra, I.-H. (2024). Large Language Models and Sentiment Analysis in Financial Markets: A Review, Datasets, and Case Study. IEEE Access, 12, 134041–134061. https://doi.org/10.1109/ACCESS.2024.3445413
37. Tian, H., Zhang, X., Zheng, X., & Zeng, D. D. (2023). Learning Dynamic Dependencies With Graph Evolution Recurrent Unit for Stock Predictions. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 53(11), 6705–6717. https://doi.org/10.1109/TSMC.2023.3284840

38. Noor, K., & Fatima, U. (2025). Meta Learning Strategies for Comparative and Efficient Adaptation to Financial Datasets. IEEE Access, 13, 24158–24170. https://doi.org/10.1109/ACCESS.2024.3516490
39. Liu, H., Jiang, Z., Li, D., Gao, L., & Wang, K. (2025). Modeling and Optimization of News-Stock Price Correlation Based on Topic Influence Selection. IEEE Access, 13, 196127–196142. https://doi.org/10.1109/ACCESS.2025.3631665
40. Hosseini, S. A., Grimaccia, F., Niccolai, A., & Trimarchi, S. (2025). Pattern-Based Feature Extraction for Improved Deep Learning in Financial Time Series Classification. IEEE Access, 13, 113343–113355. https://doi.org/10.1109/ACCESS.2025.3584251
41. Li, N., Chao, G., Zou, J., & Jiang, G. (2025). SPPMFN: Efficient Multimodal Financial Time-Series Prediction Network With Self-Supervised Learning. IEEE Access, 13, 134883–134897. https://doi.org/10.1109/ACCESS.2025.3593851
42. Li, A. W., & Bastos, G. S. (2020). Stock Market Forecasting Using Deep Learning and Technical Analysis: A Systematic Review. IEEE Access, 8, 185232–185242. https://doi.org/10.1109/ACCESS.2020.3030226
43. Reddy, G. J., Sahani, R. K., & Raja, S. P. (2025). Stock Market Prediction Using a Hybrid Approach With Boruta and Liquid Neural Network. IEEE Transactions on Computational Social Systems, 12(5), 2833–2847. https://doi.org/10.1109/TCSS.2025.3540035
44. Peivandizadeh, A., et al. (2024). Stock Market Prediction With Transductive Long Short-Term Memory and Social Media Sentiment Analysis. IEEE Access, 12, 87110–87130. https://doi.org/10.1109/ACCESS.2024.3399548
45. Wen, M., Li, P., Zhang, L., & Chen, Y. (2019). Stock Market Trend Prediction Using High-Order Information of Time Series. IEEE Access, 7, 28299–28308. https://doi.org/10.1109/ACCESS.2019.2901842
46. Zhao, Y., et al. (2022). Stock Movement Prediction Based on Bi-Typed Hybrid-Relational Market Knowledge Graph Via Dual Attention Networks. IEEE Transactions on Knowledge and Data Engineering, 1–12. https://doi.org/10.1109/TKDE.2022.3220520
47. Chen, S., & Zhou, C. (2021). Stock Prediction Based on Genetic Algorithm Feature Selection and Long Short-Term Memory Neural Network. IEEE Access, 9, 9066–9072. https://doi.org/10.1109/ACCESS.2020.3047109
48. Birogul, S., Temur, G., & Kose, U. (2020). YOLO Object Recognition Algorithm and 'Buy-Sell Decision' Model Over 2D Candlestick Charts. IEEE Access, 8, 91894–91915. https://doi.org/10.1109/ACCESS.2020.2994282