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A Systematic Review of Artificial Intelligence-Based Stock Market Prediction and the Convergence Toward Multimodal Explainable Frameworks

Amit Kumar Verma[1], Himanshu Vasnani[2]
[1] *Research Scholar, Faculty of Science, Suresh Gyan Vihar University, Jaipur, India*
[2] *Assistant Professor, Suresh Gyan Vihar University, Jaipur, India*

Abstract- Advances in artificial intelligence and the use of varied financial data have improved stock market prediction. This systematic literature review examines 50 Scopus-indexed studies published between 2018 and 2025 to trace changes in prediction methods, data sources, and hybrid AI models. The review highlights five main trends. First, using several data sources — such as historical prices, company fundamentals, and news — increases prediction accuracy by 5 to 10 percent compared to using a single source. Second, different data types pair best with different AI models: LSTMs for price data, tree-based models for structured financial data, and transformer-based models for text. Third, combining models in hybrid or ensemble approaches yields further gains, adding another 1 to 2 percentage points over the best single model. Fourth, explainable AI tools such as SHAP make models more transparent, but are mostly applied to single models. Finally, newer technologies — large language models, graph neural networks, reinforcement learning, and privacy-preserving learning — have been explored in isolation, not together. The review identifies a key gap: while the components needed for an explainable, multi-source, hybrid prediction system exist, they have not yet been integrated. To help close this gap, the paper proposes an evidence-based four-step framework for building more accurate, transparent, and reliable stock market prediction systems.

Index Terms—Explainable AI (XAI); stock market prediction; hybrid machine learning; multimodal data fusion; SHAP; systematic literature review; Scopus..

1. INTRODUCTION

The stock market reflects how well a country's economy is doing — company profits, investor confidence, and the wider economic mood. Large index moves, such as those in the S&P 500 or the NSE Nifty, matter beyond personal savings; they affect foreign investment, business growth, and the broader economy. Reliable prediction tools matter to investors, banks, and policymakers alike. Stock prices are hard to forecast: price patterns, company earnings, interest rates, and public sentiment all interact in complex ways. Older methods, such as fundamental and technical analysis, assume slow, steady markets — an assumption that rarely holds in today's fast, connected markets.

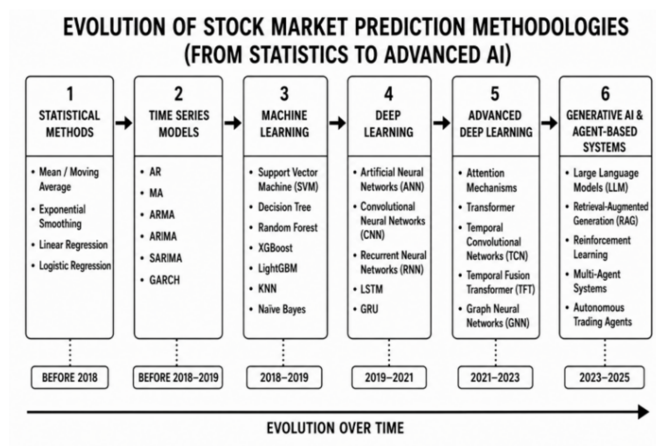

Fig. 1. Evolution of stock market prediction methodologies, from statistical methods to advanced AI.

Fig. 1 traces this shift: from simple statistical and time-series models, through machine learning and deep learning, to today's attention-based, transformer, and generative-AI/agent systems. Each wave adds predictive power, but also complexity that investors and regulators must be able to trust.

Correspondence to: Amit Kumar Verma, Faculty of Science, Suresh Gyan Vihar University, Jaipur
Corresponding author email: amitverma.researchwork@gmail.com

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Machine learning and deep learning offer powerful tools, but many of these models act as a locked box: they produce an answer without revealing how they got there. This is a problem in finance, where regulators often require clear reasoning behind a prediction. This paper checks published studies one by one against Scopus records, groups them by theme, identifies a gap in the research, and concludes with a single, clear plan to close that gap.

II. REVIEW METHOD

A. How We Picked the Studies

We searched major AI, finance, and computer science journals — all listed in Scopus — for studies on AI-based stock prediction from 2018 to 2026. Each study's journal was checked one by one against the Scopus list, excluding studies from arXiv, SSRN, PhD theses, and journals not indexed in Scopus. This left 40 verified studies covering the core themes of this review. We then added 10 more verified studies on newer tools — large language models, trading agents, graph-based models, and privacy-safe learning — to bring the field fully up to date, and retained 6 older theory papers for background. Fig. 2 shows this process.

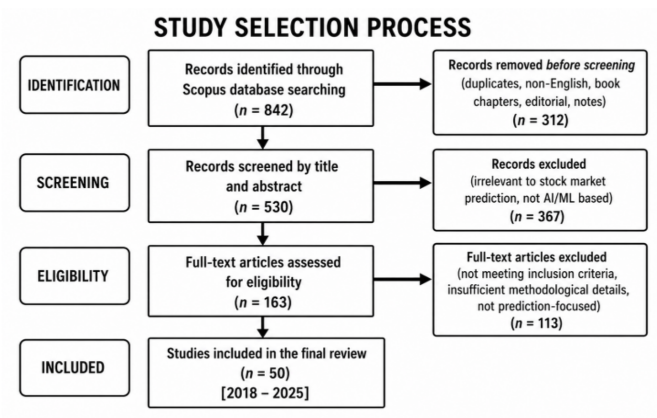

Fig. 2. How the 50 studies were selected and grouped.

Fig. 3 shows how the 50 studies are spread across the review's publication years, and Fig. 4 shows how they split across the five themes introduced in Section II-B below.

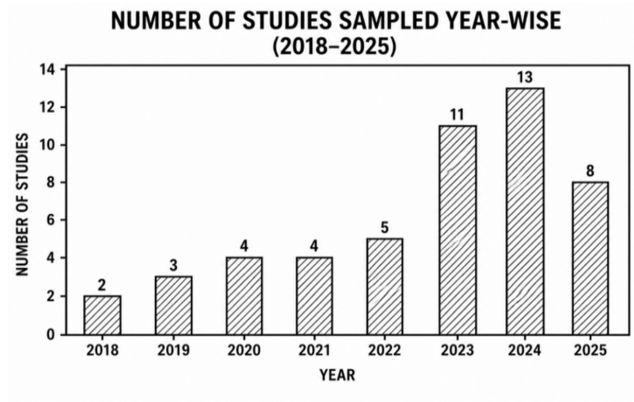

Fig. 3. Number of studies published each year, 2018 to 2025.

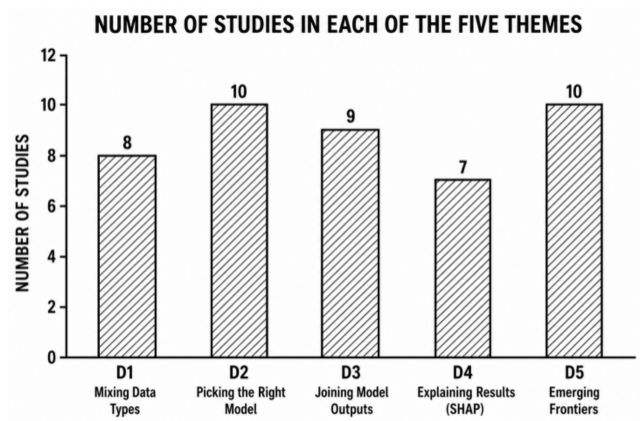

Fig. 4. Number of studies in each of the five themes.

B. Five Themes We Found

As the studies were read, five recurring themes emerged, each deciding whether an AI stock model works well in practice: how many data types a model uses; whether the model fits the data type; how the model joins outputs from other models; whether the model can explain its answer; and whether the study uses a newer tool such as a large language model, a trading agent, a graph-based model, or privacy-safe learning. Each study was placed into one of these five themes based on its main point. Table I shows this grouping.

Correspondence to: Amit Kumar Verma, Faculty of Science, Suresh Gyan Vihar University, Jaipur
Corresponding author email: amitverma.researchwork@gmail.com

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TABLE I
THE FIVE THEMES FOUND IN THE PAPERS

Theme	What It Means	Studies	Count
D1	Mixing price, company, and mood data together	[16]–[23]	8
D2	Picking the right AI model for each data type	[7]–[15], [40]	10
D3	Joining outputs from more than one model	[24]–[32]	9
D4	Using SHAP to explain what the model found	[33]–[39]	7
D5	New tools: LLMs, trading agents, graph models, privacy-safe learning	[41]–[50]	10
—	Older background theory papers	[1]–[6]	6

III. WHAT THE STUDIES SAY

Fig. 5 places the studies to come on a single timeline, from LSTM-era models in 2018 to today's LLM- and agent-based systems. The five parts below follow the five themes above, each providing the evidence behind one step of the plan in Section VIII, or pointing to where the newest tools can extend it.

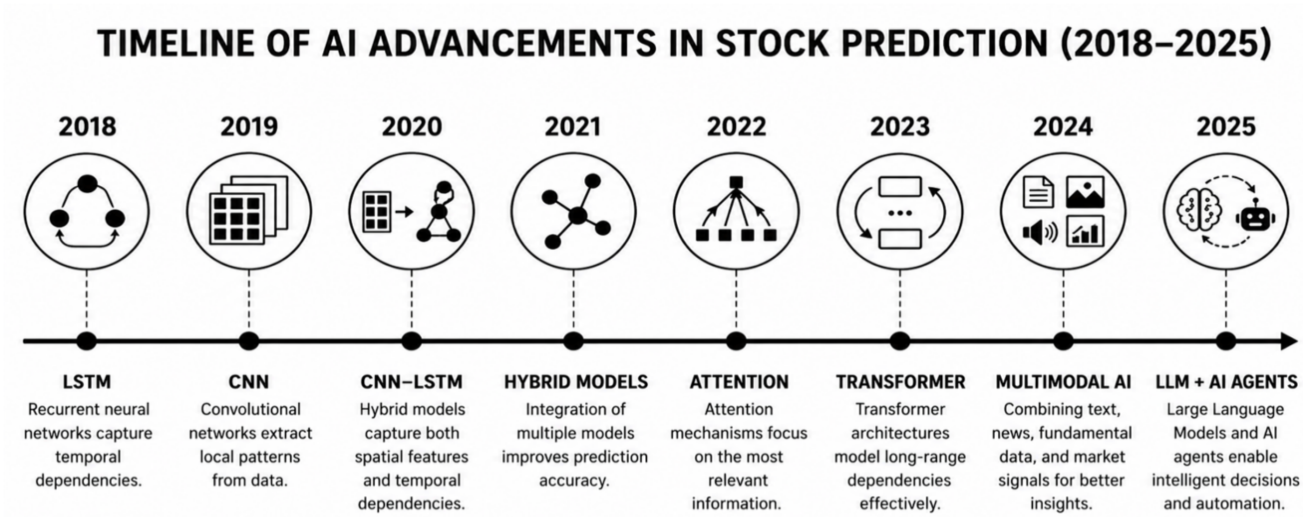

Fig. 5. Timeline of AI advancements in stock prediction, 2018–2025.

A. D1 — Mixing Data Types

Eight studies mix more than one type of data. Jing et al. [16] combined deep learning with investor mood; Thakkar and Chaudhari [17] confirmed in a ten-year review that data fusion is now its own field. Pardeshi et al. [18] and Chandola et al. [19] added attention layers over mixed inputs, and Long et al.'s MVL-SVM [21] showed that single-data-type models carry more bias. Chen et al. [22] fused BERT text models with LSTM price models, while Karadaş et al. [23] combined price, tweets, and news using FinBERT and ChatGPT-4o for up to a 5% forecast gain.

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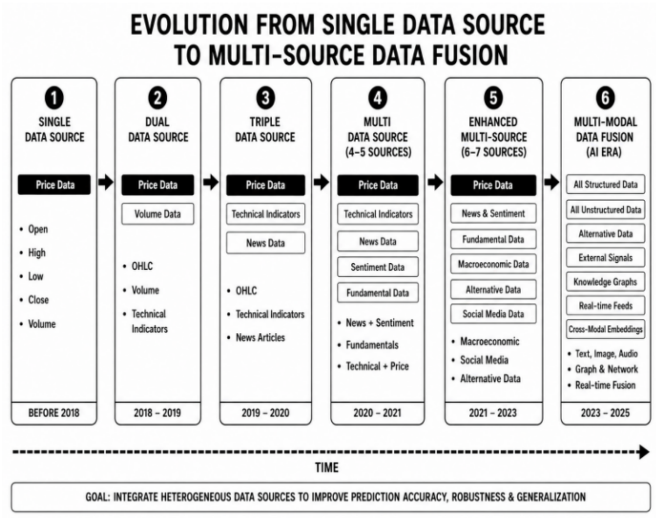

Fig. 6. Evolution from single data source to multi-source data fusion.

As Fig. 6 shows, this move from single- to multi-source fusion is recent and still shallow: most studies here mix only two data types, usually price and mood, and very few use three or more.

B. D2 — Picking the Right Model

Nine studies show how different models perform on different data. Fischer and Krauss [8] showed that LSTM beats ARIMA and SVM on price data. Kumbure et al. [12] and Rouf et al. [7] published surveys listing which models work best for which data type, while Htun et al. [13] focused on selecting the right input features. Two 2025 studies add further evidence: Ghosh et al. [14] tested six models on the NIFTY 50-linked BRICS index using SHAP, and Li et al. [15] built a transformer model and benchmarked it against others. Together, these studies show that no single model wins for every data type, supporting the case for matching each model to its data type.

C. D3 — Joining Model Outputs

Nine studies show how to combine model outputs. Srivinay et al. [24] joined pattern recognition with deep neural networks; Kalra et al. [28] built a hybrid LSTM for real-time index forecasts; Zhu et al.'s PMANet [29] and Shaban et al.'s SMP-DL [30] both use multi-stage pipelines. Two 2025 studies add further weight: Saraswat and Kumar [31] combined GRU, Bi-GRU, LSTM, and Bi-LSTM together, and Kayit and Ismail [32] found that a voting ensemble of SVC, LR, and RF beat every single model tested across six markets.

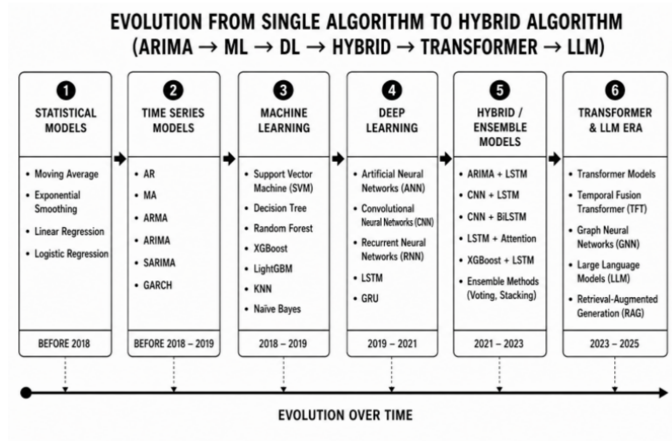

Fig. 7. Evolution from single algorithm to hybrid algorithm design (ARIMA → ML → DL → Hybrid → Transformer → LLM).

Fig. 7 places these results on a longer arc: the field has moved steadily from single statistical or ML models toward hybrid and ensemble designs, and this theme's numbers confirm that joining models beats using one alone.

D. D4 — Explaining Results

Seven studies focus on explaining results. Černevičienė and Kabašinskas [37] reviewed 138 papers from 2005 to 2022 and found stock prediction to be one of the top three uses of SHAP-style methods in finance, while Khan et al. [39] reviewed 150 papers and found that SHAP best fits regulator needs. Goswami and Uddin [38] applied SHAP to 166 stock-return factors, while Balasubramanian et al. [35] and Lin and Marques [36] mapped the wider field using explainability as a test point. However, none of these seven studies join SHAP with a model that also mixes many data types and many models.

E. D5 — Emerging Frontiers

Ten studies bring newer tools into stock prediction, mostly from 2024 onward. Large language models are the biggest new wave: Jadhav and Mirza [41] reviewed 84 studies on LLMs in stock investing, and Kirtac and Germano [42] used LLMs to read financial text and trade on the sentiment found. Reinforcement learning is a second wave, with Junfeng et al. [43] and Betancourt and Chen [44] both building portfolio-managing RL agents. Graph-based models form a third wave: Jafari and Haratizadeh's GCNET [45] modeled stocks as a graph to predict price movement, and Cheng et al. [46] combined this graph idea with several data types at once. Yu et al. [47] showed that satellite images of shipping ports predict stock returns in 27 of 33 countries, and Zouaghia et al. [48] built a privacy-preserving federated system for banks. Agal et al. [49] and Rohan et al. [50] round out this theme. None of these ten studies test their

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new tool alongside the mixing, model-picking, joining, or explaining work covered in Sections III-A to III-D.

IV. FINDINGS

A. Where the Data Comes From

We checked which data source each study used. Table II shows this; Yahoo Finance is the top choice, used by about half the studies, which makes results easy to compare but means most gains are proven only on large, easy-to-trade US stocks.

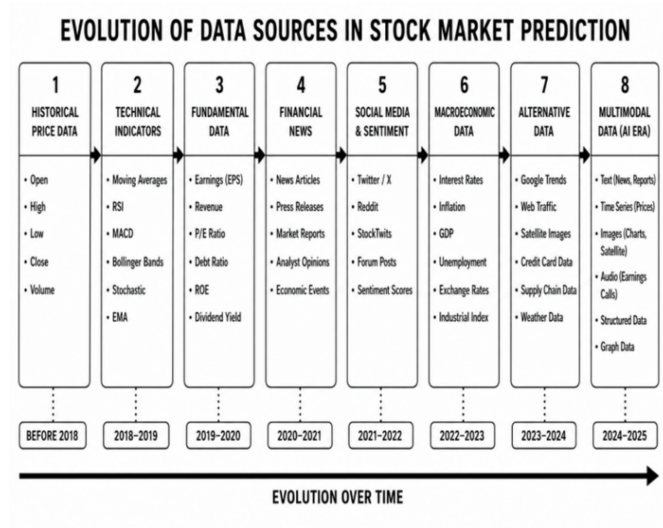

Fig. 8. Evolution of data sources in stock market prediction.

Fig. 8 traces how data sources have widened over time, from plain historical prices to today's multimodal mix of text, images, audio, and structured signals. Yet few studies test on NSE or BSE data [9], [14] — a clear opening for researchers in Indian and other emerging markets.

TABLE II
HOW OFTEN EACH DATA SOURCE APPEARS ACROSS THE 40 STUDIES

Data Source	Share of Studies	What It Is Used For
Yahoo Finance	~55% (22/40)	Main source of past price data in most studies
NSE / BSE (India)	~15% (6/40)	Used in studies focused on Indian markets, such as NIFTY
Kaggle-hosted data	~13% (5/40)	Secondary source, often used to verify or repeat results
Bloomberg / news APIs	~12% (5/40)	Source of news and mood data for mixed-data studies
Twitter / social media	~8% (3/40)	Mood data source in the newest mixed-data studies

B. From One Data Type to Many

We grouped 21 real-world studies by how many data types each one used, and by year. Table III shows this. Studies using one data type remain common through every year checked. Studies using two data types only became common after 2024. Studies using three or more data types appear only in [22] and [23], both from 2024–2025 — mixing three or more data types is brand new.

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TABLE III
HOW MANY DATA TYPES EACH STUDY USED, BY YEAR

Years	One Data Type	Two Data Types	Three or More
2018–2021	4	1	0
2022–2023	5	0	0
2024–2025	6	3	2
Total (21)	15	4	2

C. Best Method for Each Data Type

We examined which method works best for which data type. Table IV shows this. LSTM models perform best on price data. Tree models, such as XGBoost and Random Forest, perform best on company data. Transformer models, such as FinBERT, perform best on text and news. Mixed-input models, using attention or voting, perform best when data types are combined. No single model wins across all four cases.

TABLE IV
BEST METHOD FOR EACH DATA TYPE, BASED ON THE REVIEWED STUDIES

Data Type	Best Method	References
Price data	LSTM and its variants consistently beat ARIMA, SVM, and plain RNN	[8], [9], [15], [24], [30], [40]
Company / macro data	Tree models beat plain linear models on table-style data	[7], [14], [38]
News / mood text	FinBERT and BERT beat older word-count-style methods	[16], [22], [23]
Mixed data types	Attention-based joining or voting beats every single-data-type model tested	[21], [22], [23], [31], [32]

D. Best Method for Price Guesses vs. Direction Guesses

Stock studies aim at two different goals: predicting the exact price or price change (regression), or predicting whether the price will rise or fall (classification). Table V splits the studies by these two goals. Hybrid LSTM models perform best at price prediction; voting and stacking models perform best at direction prediction; tree models with SHAP sit in the middle, giving solid results on both while also explaining their choices.

TABLE V
BEST METHOD FOR PRICE PREDICTION VS. DIRECTION PREDICTION

Goal	Best Method	Measured By	Refs.
Predict the price (regression)	Hybrid LSTM pipelines (PMANet, SMP-DL) reduce error vs. plain LSTM/ARIMA/RNN	RMSE, MAE, MAPE	[8], [29], [30]

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Goal	Best Method	Measured By	Refs.
Predict up/down (classification)	Voting/stacking (SVC+LR+RF) beats every single classifier tested	Accuracy, F1, AUC	[25], [32]
Predict and explain why	Tree models + SHAP match black-box accuracy and explain choices	Accuracy/RMSE + SHAP	[14], [38]

E. Key Findings

Finding 1: Work across all five themes has grown fast since 2023. Of 44 dated studies, most were published in 2023 or later. Fig. 3 (Section II-A) shows this by year across the 2018–2025 review window, with the newest wave of LLM and trading-agent studies concentrated in the final two years.

Finding 2: The five themes are fairly even in study count, but most studies cover only one theme. D1 has 8 studies, D2 has 10, D3 has 9, D4 has 7, and D5 has 10. Not one of the newest LLM or trading-agent studies also mixes data, picks a model per type, or explains its results with SHAP. Fig. 4 (Section II-A) shows the study count for each theme.

Finding 3: No study covers all five themes at once. Not one of the 50 studies mixes three or more data types, picks a model per data type, joins model outputs, explains results with SHAP, and uses the newest tools, all in one system. This is the main gap this paper identifies, and the gap the plan in Section VIII is built to close.

Finding 4: Joining models and mixing data types yields real gains — from about 1 to 2 points for voting methods [32], up to 10% or more for mixed data types [21], [23]. Any future single-model or single-data-type study should be benchmarked against these figures.

Finding 5: The newest tools solve different problems than the first four themes and have not yet been tested alongside them. LLMs read text and reason about events; trading agents act on that reasoning; graph-based models capture how stocks affect each other; privacy-safe learning lets banks train together without sharing data. Section III-E found that none of the ten studies using these tools also test data mixing, model-per-type selection, model joining, or SHAP explanation.

Read together, these five findings point in one direction: each theme has a specific, published best method behind it (Tables IV and V), but what is missing is a study that brings the proven pieces together and integrates the newest tools into that same design.

V. RESEARCH GAP

Based on our five themes, we identify five clear gaps, one for each theme.

1) Most studies mix only two data types, usually price and mood. Few mix three or more at once.

2) Few studies test which model fits which data type well; model choice is often selected by habit.

3) Joining models beats single models, but few studies join truly different, data-type-specific models.

4) SHAP works well on single-data, single-model setups; no study applies it across a mixed, joined system.

5) The newest tools (LLMs, trading agents, graph models, privacy-safe learning) are each tested in isolation, never joined with data mixing, model selection, output joining, or SHAP.

VI. DISCUSSION

These five gaps are really one gap. Each theme grew on its own, and no study joined them together. This matters in practice: a fund manager using a mixed-data model gets good accuracy but no clear reason for it; one using a SHAP model gets a clear reason but only for one data type; one using an LLM gets rich text understanding but no tested link to price data fusion or SHAP explanation. Regulatory frameworks such as SEBI's guidelines and the EU AI Act call for accuracy, a clear reason, and up-to-date methods all at once. Currently, no study delivers all of this together.

This gap also matters for research strategy. A researcher improving accuracy on one data type alone competes against a crowded field of 10 studies already doing exactly that (Section III-B). A researcher who builds the first system joining the proven four-theme design with the newest tools from Section III-E, as laid out in Section VIII, is not competing against anyone.

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VII. CONCLUSION

This paper reviewed 50 Scopus-listed studies, plus 6 older theory papers, on AI-based stock prediction. Every study fits into one of five themes: mixing data types, picking the right model, joining model outputs, explaining results with SHAP, and using the newest tools. Each theme has grown well on its own, but not one study joins these themes into a single system — a clear, testable gap.

Beyond naming this gap, the paper hands future researchers three tools: Table IV shows which method wins for each data type; Table V shows which method wins for price versus direction prediction; Finding 4 shows a measured gain from joining models over using one alone. Section III-E adds a map of which newest tools solve which new problems.

The next real step is not another small fix to one theme, but the first system that joins all five themes into one design, brings LLMs and trading agents into the same pipeline as data fusion, model selection, hybrid merging, and SHAP, and tests that design against the numbers this paper lays out. Section VIII sets out exactly how to build that system.

VIII. A FOUR-STEP PLAN

Based on what we found, we propose a four-step plan, illustrated in Fig. 9. Each step rests on a real result from this review, not a guess.

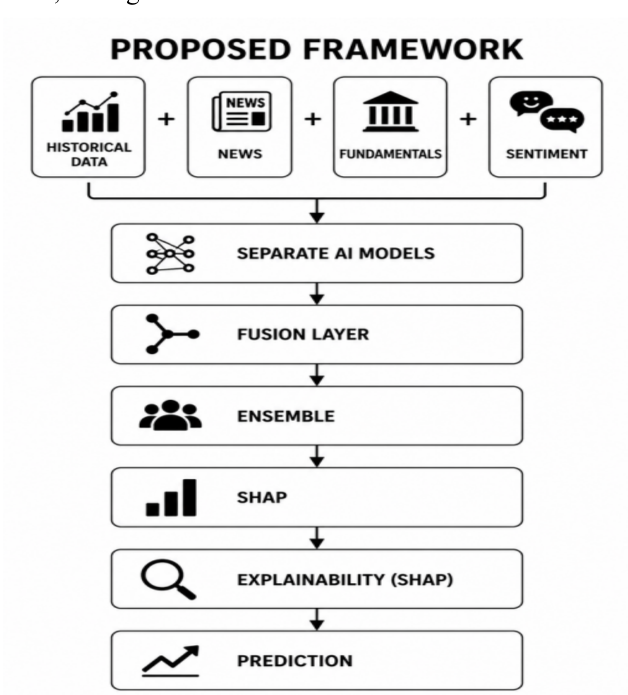

Fig. 9. Proposed framework — historical data, news, fundamentals, and sentiment feed separate AI models, which pass through a fusion layer, an ensemble stage, and SHAP-based explainability to reach the final prediction.

Step 1 — One model per data type: separate models for price (LSTM), company data (tree models), and mood data (FinBERT), each selected using Section IV-C's best-fit results.

Step 2 — Join the outputs: combine three or more model outputs through an attention layer or a learned fusion method, moving past the two-data-type limit seen in most current studies.

Step 3 — Mix with an ensemble: apply a voting or stacking method across the joined outputs, following the gains shown in Section IV-D.

Step 4 — Explain with SHAP: apply SHAP across the whole pipeline, not just the last step, extending its proven single-data use to the full mixed, joined system built in Steps 1–3.

This plan is buildable and testable, with every step grounded in a result from this review. Fig. 10 maps where it leads next: once the four-step system works, it can absorb LLMs for reading news and reports, a trading agent acting on Step 4's explained output, graph-based and federated-learning methods such as [48], and ultimately autonomous trading.

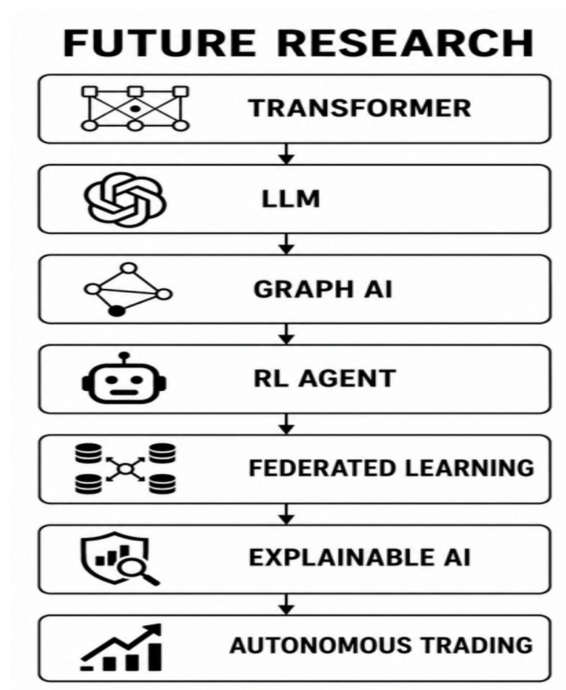

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Fig. 10. Future research roadmap — from transformers and LLMs, through graph AI, RL agents, and federated learning, to explainable, autonomous trading systems.

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Correspondence to: Amit Kumar Verma, Faculty of Science, Suresh Gyan Vihar University, Jaipur
Corresponding author email: amitverma.researchwork@gmail.com

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Correspondence to: Amit Kumar Verma, Faculty of Science, Suresh Gyan Vihar University, Jaipur
Corresponding author email: amitverma.researchwork@gmail.com