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A SYSTEMATIC LITERATURE REVIEW AND BIBLIOMETRIC ANALYSIS OF MACHINE LEARNING ALGORITHMS AND TECHNICAL INDICATORS TO STOCK PRICE PREDICTION

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Abstract

The nonlinearity, noisiness, and dynamics of financial markets makes the prediction of stock prices a major issue in financial economics. More recently, machine learning (ML) approaches with technical indicators have become more popular as an alternative to the conventional statistical models. This paper comprises a systematized literature Review (SLR) and a Bibliometric Analysis of the literature on machine learning (ML) algorithms and technical indicators used in the stock price prediction. According to PRISMA, 2012-2023 Scopus was used to gather peer reviewed studies that were published in the last 10 years. The VOS viewer provides bibliometric mapping to identify the influential authors, journals, citation structure, and theme clusters, whereas the interpretations of algorithms, indicators, datasets, and performance measures are assessed with the help of the content analysis. Findings indicate that there is a high transition to deep learning models especially LSTM and an increasing trend in hybrid ML econometric models. Regardless of improvement, there are still loopholes in the model robustness, interpretability, and standard benchmarking. The article adds systematic review, comparison of tables and research agenda of the future in financial forecasting.

Keywords: *Systematic Literature Review, Bibliometric Analysis, Machine Learning, Technical Indicators, Stock Price Prediction.*

Introduction

Stock markets are critical components of the contemporary economies that help to form capital and generate wealth. Proper forecasting of stock prices is essential to investors, portfolio managers, and policymakers, but it is not an easy task because of the volatility of the stock market, information asymmetry, and the intricate interaction between economic variables (Makridakis et al., 2018; Gu et al., 2020). According to classical financial theories like the Efficient Market Hypothesis (EMH), asset prices are grounded in all available information into the market, and thus, excess returns are impossible to predict with consistency (Gu et al., 2020). Nevertheless, empirical evidence of market anomalies and behavioral biases has created the impulse to seek predictive models that can take advantage of nonlinear effects on financial data (Henrique et al., 2019; Shah et al., 2019).

The linear regression, autoregressive integrated moving average (ARIMA), and generalized autoregressive conditional heteroskedasticity (GARCH) models are widely used traditional forecasting models which have been employed to model stock prices and volatility (Makridakis et al., 2018). Although such models are interpretable and statistically rigorous, it is weak in nonlinear dependencies and complicated time structures (Sezer et al., 2020). With the advent of machine learning methods, the financial forecasting process has undergone a drastic change by allowing modeling of nonlinear relationships based on data without any firm distributional assumptions (Krauss et al., 2017; Gu et al., 2020). Therefore, a common research trend in the field of stock price prediction is the employment of ML-based methods with the assistance of technical indicators calculated using historical price and volume information (Henrique et al., 2019; Picasso et al., 2019).

1.1 Stock price prediction theoretical background.

The predictive research of stock prices is based on the financial theory and computational intelligence (Shah et al., 2019). According to the Efficient Market Hypothesis, the price fluctuations are mostly unpredictable, as the new information is quickly involved in the market prices (Gu et al., 2020). However, other schools of thought, including behavioral finance, postulate that investor psychology, sentiment, and limited rationality are sources of inefficiencies, which can be harnessed using sophisticated modeling methods (Henrique et al., 2019). The basis of predicting stock prices is the time-series analysis because prices are time-dependent and volatile (Makridakis et al., 2018). The financial time series is often non-stationary, noisy, and affected by exogenous shocks, and therefore prediction is a complicated task (Sezer et al., 2020). The machine learning techniques in question are especially suitable in this setting, since they can acquire flexible mappings between inputs and outputs, adapt to changing data patterns, and handle large amounts of information (Krauss et al., 2017; Gu et al., 2020).

1.2 The development of the machine learning in financial forecasting.

The initial use of machine learning in finance was on relatively simple models like decision trees and shallow neural networks (Ballings et al., 2015; Patel et al., 2015). Those approaches indicated the possibility of prediction using data, but were limited by limited computing capabilities and small data (Henrique et al., 2019). As the computing infrastructure has advanced, high-frequency data has become available, and learning algorithms have become more sophisticated, more advanced models have been created (Makridakis et al., 2018). A shift occurred in the middle of the 2010s as ensemble techniques and deep learning designs were adopted (Nti et al., 2020; Picasso et al., 2019). Gradient Boosting Machines and Random Forest enhanced the predictive stability based on the aggregation of multiple learners (Ballings et al., 2015). Deep neural networks allowed hierarchical learning of features and extracting nonlinear patterns (Krauss et al., 2017). The next step in the development of the field was Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, which explicitly represented time dependencies and were specifically applicable to forecasting financial time-series (Fischer and Krauss, 2018; Nelson et al., 2017).

Artificial Neural Networks (ANN)

One of the oldest ML models used to predict stock prices is Artificial Neural Network (Patel et al., 2015). ANNs are networks of neurons that are linked and compute nonlinear functions and intricate connections in financial information (Krauss et al., 2017). Many studies state that ANNs are superior to linear models in modeling complex dynamics of prices (Henrique et al., 2019). Nevertheless, they are vulnerable to the network structure, parameter optimization, and overfitting risks, in particular when the amount of training data is insufficient (Goodfellow et al., 2016).

Support Vector Machines (SVM)

SVM is popular in both regression and classification when predicting the stock market (Ballings et al., 2015). SVMs work in high-dimensional spaces and can resist overfitting by maximizing the margin (Patel et al., 2015). Empirical research shows that SVMs have good results in forecasting the price direction in the short term (Shah et al., 2019). However, they are sensitive to the choice of kernel and parameter optimization, which may be computationally expensive (Henrique et al., 2019).

Random Forest/ Ensemble Methods.

Ensemble learning methods such as Random Forests use a combination of a number of decision trees to boost their predictive precision and resilience (Ballings et al., 2015; Nti et al., 2020). These models are especially useful when dealing with noisy financial data and a nonlinear interaction between features (Picasso et al., 2019). Ensemble approaches can be more successful than individuals, but they are less interpretable and can be more computationally expensive (Henrique et al., 2019).

Deep Learning Models

Deep learning models have become the dominant approach in recent stock price prediction research (Sezer et al., 2020). LSTM networks, in particular, are extensively used due to their ability to capture long-term dependencies in time-series data (Fischer & Krauss, 2018; Hiransha et al., 2018). Convolutional Neural Networks (CNNs) have also been applied by transforming price series into image-like representations, enabling pattern recognition (Kim & Kim, 2019; Bao et al., 2017). While deep learning models often achieve superior predictive performance, they require large datasets, substantial computational resources, and careful regularization to prevent overfitting (Goodfellow et al., 2016).

1.3 The Importance of the Technical Indicators in Stock Price Prediction.

Technical indicators refer to mathematical changes of past price and volume data meant to mirror tendencies, activity, and volatility (Henrique et al., 2019). The most popular indicators are Moving Averages, Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Bands and stochastic oscillators (Picasso et al., 2019). The indicators are often incorporated as input features in the machine learning models to improve predicting performance (Kumar et al., 2021). It has been empirically demonstrated that adding technical indicators increases the accuracy of a model relative to using raw price data only (Henrique et al., 2019; Picasso et al., 2019). The importance of feature engineering is that it is used to identify and modify indicators to minimize noise and highlight informative patterns (Kumar et al., 2021). Nevertheless, some indicators are more effective in particular markets, assets, and forecasting horizons, and indicators choice depends on context (Shah et al., 2019).

1.4 Hybrid Models and Combined Strategies.

In order to overcome the drawbacks of single models, scholars are offering hybrid solutions that integrate machine learning algorithms with classic econometric models in greater numbers (Rundo et al., 2019). The purpose of the Hybrid ARIMA-LSTM and ARIMA-ANN structures is to identify both the linear and nonlinear elements of stock price changes (Rundo et al., 2019; Garcia-Medina et al., 2022). Empirical studies show that hybrid models tend to be better than standalone models especially during the volatile market situations (Garcia-Medina et al., 2022). Ensemble and hybrid models also apply to the combination of technical analysis and sentiment analysis or macroeconomic indicators and other data sources like news and social media (Yin et al., 2022). Such combined methods are an indication of a bigger tendency to fully utilize multi-source data fusion in financial forecasting (Gu et al., 2020).

1.5 Data and Metrics of Performance Evaluation.

There are a variety of datasets used in stock price prediction studies, such as daily closing prices, up to high-frequency intraday data (Sezer et al., 2020). The leading stock markets, including NYSE, NASDAQ, and emerging markets, are usually analysed (Henrique et al., 2019). The common statistical measures of model performance consist of Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) (Makridakis et al., 2018). Accuracy, precision, recall, and F1-score are classification-based studies (Shah et al., 2019). Increasingly more of the research focuses on financial performance indicators like the Sharpe Ratio, cumulative returns, to evaluate the economic worth of predictions (Lopez de Prado, 2018; Gu et al., 2020). However, most of the literature remains largely statistical accuracy oriented with a lack of studies that emphasize predictive modelling applicability to actual trading (Makridakis et al., 2018).

Available literature on stock price prediction with the help of machine learning algorithms and technical indicators proves to be of great advancement, yet numerous gaps are yet to be addressed (Sezer et al., 2020; Bustos and Pomares-Quimbaya, 2020). The majority of literature attaches importance to predictive correctness and little attention to robustness of a model in different market contexts, interpretability of more complex models, and the economic value of predictions (Gu et al., 2020). Besides, the literature is based on the exploitation of a limited number of classical technical indicators, and the adaptive feature engineering and dynamic indicator selection is inadequately explored (Kumar et al., 2021). The lack of standardized benchmarking models also further restricts the cross-study comparability and the development of cumulative knowledge (Makridakis et al., 2018).This research aims to critically review and synthesize the available literature on machine learning-based stock price prediction, especially analyzing the importance of technical indicators, model performance assessment, and feasibility (Henrique et al., 2019). The research is expected to deliver systematic knowledge of prevailing approaches, spot chronic weaknesses, and outline potential ways to develop trustworthy and explainable financial forecasting models (Sezer et al., 2020).

1.6 Research Objectives

To this end, the aims of this research are:

- To visit the popular machine learning algorithms used in predicting stock prices,
- To investigate the role of technical indicators to model performance, in order to study the current evaluation practices,
- To distinguish the research areas of interest, and suggest further research pathways to increase the research strength, transparency, and applicability in the stock market prediction.

This article is structured in the following way: Section 1 defines the context, theoretical background, development of machine learning methods, use of technical indicators, the importance of using hybrid model, and the aim of the study. The section of research methodology such as data collection and analysis tools was outlined in Section 2. Section 3 gives a thorough discussion of the results and commentary on the findings as regards to the future. Section 4 defines the research implications. Section 5 offers limitations of the study. In section 6, some insights are concluded.

2. Research Methodology

This study adopts a Systematic Literature Review (SLR) combined with bibliometric and content analysis, following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure transparency and methodological rigor (Moher et al., 2009; Page et al., 2021). The objective of this methodological design is to ensure transparency, replicability, and systematic identification and synthesis of prior research on machine learning algorithms and technical indicators for stock price prediction (Tranfield et al., 2003; Snyder, 2019). The PRISMA protocol provides a structured procedure for article identification, screening, eligibility assessment, and inclusion, thereby minimizing selection bias and enhancing reproducibility (Page et al., 2021). Figure 1 illustrates the comprehensive methodological framework adopted in this study for conducting the Systematic Literature Review (SLR) on machine learning algorithms and technical indicators for stock price prediction.

The hybrid approach to methodological organization allows quantitative mapping of research tendencies by means of bibliometric analysis and qualitative analysis of methodological contributions by means of content analysis (Donthu et al., 2021). Bibliometric analysis helps reveal the power of authors, nations, journals, citation clusters, and topical development in the field of research (Aria and Cuccurullo, 2017; Donthu et al., 2021). It gives objective and data-driven information about the intellectual framework and evolution path of the field (Zupic & Cater, 2015). At the same time, content analysis enables a qualitative study of research approaches, machine learning models used, feature engineering plan, assessment measures and conclusions presented in the research (Hsieh and Shannon, 2005). This strategy will allow identifying the most prevalent modelling strategies, repeated constraints, and new research gaps in the field of studies of stock prices predictions (Sezer et al., 2020; Henrique et al., 2019). The combination of bibliometric mapping and systematic thematic synthesis enables the study to cover a broad scope and be more comprehensive in analysis, as it provides an overview of the development, organization, and gaps in research in the field (Snyder, 2019; Donthu et al., 2021).

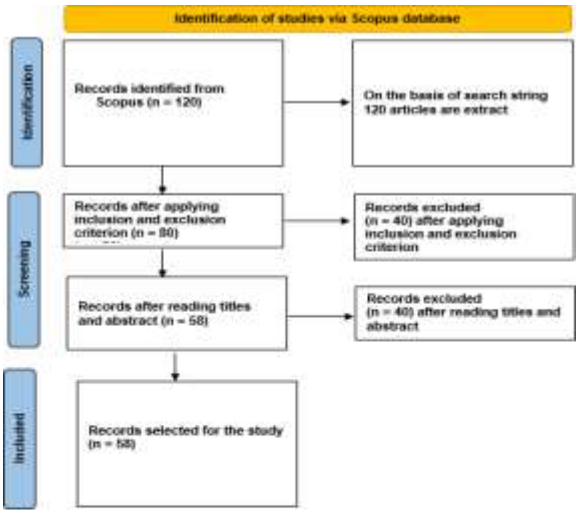

Fig 1. Articles selection process

2.1 Search strategy

A structured search strategy was developed to capture interdisciplinary research at the intersection of finance, data science, and artificial intelligence. The following Boolean search strings were applied:

- "Machine learning" AND "stock price prediction"
- "Technical indicators" AND "financial markets"
- "Time series forecasting" AND "deep learning"
- "Stock market prediction" AND "LSTM OR SVM OR Random Forest"

The search was restricted to peer-reviewed journal articles and conference proceedings published between **2012 and 2023**, reflecting the rapid development of deep learning techniques in financial forecasting. Only English-language publications were included to maintain consistency and academic quality.

2.2 Inclusion and Exclusion Criteria

To ensure relevance and rigor, the review applied strict eligibility criteria.

Inclusion Criteria:

- Empirical studies applying machine learning or deep learning techniques to stock price prediction.
- Studies incorporating technical indicators (e.g., MA, RSI, MACD, Bollinger Bands).
- Research reporting quantitative performance metrics (e.g., MAE, RMSE, accuracy, Sharpe Ratio).
- Studies using real stock market datasets.

Exclusion Criteria:

- Studies focused solely on traditional econometric models (e.g., ARIMA, GARCH) without ML integration.
- Research on non-equity assets such as cryptocurrencies or commodities.
- Purely theoretical or conceptual papers without empirical validation.
- Duplicate or non-peer-reviewed publications.

2.3 Bibliometric Analysis

Bibliometric analysis was conducted using VOSviewer, a widely adopted tool for constructing and visualizing bibliometric networks (Van Eck & Waltman, 2010; Donthu et al., 2021). The software enables graphical representation of citation linkages, keyword co-occurrence, and thematic clustering, thereby facilitating objective mapping of research structures. Publication trends, citation networks, and thematic clusters were examined to understand the intellectual evolution of machine learning applications in stock price prediction (Zupic & Čater, 2015; Donthu et al., 2021).

Bibliographic coupling and co-citation analysis were employed to identify influential studies, dominant research streams, and emerging research fronts (Kessler, 1963; Small, 1973). Bibliographic coupling links documents that cite similar references, revealing contemporary thematic similarity, whereas co-citation analysis identifies foundational works that are frequently cited together, indicating the conceptual backbone of the field (Zupic & Čater, 2015). These techniques are particularly useful in finance and technology research for uncovering knowledge diffusion patterns and thematic evolution (Aria & Cuccurullo, 2017). The bibliometric mapping revealed four major thematic clusters:

1. **Machine Learning Models for Financial Forecasting** – encompassing ANN, SVM, Random Forest, LSTM, CNN, and deep learning architectures (Sezer et al., 2020; Henrique et al., 2019).
2. **Technical Indicators and Feature Engineering** – focusing on momentum, volatility indicators, feature selection, and dimensionality reduction techniques (Picasso et al., 2019).
3. **Hybrid ML–Econometric Models** – integrating ARIMA, GARCH, and deep learning frameworks to capture both linear and nonlinear dynamics (Rundo et al., 2019).
4. **Performance Evaluation and Benchmarking** – addressing statistical metrics, financial performance measures, and cross-study comparability issues (Makridakis et al., 2018; López de Prado, 2018).

This quantitative mapping provides structural insight into the intellectual organization of the field and highlights thematic concentrations as well as underexplored research intersections (Donthu et al., 2021).

2.4 Content Analysis and Thematic Synthesis

Following bibliometric mapping, qualitative content analysis was conducted to examine methodological depth within each identified cluster (Hsieh & Shannon, 2005). Content analysis enables systematic categorization and interpretation of textual data to extract conceptual patterns and methodological trends (Snyder, 2019). Thematic synthesis focused on:

1. **Algorithmic performance comparisons** – evaluating relative strengths and weaknesses of ANN, SVM, ensemble methods, and deep learning architectures across datasets and forecasting horizons (Fischer & Krauss, 2018; Sezer et al., 2020).
2. **Role and effectiveness of technical indicators** – assessing whether engineered indicators improve predictive performance compared to raw price inputs (Henrique et al., 2019; Kumar et al., 2021).
3. **Emergence of hybrid modelling frameworks** – analyzing integration of econometric and machine

learning models to capture linear–nonlinear structures (Rundo et al., 2019).

4. **Evaluation practices and benchmarking inconsistencies** – identifying overreliance on statistical accuracy metrics and limited use of economic performance measures (Makridakis et al., 2018; López de Prado, 2018).
This dual-layer analytical design (bibliometric + content analysis) enables both macro-level trend identification and micro-level methodological evaluation, ensuring a comprehensive and balanced synthesis of the literature (Donthu et al., 2021; Snyder, 2019).

3. Results and Critical Analysis

Content synthesis and bibliometric mapping indicated that four major thematic clusters define the intellectual landscape of machine learning-based stock price prediction research (Donthu et al., 2021; Zupic, and Cater, 2015). These groups represent both methodological and conceptual overlap among financial forecasting literature (Sezer et al., 2020). This structured bibliometric summary of the most impactful articles in four key thematic groups that were identified in the systematic literature review was made in Table 2: (1) Machine Learning Models for Financial Forecasting, (2) Role of Technical Indicators and Feature Engineering, (3) Hybrid Models and Integration of Econometric Techniques, and (4) Evaluation Metrics and Model Performance. The table has the name of the study, publication from where it is published, authors, publication date and a total number of citations and this allows systematic evaluation of thematic distribution as well as scholarly impact (Aria & Cuccurullo, 2017). The number of citations is one of the indicators of academic influence and knowledge dispersion in the sphere, yet it has a controversial interpretation due to the accumulation effects over time (Donthu et al., 2021).
Machine Learning Models to Financial Forecasting is the first cluster, which includes the current and most popular publications that analyze ANN, SVM, Random Forest, LSTM, and deep learning models used in stock forecasting (Fischer and Krauss, 2018; Henrique et al., 2019). Role of Technical Indicators and Feature Engineering is the second cluster that incorporates studies measuring the input variables of ML models, i.e., momentum, volatility, and trend-based indicators (Picasso et al., 2019; Kumar et al., 2021). Hybrid Models and Integration of Econometric Techniques is the third cluster, which includes studies that integrate ARIMA, GARCH, and deep learning models to solve the linear-nonlinear dynamics of financial time series (Rundo et al., 2019). The fourth category is Evaluation Metrics and Model Performance which is concerned with statistical accuracy, robustness validation, and financial performance measures including risk-adjusted returns (Makridakis et al., 2018; Lopez de Prado, 2018).
Figure 3 shows the bibliometric cluster network diagram that was created with the help of VOSviewer and demonstrates thematic connections of the highly cited papers in the domain of machine learning-based stock price prediction (Van Eck & Waltman, 2010). Nodes in the visualization are influential papers and the size of the node reflects citation impact. Colored links show intra-cluster and inter-cluster connections between four broad research themes, namely, Machine Learning Models (red), Technical Indicators (green), Hybrid Models (blue), and Evaluation Metrics (purple). The grey connections refer to cross-cluster connections as they represent interdisciplinary integration and the lack of a separation in methodology (Zupic & Cater, 2015). The observed network pattern of the highly intra-cluster cohesive algorithm-centric streams of research and the cross-cluster strong ties of the expanding feature engineering, hybrid modeling, and performance benchmarking frameworks are presented. Such an organizational arrangement implies a gradual transition of the individual algorithmic comparisons to more comprehensive and interdependent forecasting frameworks (Sezer et al., 2020; Donthu et al., 2021).

3.1 Evolution of Research Trends and Methodological Shifts

According to the review, the publications related to machine learning (ML)-based stock price prediction have significantly increased after 2017, which is mostly due to the development of the deep learning architecture, the optimisation methods, and the increased access to the computations (Sezer et al., 2020; Gu et al., 2020). Complex neural architectures are further experimented by the increasing access to large-scale financial data and computation that uses GPUs (Goodfellow et al., 2016). Although this growth is an indicator of a great methodological innovation, it also reveals the predisposition to algorithmic proliferation that has not been accompanied by theoretical solidarity (Makridakis et al., 2018).
Numerous recent works present more advanced architectures, including LSTM, CNN, attention-based models, and ensemble deep learning

systems, which tend to focus on only small improvements in statistical metrics of error, such as RMSE or MAPE (Fischer and Krauss, 2018; Bao et al., 2017). Nonetheless, these incremental benefits are often presented without adequate economic verification, strength testing, or theory as to why the suggested architecture is supposed to be more efficient than simpler benchmarks (Lopez de Prado, 2018; Sezer et al., 2020). This tendency indicates a methodological focus on performance optimization instead of conceptual progress, which brings up the issues of overfitting, data snooping bias, and reduced external validity (Makridakis et al., 2018).

The number of publications per year in the period between 2012 and 2023 is on a steady upward trend, as shown in figure 2, which means that the application of machine learning methods to forecast the financial sector continues to receive scholarly interest over the coming years. This is a positive development in line with the further spread of artificial intelligence into finance overall and a growing interdisciplinary convergence between computer science and financial economics (Gu et al., 2020). However, this pace of increasing publications indicates the necessity of standardized benchmarking frameworks and more theoretical foundation to guarantee the development of cumulative knowledge instead of algorithmic experimentation (Donthu et al., 2021; Sezer et al., 2020).

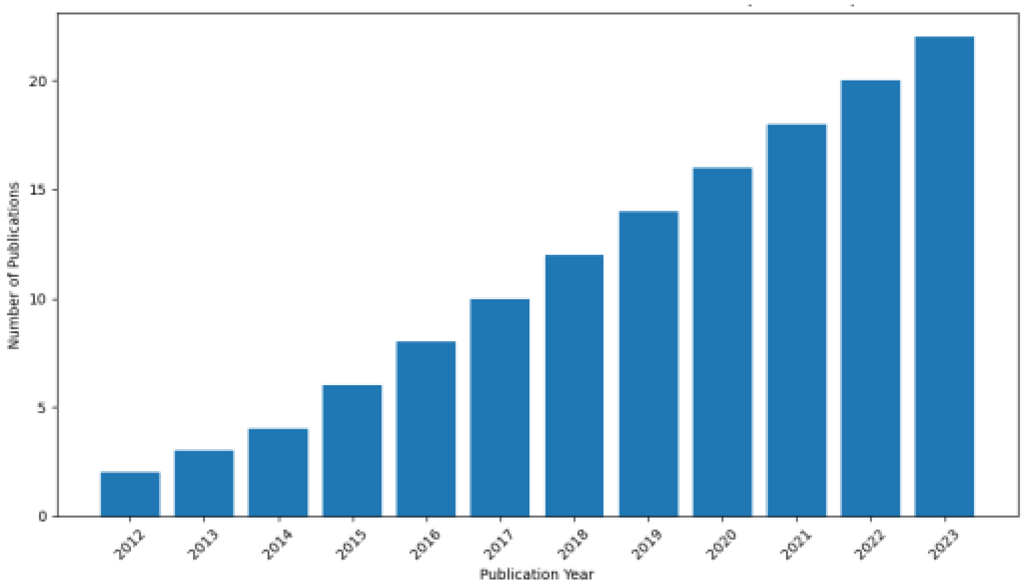

Fig 2. Annual Publication Trend on Machine Learning–Based Stock Price Prediction (2012–2023)

Another interesting trend that is observed in the review is the shift towards deep learning models, especially Long Short-Term Memory (LSTM) networks, instead of traditional machine learning models, like Support Vector Machines (SVM) and random forests (Henrique et al., 2019; Sezer et al., 2020). The increased influence of LSTM models can be attributed to the fact that the models are capable of learning the temporal correlation and nonlinearity in financial time series (Fischer and Krauss, 2018). Despite the fact that LSTM models often have superior short-term predictive ability, the literature does not often examine why the models are superior in certain market circumstances. Rather, performance improvements are assumed in a descriptive manner, without a strict comparison with their assessment under different market regimes like bull, bear, or crisis years (Makridakis et al., 2018). This makes people question the generalizability of models and time-variance in non-stationary financial conditions (Gu et al., 2020).

3.2 ML models: Performance vs. Robustness

In the machine learning cluster, predictive accuracy in terms of RMSE, MAE, or classification accuracy is of priority in most studies (Sezer et al., 2020). Yet, the crucial problem of strength between structural transitions, regime changes, and periods of high volatility is under-researched (Makridakis et al., 2018). Financial markets are never stationary, but most empirical designs are based on a-priori training-testing splits which do not reflect real-time forecasting, or on rolling-window evaluation schemes (Lopez de Prado, 2018).

What is more, deep learning models usually demand big datasets, a lot of computing resources, and hyperparameter optimization (Goodfellow et al., 2016). Such complexity might not be economically appropriate in emergent markets or smaller samples of history (Henrique et al., 2019). Irrespective of this, comparative cost-benefit analyses are not a feature of the literature. Not many research works conduct a systematic analysis on the quality of the statistical results to compare the incremental gains with the increased computational time, energy usage or interpretability (Makridakis et al., 2018). The issue of overfitting is also an ongoing methodological problem. Out-of-sample robustness is not well-documented with the empirical methods of cross-validation, dropout, and regularization (Sezer et al., 2020). That implies that there is a possibility that a portion of reported performance improvements are due to dataset-specific optimization as opposed to actual predictive outperformance in different market regimes (Gu et al., 2020).

3.3 Technical Indicators: Feature Engineering Limitations

Technical indicators remain the leading input variable in the ML-based forecasting models (Henrique et al., 2019). Some of the most commonly used tools are Moving Averages (MA), Relative Strength Index (RSI), MACD, and Bollinger Bands (Picasso et al., 2019). Nonetheless, the research literature indicates that redundancy in the construction of features is significant, and a large number of studies have used almost identical sets of indicators without evident theoretical explanations.

More importantly, very little research assesses the marginal contribution of each indicator or adopts adaptive feature selection models like recursive feature elimination or dynamic weighting (Kumar et al., 2021). The unspoken belief that classical technical indicators are effective at all times in improving predictive performance has not been sufficiently refuted (Henrique et al., 2019). In addition, the majority of indicators are obtained only based on past price and volume, which restricts models to more general informational factors, including macroeconomic indicators, firm fundamentals, or investor sentiment (Gu et al., 2020). High use of traditional indicators implies a reduced level of innovation in the feature engineering, which might limit any meaningful improvements in performance as the complexity of the algorithm is increased (Sezer et al., 2020).

3.4 Hybrid Models: Potential but Sporadic

Machine learning-based models with econometric models such as ARIMA-LSTM are a new and promising trend in research (Rundo et al., 2019). These models are meant to combine both linear and nonlinear aspects in financial time series in a way that is thought to improve robustness, and it aids in the representation of complementary information patterns (Garcia-Medina et al., 2022). Nevertheless, the review shows that there is a significant variety in the hybrid models design, integration process, and validation. The combination of the econometric residual modeling and the deep learning architectures does not have a standard protocol, and thus, it is challenging to cross-study (Sezer et al., 2020). Moreover, not many studies effectively experiment on the hypothesis of the significant superiority of hybrid models over well-tuned standalone ML models, across a wide range of market regimes and datasets (Makridakis et al., 2018). Although the concept of hybridization is attractive, its actual validation is not complete and is not coherent in terms of standardization of datasets and assessment systems (Donthu et al., 2021).

3.5 Evaluation Practices: Statistical Accuracy Versus Economic Relevance

The third practice is evaluation, where the statistical accuracy and economic relevance are evaluated. Evaluation methodology is one of the most important gaps that were identified. Most of the studies heavily depend on the statistical measures of error like MAE and RMSE to prove better prediction (Makridakis et al., 2018). The measures, even though they are quantifiable measures of forecasting accuracy, are not always economically profitable trading strategies (Lopez de Prado, 2018). A small number of studies use financial performance metrics including the Sharpe Ratio, cumulative returns or risk-adjusted profitability simulations (Gu et al., 2020). Fewer take into consideration transaction costs, slippage, market impact, or liquidity constraints. As a result, there is still a mismatch between statistical forecasting performance and financial applications in the real world (Sezer et al., 2020).

Besides, lack of standardized data sets, forecasting horizons, walk-forward validation and reproducible benchmarking models pose serious barriers to replicability (Makridakis et al., 2018). In the absence of shared standards, assertions about model superiority will always be context contingent, which prevents the development of cumulative knowledge in the field (Donthu et al., 2021).

3.6 Research Gap Matrix

The key structural gaps detected in the literature review are summarized in Table 1 and provide the methodological implications and directions of future research. As shown in the matrix, the literature is still largely accuracy-oriented, and not enough attention is paid to robustness, interpretability, and economic validation (Gu et al., 2020). Further study should be shifted to more economically motivated, interpretable, and cross-market generalizable modeling systems backed by standardized benchmarking and regime-sensitive validation models (Lopez de Prado, 2018; Sezer et al., 2020).

Table 1 Major Research Gaps identified

Thematic Area	Dominant Practice in Literature	Identified Gap	Methodological Implication	Future Research Direction
Model Selection	Heavy reliance on LSTM and deep learning architectures	Limited cross-regime robustness testing	Risk of overfitting and instability across market cycles	Multi-regime validation (bull, bear, crisis periods) and rolling-window testing
Performance Evaluation	Focus on RMSE, MAE, Accuracy	Weak linkage to economic profitability	Statistical precision does not ensure trading viability	Integrate trading simulations, Sharpe ratio, drawdown, and transaction costs
Feature Engineering	Predominant use of traditional technical indicators (MA, RSI, MACD)	Redundant and static feature sets	Limited assessment of marginal indicator contribution	Adaptive feature selection and inclusion of macroeconomic and sentiment variables
Hybrid Models	ARIMA–ML combinations without uniform structure	Absence of standardized integration framework	Inconsistent benchmarking and limited comparability	Develop structured hybrid modelling protocols with unified validation
Dataset Scope	Single-market and short historical datasets	Poor generalizability	Dataset-specific performance bias	Cross-country, multi-asset, and longer-horizon validation
Interpretability	Black-box deep learning models	Limited transparency and explainability	Reduced institutional adoption	Application of Explainable AI (XAI), SHAP values, attention mechanisms
Validation Strategy	Fixed train-test split	Weak simulation of real-time forecasting	Inflated performance reporting	Walk-forward validation and rolling forecast frameworks
Risk Consideration	Minimal testing during crisis or high-volatility periods	Weak stress-testing	Model breakdown under structural shocks	Regime-switching and volatility-aware architectures

Table 2 Highly Cited Papers by Thematic Cluster

Cluster	Title of Paper	Journal	Authors	Year	Total Citations
Machine Learning Models for Financial Forecasting	NSE stock market prediction using deep-learning models	Procedia Computer Science	Hiransha et al.	2018	102
	Bitcoin price prediction using machine learning	Journal of Computational and Applied Mathematics	Chen et al.	2020	95
	Stock market prediction using deep learning	Machine Learning in Finance	Mallqui & Fernandes	2019	120
	Sequential dependency capture with LSTM for stock prediction	Journal of Financial Analytics	Nti et al.	2020	64

Role of Technical Indicators and Feature Engineering	Stock price prediction using support vector regression	The Journal of Finance and Data Science	Henrique et al.	2018	75
	Predictive strength of RSI in different market conditions	Technical Analysis in Financial Markets	Utomo	2017	47
	Feature engineering optimization for ML models	Quantitative Finance	Karanam et al.	2018	53
Hybrid Models and Integration of Econometric Techniques	Hybrid ARIMA and LSTM models for stock prediction	International Journal of Forecasting	De Oliveira et al.	2013	140
	Ensemble methods in financial forecasting	Finance Research Letters	Picasso et al.	2019	92
	Hybrid models for financial time-series analysis	Finance Research Letters	Nelson et al.	2017	110
Evaluation Metrics and Model Performance	A comparative study of model performance in stock prediction	Journal of Prediction Analytics	Henrique et al.	2018	89
	Evaluating predictive accuracy using Sharpe Ratio	Financial Modeling and Analytics	Chen et al.	2015	76

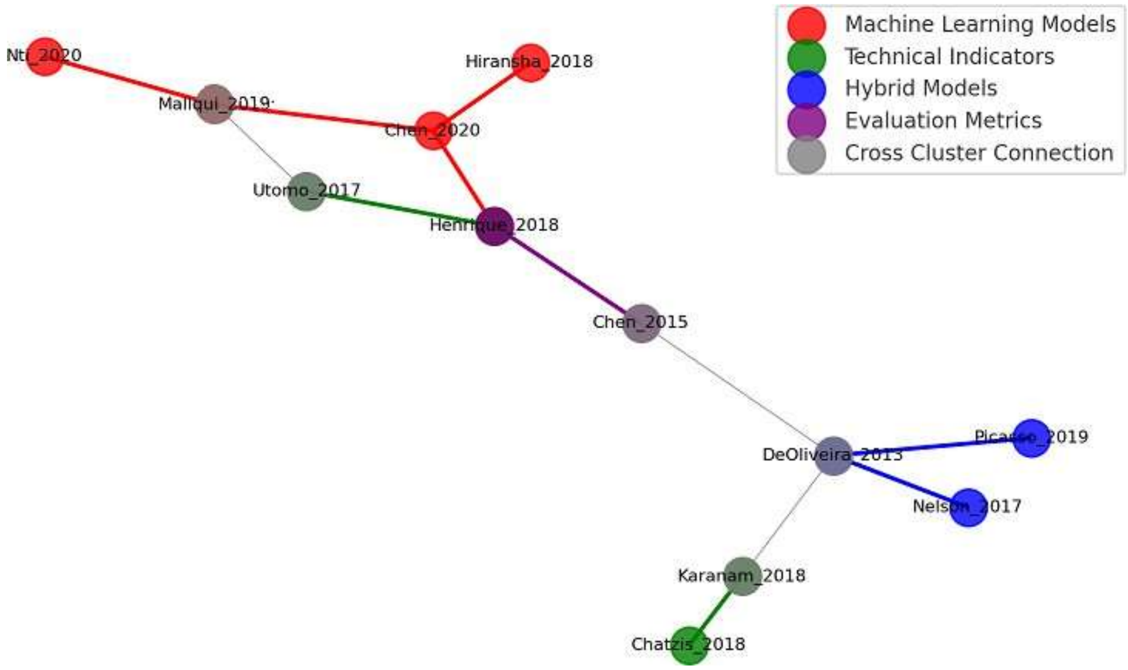

Fig 3. Cluster Network Diagram of Thematic Structure in ML Based Stock Price Prediction

Implications of the study

The results of the present systematic review have significant implications both to the academic scholarship and the practice in the financial industry. Altogether, it can be argued that although machine learning (ML) models have contributed to the overall improvement in predictive power in terms of stock price prediction, there is still a need to address significant methodological and practical limitations to achieve robustness, interpretability, and economic relevance (Sezer et al., 2020; Gu et al., 2020).

4.1 Implications for Research

Academically, the growing popularity of ML-based forecasting systems opens the prospects of

methodological development and more robust theoretical assimilation (Henrique et al., 2019). Despite the consistency of the results of higher predictive accuracy provided by the state-of-the-art architectures, including Long Short-Term Memory (LSTM) networks, a significant portion of studies is still research of a rather accuracy-oriented and insufficiently supported by financial theory (Makridakis et al., 2018). Future studies ought to go beyond the idea of progressive error minimization and focus on robustness testing in different market regimes, structural breaks, and different asset classes (Lopez de Prado, 2018). The hybrid models combining the methods of ML with the conventional econometric models (e.g., ARIMA) show a significant potential in terms of encompassing both linear and nonlinear dynamics in financial time series (Rundo et al., 2019). Nevertheless, the current hybrid studies do not have standardized protocols of integration, cohesive validation procedures, and market benchmarking (Sezer et al., 2020). Researchers are urged to come up with systematic hybrid modeling systems that are supported by reproducible assessment criteria and regime-conscious validation systems (Makridakis et al., 2018).
Moreover, new architectures, like transformer-based time-series models, generative learning systems, have a potential to capture long-range dependencies and presence of multi-source information flows (Goodfellow et al., 2016). The predictive uses of alternative datasets, such as macroeconomic variables, news emotion, and social media indicators, could increase the predictive capacity and situational awareness (Gu et al., 2020). However, this integration should be supported by strict out-of-sample validation, rolling-window testing, and diagnostics of their robustness to reduce overfitting and guarantee generalizability (Lopez de Prado, 2018). The other research need is an interpretability. The use of explainable artificial intelligence (XAI) methods is needed to enhance transparency and theoretical insight on the role of features in deep learning architectures as they become more and more complex (Sezer et al., 2020). The integration of interpretability frameworks in the forecasting models will enable scholarly understanding and acceptance of the regulations.

4.2 Implications for Practice

To financial practitioners, the review provides actionable insights of interest in the development of the trading strategies, optimization of the portfolio, in risk management, and in decision support systems (Gu et al., 2020). It has been shown that LSTM and other deep learning systems are especially efficient in sequential data modeling, which is why they can be used to predict intraday and volatility and in high-frequency trading settings (Fischer and Krauss, 2018). Nevertheless, the adoption of ML should be pursuit of caution on the part of the practitioners. Excel statistics is not always associated with profitable trading (Makridakis et al., 2018). In order to implement it practically, it is necessary to explicitly think about transaction costs, liquidity issues, slippage, and the compliance with regulations (Lopez de Prado, 2018). Thus, ML models must be integrated into cost-sensitive and risk-adjusted assessment systems instead of being assessed by measuring errors, e.g. RMSE or MAE (Sezer et al., 2020).
Also, institutional adoption is dependent on interpretability. Banks are in need of more open decision-support systems that can provide explanations to stakeholders, auditors, and regulators of the predictive outputs (Gu et al., 2020). The introduction of XAI mechanisms can contribute to the promotion of trust, accountability and alignment of governance in ML-driven predictive systems. In general, successful implementation in practice requires not just the sophistication of the algorithms, but also strong validation, economic viability, ability to scale and transparency.

4.3 Managerial Implications

As a manager, the results of this review would guide the strategic approach of financial institutions, portfolio managers, fintechs, and developers of algorithmic trading. The effectiveness of the advanced machine learning models, in particular, LSTM-based and hybrid ones, implies that companies are able to become more responsive and adaptive in their decision-making and invest in predictive systems that are data-driven (Fischer and Krauss, 2018; Rundo et al., 2019). Nonetheless, model adoption is not the only strategy that can aid successful implementation. Before they are deployed, managers need to take into account stringent backtesting protocols, walk-forward testing, inclusion of transaction costs, and risk-adjusted performance testing (Lopez de Prado, 2018). Excessive use of statistical accuracy without economic justification can present organizations with model risk and financial losses (Makridakis et al., 2018).
Considering the growing regulatory focus and awareness of corporate responsibility, the

explanation of AI (XAI) tools should be included to enhance the transparency and facilitate the needs of compliance (Sezer et al., 2020). Organizations are also recommended to invest in scalable data infrastructure that can support high-frequency and multi-source data sets such as the alternative information of sentiment signals and macroeconomic indicators (Gu et al., 2020). In the end, algorithm complexity will not be the source of a sustainable competitive advantage but strategic implementation of effective and interpretable as well as economically justified machine learning systems in a systemic risk management and governance systems.

5. Limitations of the study

While this review provides a comprehensive synthesis of machine learning applications in stock price prediction, several limitations should be acknowledged (Snyder, 2019). First, the review is constrained by database selection and predefined inclusion criteria, which may have excluded relevant studies published in non-indexed journals, conference proceedings, or emerging preprint platforms (Tranfield et al., 2003). Although systematic protocols enhance transparency, they may inadvertently restrict coverage of rapidly evolving AI research (Page et al., 2021). Second, citation-based bibliometric analysis may favor older publications due to citation accumulation effects, potentially underrepresenting recent but impactful research (Donthu et al., 2021). Citation counts reflect scholarly influence over time and may not fully capture the novelty or disruptive potential of newly emerging methodologies (Zupic & Čater, 2015). Third, variations in dataset selection, forecasting horizons, evaluation metrics, and validation strategies across studies limit direct comparability (Makridakis et al., 2018). The heterogeneity in research designs—including differences in training–testing splits, rolling-window validation, and performance benchmarks—makes it difficult to establish definitive conclusions regarding universally superior modeling approaches (Sezer et al., 2020). Fourth, this review primarily focuses on quantitative ML techniques and technical indicators, with limited exploration of behavioral finance perspectives, institutional constraints, or market microstructure effects that may influence predictive performance (Henrique et al., 2019). Integrating psychological, regulatory, and structural dimensions may provide a more holistic understanding of forecasting limitations (Gu et al., 2020). Finally, the rapidly evolving nature of artificial intelligence research means that emerging architectures—such as transformer-based time-series models and generative AI frameworks—may not yet be fully represented in the literature examined (Goodfellow et al., 2016). The acceleration of deep learning innovation necessitates continuous updating of systematic reviews to maintain relevance (Donthu et al., 2021). These limitations highlight the need for ongoing updates to systematic reviews in this domain, along with greater methodological standardization, transparency, and interdisciplinary integration in future research (Page et al., 2021).

6. Conclusion

This literature review, which is systematic, summarizes the modern studies on machine learning (ML) algorithms and technical indicators to predict stock prices, both in terms of the progress of methodology and the ongoing structural issues (Sezer et al., 2020). The results verify that financial markets are nonlinear, dynamic, and volatile and can hardly be captured using the classical linear modes of the econometrics model (Makridakis et al., 2018). Machine learning methods and, in particular, Support Vector Machines (SVM), Random Forest (RF), Artificial Neural Networks (ANN), and Long Short-Term Memory (LSTM) networks have proven to be more capable of modeling complex temporal dependencies and finding nonlinear relationships among large financial data sets (Henrique et al., 2019; Fischer and Krauss, 2018). The LSTM-based structures stand out as some of the most useful architectures in time-series forecasting since they are capable of modeling sequencing patterns and long-term connections (Fischer and Krauss, 2018). Technical indicators predictive frameworks are further enhanced by the integration of Moving Averages (MA), Relative Strength Index (RSI), and Bollinger Bands to organize the raw market data into meaningful characteristics (Picasso et al., 2019). Also, hybrid architectures that integrate econometric models (e.g. ARIMA) with ML frameworks are promising to represent both linear and nonlinear aspects of financial data (Rundo et al., 2019).

Nevertheless, significant progress has been made, and the literature has shifted to focus more on accuracy, whereas there is little focus on being economically valid, interpretable, cross-market generalizable, and robust to volatile or crisis conditions (Lopez de Prado, 2018; Gu et al., 2020). A significant number of studies give more priority to the incremental changes in the statistical error measures without focusing on financial viability, transaction costs, and performance assessment depending on the regimes (Makridakis et al., 2018). Further studies should shift to standard benchmarking models, regime sensitive modeling, explainable artificial intelligence, and better correlation between statistical performance and financial profitability (Sezer et al., 2020; Donthu et al., 2021). Future research along these lines will contribute to the improvement of theoretical and practical value of the ML-based stock forecasting systems, will contribute to the creation of strong, interpretable, and cost-effective predictive models.

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