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FORECASTING STOCK MARKET MODEL: A SYSTEMATIC LITERATURE REVIEW

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Abstract— *The increasing digitisation of stock markets and the growing diversity of financial data sources have intensified the need for accurate, robust, and risk-aware stock market forecasting. This systematic literature review synthesises recent evidence to examine the effectiveness of forecasting methods under different data and market conditions, the characteristics of commonly used benchmark datasets, the contribution of preprocessing strategies, and the evaluation and validation practices applied in stock market forecasting. Following the PRISMA framework, 71 peer-reviewed studies retrieved from the Scopus database were systematically screened, classified, and analysed. The evidence mapping shows that sequence-based deep learning models, including LSTM, GRU, and CNN–LSTM, represent the largest methodological group at approximately 41%, followed by transformer- and attention-based approaches at around 16%. Volatility-oriented econometric and classical statistical models account for approximately 18% and 14%, respectively, while probabilistic and quantile-based approaches remain limited. The findings indicate that forecasting performance is strongly context-dependent: classical models remain effective for relatively stationary univariate series, volatility-oriented models are particularly relevant when clustering and spillover effects are present, and deep learning and transformer-based approaches are more suitable for multivariate, nonlinear, and feature-rich settings. Overall, the review highlights the need for greater integration of uncertainty-aware evaluation, regime-sensitive validation, and risk-oriented forecasting frameworks.*

Keywords: *Deep Learning, Forecasting, Stock Market, Systematic Literature Review, Transformer.*

Intisari— *Meningkatnya digitalisasi pasar saham dan semakin beragamnya sumber data keuangan telah memperkuat kebutuhan terhadap peramalan pasar saham yang akurat, tangguh, dan mempertimbangkan aspek risiko. Systematic Literature Review (SLR) ini mensintesis bukti empiris terkini untuk mengkaji efektivitas metode peramalan pada berbagai karakteristik data dan kondisi pasar, karakteristik dataset acuan yang umum digunakan, kontribusi strategi prapemrosesan, serta praktik evaluasi dan validasi dalam peramalan pasar saham. Dengan mengikuti kerangka PRISMA, sebanyak 71 studi yang telah melalui proses peer review dan diperoleh dari basis data Scopus diseleksi, diklasifikasikan, dan dianalisis secara sistematis. Hasil pemetaan bukti menunjukkan bahwa model deep learning berbasis sekuens, termasuk LSTM, GRU, dan CNN–LSTM, merupakan kelompok metodologis terbesar dengan proporsi sekitar 41%, diikuti oleh pendekatan berbasis transformer dan attention sekitar 16%. Model ekonometrika berorientasi volatilitas dan model statistik klasik masing-masing mencakup sekitar 18% dan 14%, sedangkan pendekatan probabilistik dan berbasis kuantil masih relatif terbatas. Temuan menunjukkan bahwa kinerja peramalan sangat bergantung pada konteks: model klasik tetap efektif untuk deret univariat yang relatif stasioner, model berorientasi*

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volatilitas lebih relevan ketika terjadi klaster volatilitas dan efek limpahan, sedangkan pendekatan deep learning dan transformer lebih sesuai untuk data multivariat, nonlinear, dan kaya fitur. Secara keseluruhan, tinjauan ini menegaskan perlunya integrasi yang lebih kuat antara evaluasi berbasis ketidakpastian, validasi sensitif terhadap rezim pasar, dan kerangka peramalan berorientasi risiko.

***Kata Kunci**: Pembelajaran Mendalam, Peramalan, Pasar Saham, Tinjauan Literatur Sistematis, Transformer.*

INTRODUCTION

Stock price forecasting that is both accurate and risk-aware has become increasingly relevant as financial markets become more digital, retail participation expands, and data sources grow beyond historical prices to include technical indicators, macroeconomic variables, and news-based sentiment [1], [2], [3], [4], [5], [6]. The study shows a variety of methodological approaches. Conventional time-series models such as ARIMA/ARFIMA, Holt-Winters, and State space models remain efficient for relatively stable univariate data in short-term forecasts [7], [8], [9], [10]. Models centered on volatility in the The VAR/GARCH family tackles the issue of volatility clustering and spillovers across assets, which are crucial for management of risk [11], [12], [13], [14]. Moreover, specialized temporary indicators, comprising α-Sutte/BetaSutte and SutteARIMA offer rapid monitoring trends in data-scarce environments [7], [15]

As nonlinearity and data intricacy increase, models utilising sequence based deep learning like RNN, LSTM, GRU, and their adaptations, along with mixed CNN–LSTM frameworks are becoming more efficient, options to linear approaches, frequently being noted to excel during unstable times or when integrating technical and macroeconomic elements [1], [2], [16], [17], [18]. Recently, transformer-based architectures such as the Temporal Fusion Transformer and transformer-GRU hybrids have demonstrated benefits in multivariate, regime-shifting scenarios by effectively capturing both short- and long-term dependencies and incorporating event- or sentiment-driven signals via attention mechanisms [19], [20], [21], [22].

The reviewed empirical studies mainly focus on Indonesian blue-chip stocks and indices (IHSG/IDX, IDX30, LQ45), individual shares like BMRI, BBRI, ASII, ANTM, and BBNI, cross-market measures, and commodity–energy price series encompassing gold, coal, oil, carbon, and gas. Numerous research efforts enhance price information by incorporating macroeconomic or sentiment attributes [1], [7], [15], [23], [24], [25], [26], [27], [28]. The structural traits of these datasets, including stationarity, volatility clustering, seasonality, regime shifts, and cross-series interactions, significantly affect model performance and necessitate the application of customized preprocessing and evaluation approaches [11], [12], [13], [14], [19], [25]. Preprocessing pipelines generally consist of transformations that induce stationarity (log-returns, differencing), representations that account for volatility (returns with rolling dispersion), smoothing and denoising techniques (MA, EMA, LOWESS), scaling or normalization, meticulous sequence windowing, and enhancement of features with technical, macroeconomic, and sentiment variables [1], [8], [9], [16], [17], [19], [20], [21], [22], [23], [27], [29], [30], [31], [32]. Clear regime or intervention labeling is frequently essential concerning policy shocks, auto-reject occurrences, and phases of pandemics [26], [28], [33], [34].

Assessment methods are progressively utilising a blend of point-error metrics, directional accuracy indicators pertinent to trading choices, and probabilistic or risk-based evaluations performed through rolling or walk-forward, multi-horizon, and event-split validation approaches. These practices aid in reducing look-ahead bias and effectively account for regime changes. [1], [3], [12], [14], [18], [19], [22], [26], [33], [35], [36]. However, a number of problems were still unresolved. (including AIC/BIC, Ljung–Box, ARCH–LM) tests continued to be standard for linear benchmarks prior to any evaluation against ML/DL models [7], [9], [10]. Alongside the narrative synthesis, a quantitative evidence mapping also accompanies the final collection of 71 articles. Approximately 41% of the reviewed studies employ sequence modelling deep learning methods (LSTM/GRU/CNN-LSTM), while an additional 16% apply transformers or attention mechanisms. In comparison, traditional statistical modelling and volatility-centric econometric modelling account for 14% and 18%, respectively, reflecting a distinct preference.

Despite the importance of uncertainty assessment in real-world financial decision-making, only 6% of the examined studies make use of probabilistic/quantile-based modeling techniques that take uncertainty estimations into account. This seems to be a relatively undeveloped field. In terms of geographic direction, it is noted that emerging markets receive a lot of attention in the

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pertinent literature. Of these research, about 48% look at Indonesian stock market indices/blue chips (IHSG, LQ45, IDX30, BMRI, BBRI, ASII), and another 29% look at developed markets such as the US, Europe, China, and so forth. This demonstrates unequivocally that stock market forecasting has become a very dynamic study topic in emerging nations, with its own set of difficulties in settings that are comparatively more unexpected.

However, there are still a number of gaps in the literature despite these methodological advancements. The magnitude of these residual gaps is further demonstrated by a more thorough quantitative analysis. The gap between volatility modeling and learning representations is still significant, as evidenced by the fact that less than 12% of the reviewed literature consistently uses volatility forecasts, such as GARCH or realized measures, as structured inputs in deep learning models. Additionally, less than 8% of the surveyed literature evaluates backtesting tasks requiring risk or regime-dependent validation, and less than 10% evaluates calibration in probabilistic measures like interval coverage or CRPS.

These figures show that while forecasting accuracy has improved, there is still a lack of consistency in the literature regarding uncertainty measurement, volatility-aware learning, and assessments relevant to decision-making. These encompass the restricted access to standardized benchmarks that are open and regime-specific; inadequate correlation of methodological categories with market regimes; insufficient application of calibrated probabilistic metrics and authentic backtesting; and absence of systematic ablation studies assessing preprocessing options and feature setups [1], [6], [19], [22], [26], [31], [37], [38].

To address these gaps, this review synthesizes evidence through four research questions. Specifically, the review examines (RQ1) the comparative effectiveness of stock market forecasting methods across different data characteristics, forecasting settings, and market conditions; (RQ2) the benchmark datasets most frequently employed and the extent to which their structural properties influence model performance; (RQ3) the preprocessing strategies commonly adopted and their contributions to improving forecasting accuracy, stability, and robustness; and (RQ4) the evaluation and validation approaches used to assess forecasting performance, including the metrics applied to capture predictive accuracy, directional performance, uncertainty, and risk-related aspects.

MATERIALS AND METHODS

A literature review focused on quantitative analysis was performed to uncover trends, patterns, and significant contributions in the field of stock price forecasting research. Consistent with the PRISMA framework, this research utilized a systematic and replicable literature review method with a well-defined subject area. The search for literature was carried out in the Scopus database (https://www.scopus.com). The query used for the search was: TITLE-ABS-KEY (forecasting AND "stock market" AND models), applied to the title, abstract, and keyword fields. The criteria for inclusion were: (1) literature released on or before November 4, 2025, within the specified publication timeframe of this review; (2) documents written in English; and (3) research concentrating on stock price prediction models.

Review protocol, screening, quality appraisal, and scope limitations. This review did not use an external preregistration platform. However, an internal review protocol was prepared before screening to define the review scope, research questions, inclusion and exclusion criteria, extracted data items, and synthesis plan. The extracted data items included publication year, market or dataset context, target variable, forecasting horizon, model family, input features, preprocessing techniques, evaluation metrics, and validation design. The synthesis was planned to address the four review questions through structured thematic mapping and descriptive evidence aggregation. Title and abstract evaluation followed by full-text eligibility assessment were carried out sequentially based on the PRISMA guidelines.

To improve the interpretability of the synthesis, the included studies were also assessed using an adapted descriptive quality appraisal checklist covering five aspects: (1) clarity of dataset description, (2) appropriateness of forecasting target and horizon definition, (3) transparency of preprocessing and feature construction, (4) adequacy of validation design and evaluation metrics, and (5) reporting of robustness, uncertainty, or risk-related assessment. This appraisal was used descriptively to contextualise the overall strength of the reviewed evidence rather than to exclude studies from the corpus. The review was intentionally bounded to Scopus-indexed journal articles in order to maintain a clearly defined and manageable corpus with consistent bibliographic metadata and feasible full-text screening and coding.

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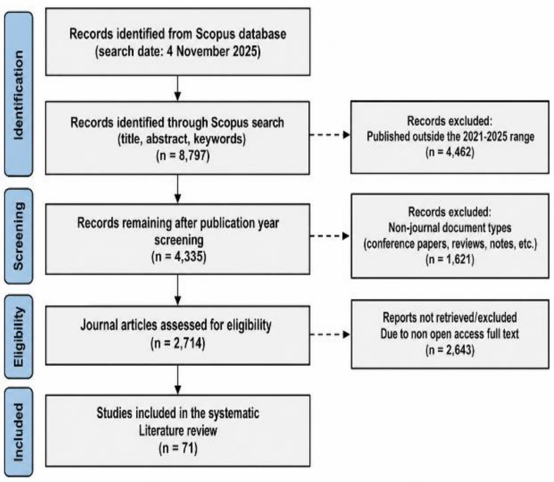
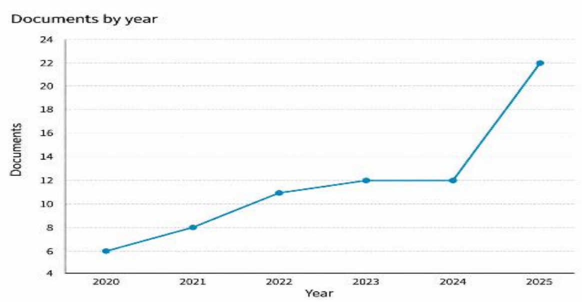
However, this decision limits coverage of conference papers, preprints, and studies indexed primarily in IEEE Xplore, Web of Science, arXiv, SSRN, Google Scholar, ACM Digital Library, or other sources. These exclusions may introduce coverage bias, particularly in computer science where some important contributions appear outside journal-only corpora. Therefore, the findings of this review should be interpreted within the scope of the selected corpus rather than as a complete representation of the entire field. Coding Scheme and Supplementary Mapping. To improve reproducibility, a supplementary coding table is provided for the 71 included studies. For each study, the coding scheme records the market or dataset context, target variable, forecasting horizon, model family, input features, preprocessing pipeline, evaluation metrics, and validation design. This supplementary mapping supports transparent replication of the thematic classification and percentage-based evidence summaries used in this review. Because the reviewed studies differ in markets, forecasting targets, horizons, input features, and evaluation protocols, the synthesis is interpreted through descriptive stratification rather than pooled comparison. Specifically, findings are discussed according to target type (price, return, or volatility), forecasting horizon, market context, feature richness, and validation design. This approach is intended to reduce overgeneralisation across heterogeneous study settings and to preserve context-sensitive interpretation of the reviewed evidence.



Source: (Research Results, 2025)
Figure 1. PRISMA Information Flow of Systematic Literature Review

Figure 1 presents the PRISMA flow diagram used to document the identification, screening, eligibility, and inclusion stages of the review. A total of 8,797 records were initially identified from the Scopus database through searches conducted in the title, abstract, and keyword fields using the stock market forecasting topic. During the screening stage, 4,462 records were excluded because they were outside the predefined publication window, leaving 4,335 records. A further 1,621 records were excluded because they were not journal articles, including conference papers, review papers, notes, and other non-journal document types. This resulted in 2,714 journal articles for eligibility assessment. In the eligibility stage, an open-access filter was applied to ensure transparency, reproducibility, and full-text accessibility. After this final screening step, 71 journal articles were retained and included in the systematic literature review. Overall, the included studies showed varying levels of reporting quality, particularly in validation design, preprocessing transparency, and uncertainty reporting, which should be considered when interpreting the aggregated findings.

As a whole, the PRISMA based selection procedure systematically refined the initial search results into a focused corpus of eligible journal articles. This process ensured that the final dataset was aligned with the scope of the review and provided a transparent basis for the subsequent analysis of forecasting methods, preprocessing strategies, benchmark datasets, and evaluation practices in stock market forecasting studies. The annual publication pattern of research on stock market forecasting from 2020 to 2025 is depicted in Figure 2. In all, the quantity of publications shows an increasing pattern over time, indicating sustained and growing research interest in this topic. The volume of publications was relatively limited in 2020, followed by a gradual increase in 2021 and 2022. The trend continued in 2023 and remained substantial in 2024, before rising markedly in 2025. This pattern suggests that stock market forecasting has become an increasingly active area of research, thereby reinforcing the relevance of a systematic literature review to synthesise the rapidly expanding body of work.



Source: (Research Results, 2025)
Figure 2. Publications Every Year

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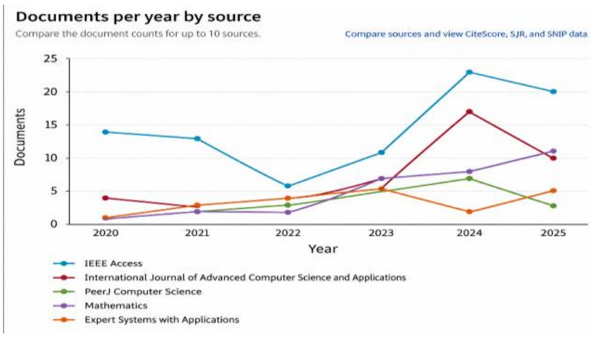
Figure 3 presents the distribution of publications during 2020 until 2025 period. IEEE Access appears as one of the most prominent publication venues in the reviewed corpus, indicating its important role in disseminating research on stock market forecasting models. Other notable sources include the *International Journal of Advanced Computer Science and Applications* and *Mathematics*, both of which also contributed a noticeable number of publications. Although the publication patterns of sources such as *PeerJ Computer Science* and *Expert Systems with Applications* appear more varied, these journals still demonstrate consistent attention to topics related to machine learning, expert systems, and predictive modelling in stock market applications. Overall, this distribution suggests that stock market forecasting research is supported by a multidisciplinary publication landscape spanning artificial intelligence, data analytics, and statistical modelling.



Source: (Research Results, 2025)
Figure 3. Document by Source (Year)

RESULTS AND DISCUSSION

Core Research Issues in Stock Market Forecasting

It is crucial to outline the main concerns that serve as the basis for stock market forecasting research before delving into the four research topics listed below. The main obstacles in this sector are not solely methodological, despite the fact that numerous forecasting models have been put out in the literature. Rather, they result from the interplay of three primary sources of complexity: evaluation, modeling, and data. Consequently, the following is a summary of the fundamental problems that underpin this field of study:

1. The misalignment of data methods.

These datasets vary across several aspects, including stationarity, volatility patterns, cross-asset relationships, and the occurrence of structural breaks caused by policy shifts, regulatory changes, or major economic events.

2. Benchmark datasets and market regime definitions.

The existing literature predominantly employs heterogeneous datasets that vary in terms of market coverage, observation periods, sampling frequencies, and target variables. In addition, market regimes, such as stable periods, crisis phases, or event-driven intervals, are often not clearly defined or consistently annotated. This limitation reduces the comparability and reproducibility of forecasting results across studies.

3. Preprocessing and feature design.

Preprocessing can substantially influence forecasting outcomes because it determines how raw market data are transformed before modelling. Typical steps include transformation, scaling, windowing, and feature engineering. However, many studies do not clearly explain which preprocessing components drive performance gains, and only a limited number apply ablation analysis to test the contribution of each component.

4. The predominance of evaluation that is focused on accuracy.

Point-error measures like RMSE and MAE are used in most research to assess predicting performance. However, assessment methods that include risk-sensitive analysis, realistic trading-based validation, and uncertainty estimation are still somewhat uncommon. Therefore, in real-world decision-making situations, great predicted accuracy does not always equate to practical value.

Thematic Analysis Using Research Questions

The developed research questions (RQs) are matched with the prevalent methodological categories found in the literature and chosen representative references in Table 1, which offers a methodical thematic mapping. This mapping is intended to provide a structured overview of the application of various forecasting approaches across different data characteristics, preprocessing strategies, and evaluation practices within stock market forecasting studies.

Table 1. Systematic Mapping Between Research Questions (RQs)

Research Question	Methods / Themes	Key References
RQ1: Which forecasting methods are most effective, and under which conditions?	Classical statistical forecasting models, including ARIMA, ARFIMA, Holt–Winters, and SutteARIMA	[7]–[10], [15], [41]

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Research Question	Methods / Themes	Key References
	Volatility-based and multiseries forecasting models, including GARCH, VAR–GARCH, and state-space models	[11]–[13], [25], [42], [43]
	Sequence-based deep learning models, including LSTM, GRU, CNN-LSTM, and other RNN variants	[1], [2], [16]–[18], [23], [32], [37], [44]–[47]
	Transformer-based and attention-based forecasting models	[3], [19]–[22], [48]–[50]
	Hybrid linear–nonlinear forecasting approaches	[33], [51], [52]
RQ2: Which benchmark datasets are most commonly used, and how do their structural characteristics affect model performance?	Indonesian stock market indices and blue-chip stocks, including IHSG, LQ45, IDX30, and sectoral stocks	[1], [2], [15], [17], [22], [23], [26], [45]
	International stock indices and cross-market datasets, including CSI 300, S&P 500, BRIC markets, and airline stocks	[5], [7], [41], [47], [51]
	Macroeconomic, commodity, and sectoral datasets, including energy, oil, gold, inflation, and geopolitical risk indicators	[25]–[29], [43], [53], [54]
	High-frequency and market microstructure datasets, including realised volatility and limit order book-based data	[40], [42]
RQ3: Which preprocessing techniques are most frequently applied, and how do they improve accuracy and robustness?	Stationarity-oriented transformations, including differencing, log-return transformation, and detrending	[7], [10]–[13], [35]
	Volatility-aware preprocessing and feature engineering, including GARCH-based volatility, rolling statistics, and realised volatility	[12], [13], [42], [43], [55]
	Scaling, normalisation, and sequence framing techniques	[1], [2], [16], [17], [23], [44]
	Feature enrichment using technical indicators, macroeconomic variables, and sentiment-based features	[20], [21], [23], [31], [53], [56]
RQ4: How is forecasting performance evaluated, and which metrics best represent forecasting quality?	Point-error evaluation metrics, including RMSE, MAE, and MAPE	[1], [5], [9], [17], [22], [23]
	Directional accuracy and trend-based evaluation metrics	[33], [47], [71]
	Probabilistic and Bayesian evaluation approaches, including quantile loss, uncertainty estimation, and Value-at-Risk	[29], [30], [57], [58]
	Backtesting and robustness evaluation across different market regimes	[12], [33], [39], [53], [59]

Source: (Research Results, 2025)

1. Forecasting Methods

In addressing Research Question 1, “Which forecasting methods are most effective, and under what conditions?”, the literature is synthesised by comparing statistical, machine learning, deep learning, hybrid, and probabilistic forecasting approaches. The comparison is conducted based on four key dimensions that influence methodological performance. The first dimension concerns the structure and type of data, including whether the time series is univariate or multivariate and whether it incorporates technical indicators, macroeconomic variables, or sentiment-based information. The second dimension refers to stochastic characteristics, such as stationarity, seasonal patterns, long-memory behaviour, and the presence of volatility clustering.

The third dimension relates to the forecasting horizon, which may involve short-term or medium-term prediction tasks. The fourth dimension concerns market conditions or regimes, including stable periods as well as periods affected by major events, high volatility, policy shocks, or structural changes in the market. Greater emphasis is placed on studies that report out-of-sample accuracy, risk-aware evaluation metrics, and model robustness across different datasets or market conditions, as these provide a more rigorous basis for selecting appropriate forecasting methods. To reduce overgeneralisation across heterogeneous studies, the synthesis of RQ1 is interpreted through descriptive stratification. In particular, the reviewed evidence is differentiated according to

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forecasting target (price, return, or volatility), forecasting horizon (short- or medium-term), data structure (univariate or multivariate), and market context (Indonesian or non-Indonesian). This stratified interpretation is important because method suitability and reported performance patterns vary substantially across these study conditions.

To address RQ1, the reviewed studies indicate that forecasting effectiveness should be interpreted according to the evaluation metrics used and the context in which each model is applied. Stock price forecasting methods can be broadly grouped into four methodological families, with their reported effectiveness depending on data characteristics, forecasting objectives, and market regimes. In the reviewed studies, effectiveness is reflected through the evaluation metrics reported by each study, including point forecast error measures such as RMSE, MAE, MAPE, and sMAPE, as well as directional and, where available, probabilistic or risk-oriented metrics. Traditional statistical models, including Holt–Winters, ARIMA/ARFIMA, VAR/GARCH variants, and state-space frameworks, are often noted for delivering robust baseline performance for relatively stable univariate series exhibiting recognizable seasonality and short-term forecasting.

Their noted advantages become clearer when a linear structure prevails, whereas GARCH-type elements or intervention analysis prove especially beneficial amid volatility clustering, policy shocks, regime changes, auto-rejection phases, or price spikes that can be more explicitly captured via intervention or jump-diffusion models [7], [8], [10], [11], [12], [14], [25], [33], [34]. For limited samples and brief trend assessments, tailored indicators like α-Sutte/BetaSutte and SutteARIMA are noted as effective and competitive in particular scenarios, including BMRI and DJI stock-market forecasting [7], [15]. As nonlinearity increases in significance while datasets stay moderately sized and technical indicators are present, traditional machine-learning techniques like SVR, KNNR, Random Forest/Decision Trees, ELM, and ANFIS are frequently noted to deliver consistent predictive performance with comparatively efficient training, especially in short- to medium-term forecasting under normal conditions and using technical indicators as key variables [4], [9], [24], [38], [39], [40], [41].

As the data becomes increasingly multivariate and includes more complex inputs like technical indicators, macroeconomic factors, and news sentiment, or when markets experience heightened volatility and dynamic shifts, sequence-based deep learning models—including RNN, LSTM, GRU, Bi-LSTM, CNN-LSTM, EMA-LSTM, and activation advancements like RunReLU—are often found to outperform traditional baselines, particularly for short- to medium-term forecasts and intricate nonlinear trends. The performance they report is frequently enhanced when linear structures are addressed using hybrid combinations like ARIMA-LSTM, when local smoothing is included, or when hyperparameters are adjusted via metaheuristic methods like GA/WOA in highly turbulent scenarios [1], [2], [16], [17], [18], [23], [30], [31], [35], [37], [42], [43], [44], [45], [46].

Variants based on Transformer, such as the Temporal Fusion Transformer and hybrid transformer–GRU models that integrate sentiment and technical indicators, have been shown to provide benefits in multivariate, feature-rich, and regime-switching environments by effectively capturing both short- and long-term dependencies using attention mechanisms [3], [19], [20], [21], [22]. In contrast, when the focus is on risk management and uncertainty communication, probabilistic and quantile-based methods, including Bayesian nonparametric quantile GAM, semi-shared Bayesian multi-series models, and Prophet as a baseline for trend-seasonality, offer valuable insights as they deliver interval and quantile forecasts that are more applicable for decision-making in scenarios characterized by significant heteroskedasticity, substantial cross-series interconnections, or VaR-focused goals [47], [48], [49].

Overall, the reviewed evidence suggests that no single method is universally superior across all forecasting settings. Instead, statistical models are generally more suitable when linear and relatively stationary structures prevail and explicit risk metrics are needed; conventional machine-learning models are often effective for moderate nonlinearity and medium-sized datasets; deep learning and transformer-based approaches appear more suitable for multivariate, highly nonlinear, and volatile settings; and probabilistic or quantile-based methods are particularly valuable when explicit uncertainty estimation is required. The integration of technical indicators, event-related sentiment, political events, and macroeconomic or commodity variables is frequently associated with improved performance in Indonesian market studies, particularly for blue-chip equities and event-driven periods, with method selection therefore depending jointly on forecasting horizon, data structure, predictor richness, and prevailing market regime [1], [3], [18], [19], [20], [21], [23], [25], [26], [27].

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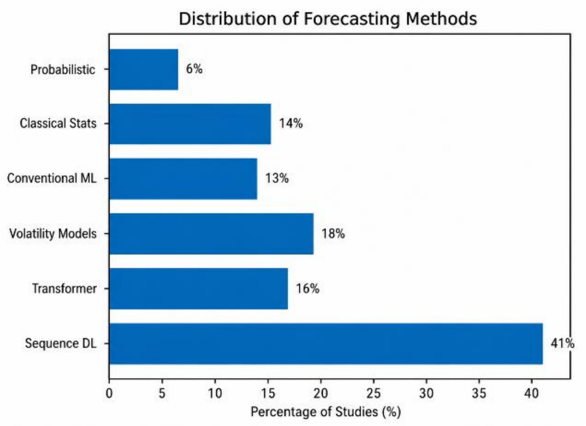
Across the reviewed corpus, price forecasting remains the most common target and is more frequently associated with sequence-based deep learning and transformer-based approaches, particularly in multivariate and feature-rich settings. Return forecasting is less uniformly addressed and is often discussed in relation to directional performance or short-horizon predictive behaviour. Volatility forecasting, by contrast, is more commonly linked to GARCH-type, state-space, and other risk-sensitive modelling strategies.

In addition, short-horizon studies more often report the use of technical indicators and sequential architectures, whereas medium-horizon studies more frequently emphasise broader contextual variables, including macroeconomic and event-related features. Indonesian market studies are also more likely to highlight blue-chip equities, event sensitivity, and market-specific feature engineering compared with broader cross-market studies. Figure 4 and Table 2 present a summary of the references number according to the group of methods used in stock price forecasting studies.



Source: (Research Results, 2025)

Figure 4. Distribution of Forecasting Methods

The References distribution shows that sequence based deep learning approaches are the most researched methods, followed by conventional machine learning models and transformer and feature-based approaches. Meanwhile, classical statistical methods, volatility models, and structural intervention techniques remain important baselines despite having fewer references. The diversity in the number of references in each category shows the variety of research focuses and reflects how data complexity, market dynamics, and risk analysis needs drive the selection of different methods in the current literature.

Table 2. Comparative Distribution of Forecasting Method Categories.

Forecasting Method	**Number of References**	**Sources References**
Classical statistics (univariate linear)	4	[7], [8], [10], [41]
Volatility & multiseries (statistical)	5	[11]–[13], [25], [42], [43]
Intervention / structural shocks	5	[14], [35], [36], [53], [54]
Sutte style bespoke indicators	2	[7], [15]
Conventional machine learning	6	[4], [9], [24], [60]–[63],[71]
Sequence deep learning	16	[1], [2], [16]–[18], [23], [32], [37], [44], [45], [47], [48], [50], [51], [56], [59], [64]
Linear–nonlinear hybrids	3	[33], [41], [51]
Metaheuristic optimization	2	[39], [65]
Transformers & feature-rich variants	5	[3], [19]–[22], [49], [52]
Probabilistic/quantile & Bayesian	4	[29], [30], [53], [57]
Macro/commodities & sector context	4	[25]–[28], [42], [64]
Order-book & microstructure-based DL	2	[40], [66]
Survey/progress & benchmarking studies	1	[6]

Source: (Research Results, 2025)

2. Benchmark Datasets

The datasets examined in this research are intended to address Research Question 2, which looks into the most popular benchmark datasets and how predicting performance is impacted by their structural characteristics. The literature examined indicates a significant dependence on data from the Indonesian stock market, especially key indices like IHSG/IDX, IDX30, and LQ45. Numerous studies additionally concentrate on actively traded blue-chip stocks like BMRI, BBRI, ASII, ANTM, and BBNI, frequently enhanced by cross-market instruments such as BRIC and Tesla to seize wider market dynamics. Additional studies broaden the analytical framework by including series of commodity and energy prices such as gold, coal, oil, carbon, and natural gas to consider macro-financial relationships and external disturbances.

Moreover, an expanding collection of research utilizes macro-financial datasets combining technical indicators with macroeconomic factors, in addition to sentiment- or event-driven signals, highlighting a growing focus on multivariate and

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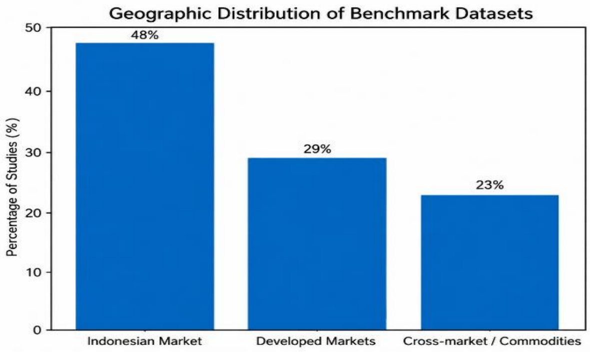
feature-intensive forecasting environments [1], [2], [3], [6], [7], [9], [11], [13], [14], [15], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [31], [32], [34], [38], [39], [43], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68].

To account for heterogeneity in benchmark usage, the reviewed datasets are interpreted through descriptive stratification according to market context, forecasting target, and data structure. In particular, the synthesis distinguishes between Indonesian and non-Indonesian datasets, equity price versus return or volatility targets, and univariate versus multivariate benchmark configurations. This distinction is necessary because dataset characteristics such as stationarity, volatility clustering, feature richness, and regime sensitivity differ substantially across these categories and directly influence model design and evaluation.



Source: (Research Results, 2025)
Figure 5. Benchmark Dataset Distribution

The empirical evidence shows that the structure of a dataset significantly influences forecasting effectiveness. Comparatively stable univariate time series exhibiting clear cyclical patterns often prefer traditional methods like ARIMA/ARFIMA and Holt-Winters. In contrast, datasets marked by volatility clustering and cross-asset spillovers elevate the importance of GARCH/VAR-GARCH and state-space models, while sudden structural shifts like auto-reject events, policy measures, or pandemic times frequently necessitate intervention analysis or jump-diffusion approaches.

As data grows multivariate and rich in features, including technical indicators, macroeconomic factors, or sentiment signals, the edge in prediction progressively transitions to sequence-oriented deep learning and transformer models. These models are often stabilised using a combination of linear and nonlinear techniques along with hyperparameter tuning, as attention and memory mechanisms seem more effective in capturing nonlinear and time-varying relationships among various indicators.

In line with these methodological trends, numerous studies utilize Indonesian stock indices and blue-chip stocks such as IHSG/IDX, IDX30, LQ45, BMRI, BBRI, ASII, ANTM, and BBNI as reference datasets. Additional studies expand the analytical focus to cross-market instruments like BRIC and Tesla, along with commodity and energy price series (gold, coal, oil, carbon, and natural gas) and macro-financial panels that merge price data with technical indicators, macroeconomic trends, and sentiment-based information.

In these varied contexts, predictive accuracy is strongly linked to structural traits: stationary univariate datasets enhance traditional statistical models; volatility-influenced and interconnected markets leverage econometric volatility methods; regime changes require adaptable or intervention-driven designs; and multivariate, feature-dense datasets prefer deep learning and transformer-based techniques. As a result, the choice of method is fundamentally reliant on the data, underscoring the necessity of matching forecasting methods to the structural characteristics of the reference dataset, as outlined in the following table.

Table 3. Benchmark Dataset Cluster

Benchmark Dataset Cluster and Structural Characteristics	Methods Frequently Identified as Appropriate	References
Indonesian stock indices and blue-chip stocks covering IHSG/IDX, IDX30, LQ45, as well as selected stocks such as BMRI, BBRI, ASII, ANTM, and BBNI. These datasets commonly use daily closing prices and tend to exhibit quasi-stationary behaviour during stable market periods, volatility clustering around major events, and occasional structural breaks.	ARIMA/ARFIMA and Holt–Winters are often effective in stable market conditions and short-horizon forecasting tasks because of their ability to capture relatively stable linear patterns. GARCH/VAR-GARCH and state-space models are more suitable when volatility clustering and spillover effects are present. Meanwhile, LSTM/GRU and transformer-based models are frequently reported to achieve strong performance when technical indicators, macroeconomic variables, or sentiment-based features are included.	[1]–[3], [9], [14], [15], [17], [22], [23], [26], [33], [34], [36], [48]–[50], [59], [63], [65], [67]
Cross-market datasets and flagship single stocks,	ARIMA, Holt–Winters, and Sutte-based indicators provide	[7], [24], [41], [47], [53]

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Benchmark Dataset Cluster and Structural Characteristics	Methods Frequently Identified as Appropriate	References
including BRIC markets and Tesla. These datasets are characterised by heterogeneous market regimes, international spillover effects, news-driven or event-driven price jumps, and medium-length time series.	efficient and competitive baselines for short-term forecasting. Sequence-based deep learning models, particularly LSTM and GRU, tend to offer advantages when event-related and sentiment-based features are incorporated to capture regime shifts.	
Commodity and energy price datasets, including gold, coal, oil, carbon, and gas prices. These datasets are generally associated with strong volatility, long-memory behaviour, heavy-tailed distributions, and cross-asset linkages with equity markets.	GARCH/VAR-GARCH and state-space models are suitable for modelling volatility persistence and spillover effects. Probabilistic and quantile-based approaches, such as Bayesian models and BNP-QGAM, are appropriate for risk-aware forecasting objectives. In addition, LSTM and transformer-based models are effective for multivariate commodity–equity forecasting panels.	[11], [25], [28], [29], [42], [43], [53], [64]
Macro-finance panels, which combine price data with technical indicators, macroeconomic variables, and sentiment or event-based features. These datasets are typically multivariate, nonstationary, and characterised by time-varying dependencies and event-driven windows.	LSTM, GRU, Bi-LSTM, CNN–LSTM, EMA–LSTM, and transformer-based models, such as TFT, are frequently reported to perform well, particularly when attention and memory mechanisms are required to capture nonlinear and time-varying dependencies. Hybrid linear–nonlinear models, such as ARIMA–LSTM, as well as metaheuristic optimisation, may further improve model stability and convergence.	[19]–[22], [26], [27], [31], [34], [38], [39], [49], [50], [52], [53], [56], [59], [65], [71]
Very short or data-limited single-stock datasets, which are characterised by limited observation periods, sparse features, and a focus on near-term trend tracking.	Lightweight forecasting indicators, including α-Sutte, BetaSutte, SutteARIMA, and simple ARIMA, remain competitive for immediate forecasting horizons. However, these methods have limited capacity to capture complex nonlinear market dynamics.	[7], [15]

Source: (Research Results, 2025)

Preprocessing Techniques

In regard to RQ3, the studies examined consistently highlight the significance of preprocessing as an essential phase in aligning the structure of the dataset with forecasting goals. Instead of pointing to one universally superior preprocessing method, the examined evidence indicates that preprocessing selections should be understood in relation to data attributes, modeling goals, forecast period, and evaluation framework. Multiple preprocessing techniques have emerged as prominent throughout the literature:

1. Transformations aimed at achieving stationarity, such as seasonal and non-seasonal differencing and log-return conversion, are commonly utilized to eliminate trends and stabilize variance, enhancing the applicability of traditional models like ARIMA/ARFIMA and Holt-Winters for univariate time series [7], [8], [9], [10].
2. Numerous research works utilize volatility-informed representations, generally founded on returns and moving standard deviations, which are then modeled through GARCH, VAR-GARCH, or state-space approaches. This method is notably useful for identifying volatility clustering and heavy-tailed characteristics frequently seen in equity and commodity markets, and it might also facilitate more accurate risk calibration [11], [12], [13], [14], [25], [51], [52], [59].
3. To eliminate high-frequency noise and reveal lower-frequency patterns, smoothing and denoising techniques like moving averages (MA), exponential moving averages (EMA), and LOWESS/LOESS filters are frequently used. When linear models are combined with LSTM-based frameworks in short-term or nonstationary environments, for example, these techniques are very useful [30], [31], [65].
4. A considerable body of literature emphasises the importance of feature engineering, in which technical indicators, macroeconomic variables, and sentiment- or event-based signals are integrated to broaden the information set and improve the predictive capability of machine learning and deep learning models [3], [17], [18], [19], [20], [22], [23], [25], [26], [27], [28], [29], [32], [55], [56], [58], [61], [62], [69], [70].
5. Feature scaling and normalisation techniques, such as z-score standardisation and min–max transformation, are commonly applied to enhance optimisation stability and facilitate model convergence in LSTM, GRU, CNN-LSTM, and transformer-based models, especially when

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datasets contain heterogeneous features [1], [16], [17], [22], [23], [54], [65].

6. Sequence framing, which is generally implemented using sliding-window mechanisms with predefined look-back periods and forecasting horizons, functions as an implicit form of regularisation. This approach helps maintain temporal dependencies while reducing the risk of overfitting in sequential data modelling [2], [16], [17], [35], [55].
7. Several studies explicitly introduce regime or intervention-based labels, including auto-reject periods, policy shocks, and pandemic phases, to minimise information leakage across market regimes and improve model robustness under distributional shifts [26], [33], [34], [50], [59]. In risk-aware forecasting, preprocessing pipelines that preserve distributional characteristics through return-based transformations, limited winsorisation, and careful temporal alignment have been shown to improve interval forecasting and tail calibration in probabilistic and quantile-based models [47], [51], [52], [64].

Table 4. Preprocessing Technique

Preprocessing Technique and Purpose	Commonly Paired Models / Conditions	References
Stationarity transformations, including log-return transformation, seasonal differencing, and non-seasonal differencing, are applied to remove trends, stabilise variance, and reduce the risk of spurious regression.	ARIMA/ARFIMA and Holt–Winters models for univariate time series with seasonal or cyclical patterns.	[7]–[10]
Volatility-aware representations, such as return-based features, rolling volatility, and variance modelling, are used to capture volatility clustering, heavy-tailed behaviour, and improve risk calibration.	GARCH/VAR-GARCH and state-space models, particularly for equities and commodities characterised by volatility clustering and spillover effects.	[11]–[14], [25], [42], [43], [53]
Smoothing and denoising techniques, including moving average, exponential moving average, and LOWESS/LOESS, are employed to reduce high-frequency noise and highlight low-frequency temporal structures.	Hybrid models, such as ARIMA–LSTM, especially in short-horizon and nonstationary forecasting settings.	[32], [33], [65]
Technical indicator engineering, including MA, RSI, MACD, Bollinger Bands, and lag-based features, is used to enrich the signal space and improve nonlinear separability.	Machine learning and deep learning models for blue-chip stocks, as well as sequence models using price data combined with technical indicators.	[17], [18], [22], [23], [31], [49], [50]
Event, sentiment, and policy-based features are incorporated to represent contextual and regime-related information that is not captured by price-only data.	LSTM/GRU and transformer-based models, such as TFT, particularly in event-driven market regimes.	[3], [19]–[21], [41], [53], [56]
Macroeconomic and commodity covariates are used to capture cross-market relationships and external shock effects.	Multivariate RNNs and transformer-based models, especially for risk-aware forecasting in sectoral and energy-linked markets.	[25]–[28], [34], [53], [64]
Scaling and normalisation, including z-score standardisation and min–max transformation, are applied to accelerate convergence and stabilise the optimisation process.	LSTM/GRU, CNN–LSTM, and transformer models that employ heterogeneous input features.	[1], [16], [17], [22], [23], [48], [65]
Sequence framing, commonly implemented through sliding windows with selected look-back periods and forecasting horizons, functions as an implicit regularisation strategy and helps capture temporal dependencies.	Stateful and stateless LSTM/GRU models, particularly for short-term stock price forecasting.	[2], [16], [17], [37], [49]
Regime and intervention labelling, including auto-reject periods, policy shocks, and pandemic windows, is used to minimise information leakage and improve robustness under structural shifts.	Linear and nonlinear models applied during periods of structural breaks or regime changes.	[26], [35], [36], [41], [53]
Distribution-preserving preprocessing, including return transformation, minimal winsorisation, and careful temporal alignment, is applied to improve interval forecasting and tail calibration.	Probabilistic and quantile-based frameworks, including Bayesian models, QGAM, and Prophet.	[29], [30], [42], [43], [57], [64]

Source: (Research Results, 2025)

Model Performance

A combination of point-forecast error, directional, and probabilistic/risk metrics, supported by time-series validation processes and diagnostic evaluations, were used to assess the models' performance in the reviewed papers answering research question 4. Particularly for Indonesian blue chips and index series, the main

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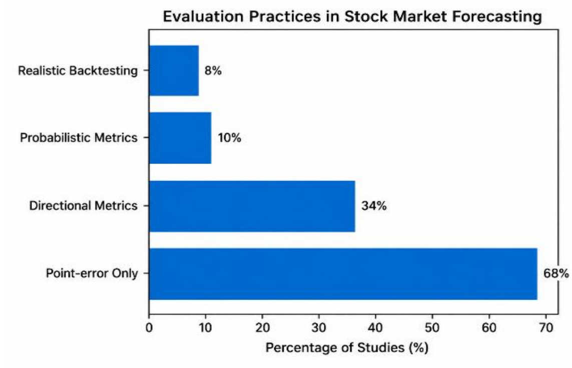
metrics for point forecasts are RMSE and MAE (scale-dependent) and MAPE/sMAPE (scale-free), applied to ARIMA/Holt–Winters, SVR, and DL baselines, in addition to transformer/LSTM comparisons [1], [7], [9], [17], [18], [19], [22], [23], [31], [35]. When larger errors call for a harsher punishment, RMSE is favored. While sMAPE is usually preferred for reducing asymmetry at lower price points, MAE and MAPE are commonly used where interpretability and comparability across assets are critical [5], [19], [22]. Certain research incorporates R^2/Theil's U as additional goodness-of-fit metrics in linear baselines [7], [9], [10].

Because the included studies differ in forecasting target, horizon, and modelling objective, evaluation practices are also interpreted through descriptive stratification. Specifically, the synthesis distinguishes between point-forecast evaluation for price prediction, directional evaluation for return-oriented or trading-related studies, and probabilistic or risk-oriented evaluation for volatility and uncertainty-sensitive applications. This stratified perspective is necessary because different metrics capture different aspects of forecasting quality and are not directly interchangeable across heterogeneous study settings.



Source: (Research Results, 2025)
Figure 6. Methods of Evaluation in Stock Market Prediction

Many studies present DA/hit ratios along with corresponding up–down classification metrics and occasionally precision/recall for "up" occurrences because trading depends on the direction of changes [3], [20], [21], [43], [51]. This is particularly true when integrating sentiment/news into LSTMs/GRUs or transformer GRU architectures. Directional measures provide an alternative viewpoint to RMSE/MAE about regime-sensitive benefits hidden by magnitude-only mistakes [19], [20], [21], [22]. In contexts where risk and tail behavior are crucial, especially within GARCH/VAR-GARCH and Bayesian or quantile-focused frameworks, the evaluation transitions to probabilistic calibration, incorporating coverage probability, interval width, CRPS, and VaR/ES back-tests [12], [14].

In shifting sectors and event periods, these metrics show projections that are either overconfident or underconfident, which RMSE/MAE is unable to detect [11], [13], [25], [28]. In order to detect regime changes, validation is essential for all approaches, including multi-horizon reporting, rolling-origin/walk-forward assessment, and out-of-sample testing periods separated by COVID-19 or election stages. [1], [3], [19], [22], [26], [33], [36]. Before comparing with ML/DL models, linear benchmarks typically include AIC/BIC for model selection and residual evaluation, Ljung-Box for residual autocorrelation assessment, ARCH-LM for conditional heteroskedasticity testing, and normality assessments to verify that error assumptions hold [7], [8], [10], [12], [13].

Table 5 summarizes the evaluation of forecasting performance throughout the corpus, categorizing metrics into point-error, directional, and probabilistic/risk types, and aligning them with validation methods and traditional diagnostics. It provides a summary of when each metric is most useful, its significance, and the modeling contexts in which it is generally used, enabling methodologically uniform benchmarking across market conditions and datasets.

In general, price forecasting studies most frequently report point-error metrics such as RMSE, MAE, MAPE, and sMAPE, particularly in short- to medium-horizon settings. Return-oriented studies are more likely to incorporate directional measures when prediction sign or trading relevance is important. Volatility and risk-sensitive studies more often rely on interval, calibration, or tail-oriented diagnostics, especially when uncertainty communication or risk management is central to the forecasting objective. This indicates that evaluation quality should be interpreted in relation to the forecasting target and study design rather than through a single metric hierarchy [71].

Table 5. Performance Assessment Metrics, Validation Protocols, and Diagnostics in the Reviewed Studies

Evaluation Aspect	Metrics / Approaches Used	Typical Models / Contexts	References
Scale-dependent point-forecast error	RMSE and MAE are commonly used to measure prediction	ARIMA, Holt–Winters, SVR, and deep learning baselines	[1], [5], [7], [9], [17]–[19], [22], [23], [33], [37]

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Evaluation Aspect	Metrics / Approaches Used	Typical Models / Contexts	References
	errors in their original scale.	applied to Indonesian blue-chip stocks and stock indices, as well as comparative studies between LSTM and transformer-based models.	
Scale-free point-forecast error	MAPE and sMAPE are employed to support error comparison across time series with different scales.	Cross-study evaluations involving datasets or stock series with varying price ranges and market characteristics.	[5], [19], [22]
Supplementary goodness-of-fit for linear baselines	R^2 and Theil's U are used as additional indicators of model fit and comparative forecasting performance.	Classical statistical models during model specification, comparison, and selection processes.	[7], [9], [10]
Directional performance	Directional Accuracy, hit ratio, and up–down precision/recall are used to evaluate the ability of models to predict market movement direction.	Models incorporating technical indicators, news, and sentiment features, including LSTM, GRU, and transformer–GRU architectures.	[3], [19]–[22], [47], [71]
Probabilistic calibration	Prediction interval coverage, mean or median interval width, and CRPS are used to assess uncertainty representation and calibration quality.	Bayesian nonparametric QGAM and semi-shared Bayesian multi-series forecasting models.	[29], [30]
Risk and tail-oriented evaluation	VaR and Expected Shortfall are evaluated using Kupiec and Christoffersen backtesting procedures.	GARCH and VAR-GARCH models, particularly in equity and commodity volatility forecasting studies.	[11]–[14], [25], [28]
Validation protocol	Rolling-origin validation, walk-forward testing, multi-horizon evaluation, and event-based out-of-sample splits such as pre/post COVID-19 or election periods.	Applied across various model families, particularly in studies requiring regime-aware evaluation and robustness testing.	[1], [3], [19], [22], [26], [35], [38]
Model selection and diagnostic testing for linear models	AIC, BIC, Ljung–Box test, ARCH–LM test, and normality checks are used for model selection and residual diagnostics.	ARIMA, ARFIMA, state-space models, and GARCH-based modelling frameworks.	[7], [8], [10], [12], [13]

Source: (Research Results, 2025)

Discussion

Throughout this review, the findings are interpreted as reported associations and context-dependent performance patterns within the included studies, rather than as universal or causal claims about model superiority. The results of this systematic literature review indicate that stock market forecasting has evolved into a methodologically diverse research area, while remaining strongly influenced by dataset characteristics and market conditions. The reviewed literature shows that sequence-based deep learning and transformer-based models now occupy a dominant position in stock market forecasting, particularly in settings involving multivariate and information-rich datasets, including those from emerging markets such as Indonesia. At the same time, the findings also confirm that statistical and volatility-oriented models continue to play an important role, especially in relatively stable or less turbulent market conditions. This suggests that newer forecasting approaches have not rendered earlier methodologies obsolete; rather, they have redefined their relevance within broader and more context-sensitive forecasting frameworks.

The findings further reveal a mismatch between the rapid advancement of forecasting architectures and the comparatively slower development of rigorous evaluation practices. Although deep learning and transformer-based approaches have become increasingly prominent, uncertainty-aware forecasting and decision-oriented validation remain relatively underexplored. The limited adoption of probabilistic metrics, volatility-informed deep

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learning, and realistic trading backtesting indicates that most studies continue to prioritise point-forecast accuracy.

CONCLUSION

The comprehensive review of literature combines a sum of 71 research papers on stock price forecasting assignments. The research is classified according to predictions, methods, data traits, information preparation, and assessment methods. This systematic literature review synthesises the related work and develops a structured taxonomy and quantitative evidence map illustrating how forecasting approaches are positioned across different methodological and market contexts. The findings show that forecasting performance is strongly context dependent. Classical statistical models remain effective for stationary univariate series over short horizons. Volatility-oriented and multiseries models are reported to perform well when markets exhibit clustering and spillover effects. During regime shifts or policy-driven disruptions, intervention-based and jump-diffusion approaches become more relevant. As datasets evolve into multivariate and feature-rich panels, model performance patterns also change. Deep learning and transformer-based architectures are frequently reported to perform well in these settings and often appear more suitable than traditional methods under multivariate and feature-rich conditions in these settings. Their advantages become clearer when technical indicators, macroeconomic variables, and sentiment information are included. Hybrid linear and nonlinear implementations further enhance stability and performance when supported by appropriate optimisation. Despite these advances, several gaps remain in the literature. Open benchmark datasets that are standardised by market regime are still lacking. The integration of volatility modelling into deep learning frameworks remains limited, and uncertainty-aware evaluation is rarely applied. Consequently, future studies should emphasize regime annotated benchmarks, hybrid volatility deep learning architectures, probabilistic predictions, and practical validation using rolling tests and trading-focused backtesting.

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