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10. Rethinking Role of Traditional vs. Advanced Stock Price Forecasting Models: A Critical Literature Review

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Abstract

Stock price forecasting has been a central question in finance for some time, with traditional models founded on the Efficient Market Hypothesis (EMH) and technical and fundamental analysis, which are often criticized for their inability to account for sentiment market dynamics and non-linear sentiment. Recent technological advances in Machine Learning (ML), Artificial Intelligence (AI), and Natural Language Processing have expanded and developed new sophisticated forecasting models. These new advanced models have expanded forecasting horizons by incorporating behavioral biases, multidimensional datasets, and investor sentiment. This paper critically reviews the literature on the evolution of stock forecasting methods, highlights the limitations of isolated approaches, and advances the development of more accurate, practically relevant forecasting models.

Keywords: *forecasting; models; fundamental analysis; technical analysis; sentiment analysis; machine learning; artificial intelligence; hybrid models.*

10.1 Introduction

Stock market price forecasting continues to attract attention to both academics and practitioners, although traditional theories repeat that price movements are highly unpredictable. In practice, stock prices have an external component influenced by a wide variety of economic conditions, investor psychology, and company fundamentals. While long-term trends are more linked to intrinsic values, short-term fluctuations are driven by market sentiment, behavioral biases, and news.

Historically, two dominant approaches have been mostly used: fundamental analysis and technical analysis. Fundamental analysis considers intrinsic value by examining primarily financial statements, macroeconomic indicators, and industry dynamics. On the other hand, technical analysis evaluates historical price and volume data to identify market patterns (Nguyen et al., 2015; Park & Irwin, 2007).

Taking into consideration the weaknesses of the previous two techniques, sentiment analysis has emerged as a good replacement for investors. Sentiment analysis possesses a more advanced and complementary approach, extracting behavioral signals and investor mood from analysts' reports, financial news, and social media platforms. Classical models, the Fama-French Model and the Capital Asset Pricing Model (CAPM), modern research emphasizes the importance of sentiment and crowd psychology with sector characteristics (Kumar & K S, 2024).

Moving forward with rapid advances in machine learning (ML) and artificial intelligence (AI), the forecasting process has changed as well. These two new technologies allowed us now to enable the modeling of non-linear and high-dimensional datasets, which was not the case previously. Now, these methods integrate fundamental, technical, and sentiment analyses into hybrid systems, improving predictive accuracy and robustness weaknesses (Abu-Mostafa & Atiya, 1996; Shah et al., 2019; Zhong & Enke, 2017). Forecasting stock market prices can be now classified into four main categories: statistical, pattern recognition, sentiment-driven, and machine-based with hybrid frameworks.

According to Belton (2021), these technological developments have reshaped investment practices, putting AI-driven hybrid models at the center of contemporary stock market prediction. A combination of digital trading platforms with the availability of real-time market and sentiment data allows us to believe that we can democratize access to financial markets. Figure 1 below presents the taxonomy of existing stock prediction techniques.

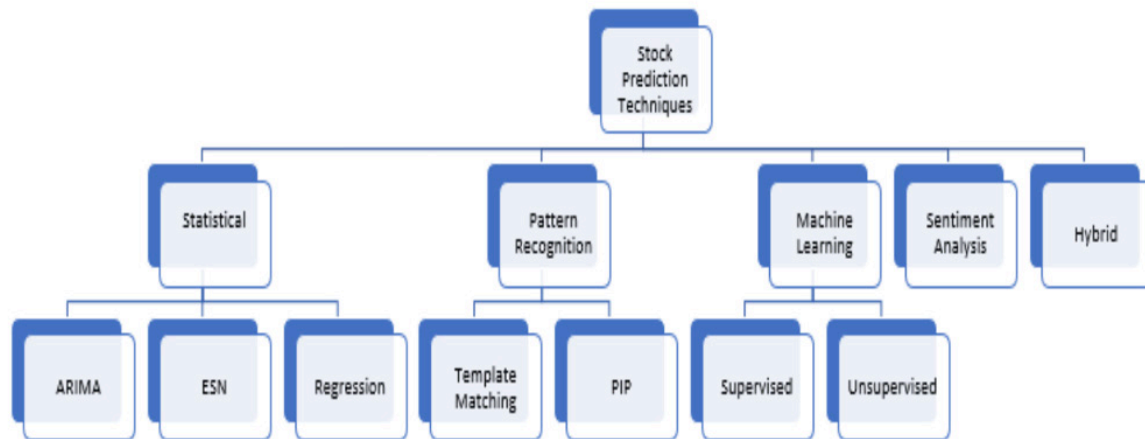


Figure 1. Taxonomy of stock prediction techniques. (Source: Belton, 2021)

10.2 Traditional Forecasting Models

10.2.1 Fundamental Analysis in Stock Forecasting

Fundamental analysis evaluates securities by examining intrinsic factors, including financial statements, industry trends, management quality, and macroeconomic conditions (Christodoulaki & Kampouridis, 2022). It aims to estimate fair value and determine whether assets are over- or undervalued. Hu et al., (2015) Divide this approach into three components: macroeconomic analysis (e.g., GDP, CPI), industry analysis (demand, competition, regulation), and company analysis (operational and financial performance). Empirical evidence supports its effectiveness: Avijan Dutta et al., (2012) it achieved 74.6% accuracy in forecasting stock performance using financial ratios. Two widely used metrics are the Price-to-Earnings (P/E) ratio, often linked to expected returns, and the Price-to-Book (P/B) ratio, which signals potential under- or overvaluation (Molodovsky, 1953). Despite its utility, fundamental analysis struggles to capture nonlinear market dynamics (Deboeck, 1994) and is resource-intensive. Yet, its premise—that securities are often mispriced—remains central (Namdari & Li, 2018). Contemporary research emphasizes the importance of integrating fundamental concepts with machine learning to enhance predictive accuracy. By focusing on growth, profitability, sustainability, and economic context, fundamental analysis remains indispensable for investment decisions (You & Cao, 2021), supporting both traditional valuation and modern forecasting frameworks.

The Efficient Market Hypothesis (EMH), proposed by Fama (1970), holds that prices fully reflect available information, making consistent outperformance unlikely. It underpins classical finance by suggesting that historical patterns are noise rather than exploitable signals. Evidence includes findings that most active managers underperform passive benchmarks; Bohn (2017) estimated 75% fail to beat market-weighted portfolios. EMH is classified into three forms: weak, where historical data are already priced in, limiting technical analysis; semi-strong, where prices rapidly adjust to new information, reducing the value of fundamentals; and strong, where even

insider knowledge is fully incorporated, precluding sustained abnormal returns (Fama & French, 1996; Naseer & Bin Tariq, 2015) earnings/price, cash flow/price, book-to-market equity, past sales growth, long-term past return, and short-term past return. Because these patterns in average returns apparently are not explained by the CAPM, they are called anomalies. We find that, except for the continuation of short-term returns, the anomalies largely disappear in a three-factor model. Our results are consistent with rational ICAPM or APT asset pricing, but we also consider irrational pricing and data problems as possible explanations.”;”container-title”:”The Journal of Finance”,”DOI”:”10.1111/j.1540-6261.1996.tb05202.x”,”ISSN”:”0022-1082, 1540-6261”,”issue”:”1”,”journalAbbreviation”:”The Journal of Finance”,”language”:”en”,”page”:”55-84”,”source”:”DOI.org (Crossref. Critics argue EMH oversimplifies markets and ignores anomalies. Abu-Mostafa & Atiya, (1996) highlighted correlations among economic variables, while Zhong & Enke, (2017) found evidence of partial predictability in prices and derivatives. Empirical studies have also identified recurring inefficiencies Chong et al., (2017). Behavioral finance counters EMH by stressing biases such as overconfidence, herding, and loss aversion. R. Kumar & K S, (2024) noted that sentiment often drives deviations from fundamentals, creating trends exploitable through forecasting.

10.2.2 Technical Analysis and Its Applications

Technical analysis predicts price movements using historical market data-mainly price and volume based on the assumptions that markets reflect all known information and that price patterns repeat (Murphy & Murphy, 1999). It is especially favored by short-term traders who rely on charts, patterns, and indicators such as moving averages, MACD, and candlestick charts (Viktorovich, 2024). Empirical studies support its profitability. Park & Irwin, (2007) found significant returns despite concerns of data bias, while Schwager, (2012) observed many successful traders rely on technical strategies. Research confirms its effectiveness across assets and indices (Avramov et al., 2015; Brock et al., 1992)our results provide strong support for the technical strategies. The returns obtained from these strategies are not consistent with four popular null models: the random walk, the AR(1; Osler, 2003). Dow Theory remains its foundation, emphasizing that prices reflect information, move in trends, and repeat over time. Critics argue that technical analysis relies on rigid, expert-defined rules (Deboeck, 1994) and overlooks external shocks. Recent studies advocate hybrid approaches, integrating technical indicators with machine learning, which outperform traditional models such as SVM and Decision Trees. Hu et al., (2015) identified seven domains of technical analysis: sentiment, flow-of-funds, raw data, trend and momentum, volume, cycles, and volatility. Ding et al., (2023) linked technical signals to market sentiment, showing short-term gains but long-term reversals. Smith et al., (2014) also found hedge fund managers using technical analysis achieved superior returns during high sentiment periods. Overall, while limited when applied in isolation, technical analysis remains relevant, particularly when combined with sentiment analysis and computational intelligence.

10.3 Advanced Forecasting Models

10.3.1 Role of Sentiment Analysis in the Financial Markets

Sentiment analysis (SA), or opinion mining, is a Natural Language Processing (NLP) method that classifies text—such as news, reviews, or social media posts—as positive, negative, or neutral (Liu, 2015). Though challenged by context, sarcasm, and cultural nuance, its accuracy improves with quality datasets and advanced algorithms. In finance, investor sentiment captures optimism or pessimism about cash flows and risks, often independent of fundamentals (Baker & Wurgler, 2007). Studies show stock prices correlate with online events, leading to event-driven prediction models using financial news and platforms like Twitter or StockTwits (X. Ding et al., 2014; T. Chen & Chen, 2016). Aggregated “wisdom of crowds” sentiment has proven predictive across domains, including markets (K. Nirmala Devi & V. Murali Bhaskaran, 2015). Unlike fundamental or technical analysis, SA highlights psychological and emotional drivers, providing an additional decision-making signal. By capturing mood and behavioral biases, sentiment analysis enriches market understanding and improves accuracy when integrated with traditional approaches (Arauco Ballesteros & Martínez Miranda, 2024).

10.3.2 Advancements and Applications of Sentiment Analysis

Recent studies highlight the value of sentiment analysis (SA) in finance, especially when paired with natural language processing (NLP) and text mining to capture insights missed by traditional models (Deep, 2023). SA, machine learning (ML), and data mining are now central tools for measuring public mood and forecasting asset prices (Alsing & Bahceci, 2015). Sectoral effects vary: sentiment boosts returns in durables and utilities but has negative effects in high-tech and energy, with interest rates and risk spreads further shaping outcomes (R. Kumar & K S, 2024). One limitation is the lack of standardized sentiment measures, as many studies assume homogeneity across industries. Yet evidence shows systematic links between sentiment, industry cycles, and macroeconomic factors (R. Kumar & K S, 2024). (Shiller, 1980) demonstrated that while short-term prices are volatile and sentiment-driven, long-term values realign with fundamentals, a pattern also noted before the dot-com crash. Sentiment thus serves both as a driver of short-term divergence and an indicator of turning points (Saettele, 2017; Molina, 2021). Applications include automated analysis of news and social media for forecasting (Bollen et al., 2011). Methods typically use ML- or lexicon-based classification (Bhardwaj et al., 2015). Empirical studies confirm that sentiment signals improve volatility and short-term price forecasts (Seng & Yang, 2017; Shah et al., 2019). Domain-specific challenges—such as limited datasets—have spurred innovations like FinBERT, a financial adaptation of BERT that improves sentiment-based prediction accuracy (P. Chen et al., 2024). Overall, SA enhances understanding of investor psychology and complements fundamental and technical approaches, strengthening short- to medium-term financial forecasting.

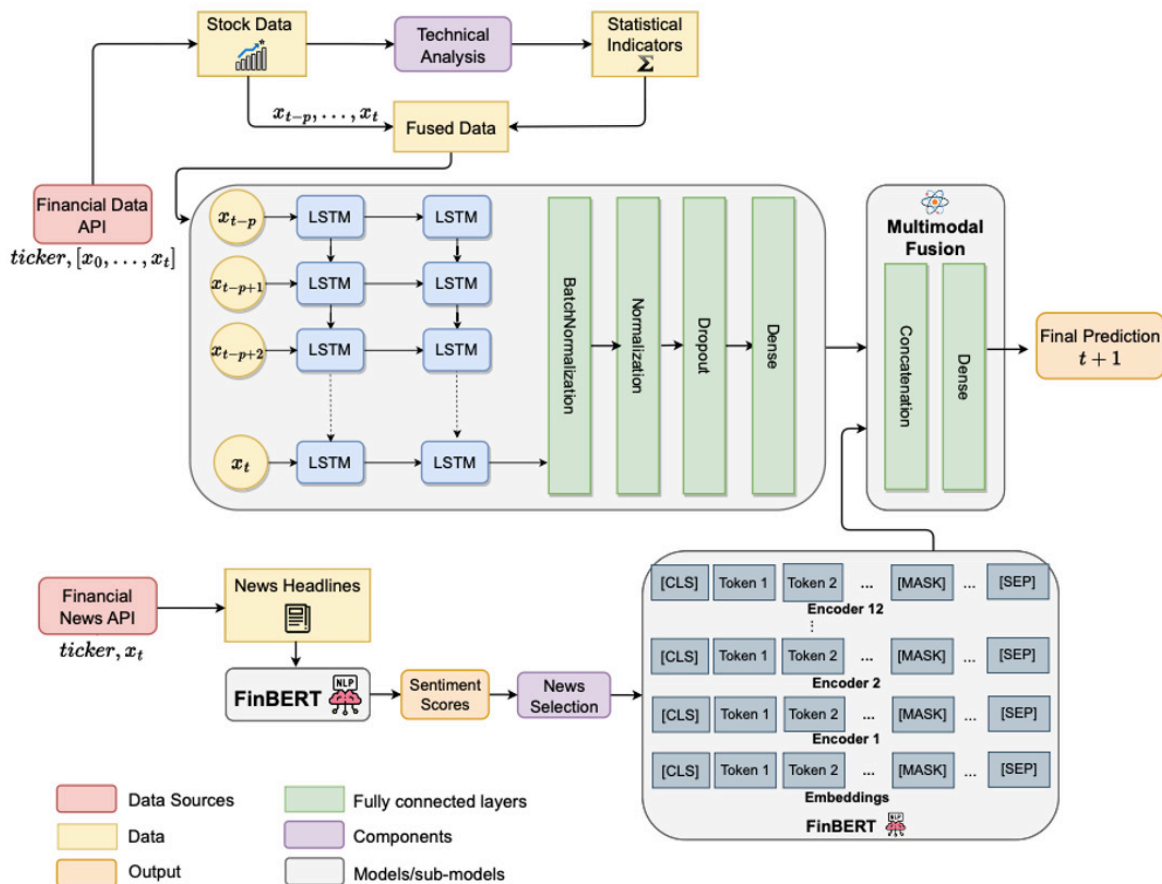


Figure 2. Overview of the proposed multimodal fusion model for stock market prediction (Chen et al., 2024)

10.3.3 Integration of Sentiment Analysis with Advanced Models

Recent work emphasizes combining deep learning with sentiment analysis to enhance forecasting. Jing et al., (2021) and Kumar & K S, (2024) showed that merging textual sentiment with computational models produces more robust investment strategies. While research often targets short-term predictions, (Bohn, 2017) found that integrating textual data from financial reports with fundamentals improves long-term accuracy. Sarmiento, (2017) used tweet classification for real-time investor expectations, and Zhao & Yang, (2023) proposed sentiment indices from social media that improved forecasts when paired with traditional metrics. Extensions include ESG sentiment. Lee et al., (2024) developed an ESG-based sentiment index with technical indicators for S&P 500 prediction, though noting industry-specific adjustments are needed. P. Shah et al., (2024) stressed big data methods for processing large-scale sentiment sources. Hybrid models demonstrate particular promise. Shankar et al., (2024) integrated LSTM, ARIMA, and Twitter sentiment, outperforming standalone models. Vallarino, (2025) combined LSTM with Transformers, surpassing price-only approaches. Lin et al., (2022) showed multilingual sentiment with structured data, optimized via genetic algorithms, improved forecasts in non-English markets. Sentiment is especially relevant during crises: Das et al., (2022) showed aggregated sentiment across platforms

significantly improved predictions during COVID-19. Overall, integrating sentiment with deep learning, hybrid models, and specialized indices strengthens both short- and long-term forecasting, confirming sentiment's central role in financial prediction.

10.3.4 Machine Learning and Hybrid Models in Forecasting

Machine learning (ML), a branch of artificial intelligence, enables systems to learn patterns from data and improve predictions in dynamic environments like financial markets (Hurwitz & Kirsch, 2018). Key approaches include supervised learning (labeled data), unsupervised learning (hidden structures via clustering or dimensionality reduction), and reinforcement learning (trial-and-error optimization). Ensemble methods and text analytics further improve performance, though forecasting remains challenging due to volatility and nonlinearity (Rouf et al., 2021). A major advancement is deep learning, which uses layered neural networks to capture complex, nonlinear interactions (Nielsen, 2015; Sherstinsky, 2020; Hopfield, 1982) based on aspects of neurobiology but readily adapted to integrated circuits. The collective properties of this model produce a content-addressable memory which correctly yields an entire memory from any subpart of sufficient size. The algorithm for the time evolution of the state of the system is based on asynchronous parallel processing. Additional emergent collective properties include some capacity for generalization, familiarity recognition, categorization, error correction, and time sequence retention. The collective properties are only weakly sensitive to details of the modeling or the failure of individual devices.”,”container-title”:”Proceedings of the National Academy of Sciences”,”DOI”:”10.1073/pnas.79.8.2554”,”ISSN”:”0027-8424, 1091-6490”,”issue”:”8”,”journalAbbreviation”:”Proc. Natl. Acad. Sci. U.S.A.”,”language”:”en”,”page”:”2554-2558”,”source”:”DOI.org (Crossref early work showed how interconnected units could perform pattern recognition and recall, even with incomplete inputs-a quality reflected in modern financial forecasting models. Overall, ML’s adaptability and deep learning’s capacity for complex data modeling make them central to contemporary stock market prediction research.

Table 1: Machine Learning Techniques and Applications in Stock Market Forecasting

ML Type	Description	Application in Stock Forecasting
Supervised Learning	Trains on labeled data (input-output pairs) to predict future outcomes.	Predicting stock prices, returns, and trends using historical labeled datasets (e.g., regression, classification models).
Unsupervised Learning	Analyzes unlabeled data to find hidden patterns and groupings.	Detecting clusters or anomalies in stock behavior (e.g., identifying similar performing stocks or market regimes).
Reinforcement Learning	Learns optimal strategies by trial and error through interaction with the environment.	Developing algorithmic trading strategies that adapt to market dynamics over time.
Ensemble Methods	Combines predictions from multiple models to improve accuracy.	Aggregating multiple forecasting models (e.g., Random Forests, Gradient Boosting) to reduce overfitting and enhance performance.
Text Data Analytics	Processes and analyzes unstructured textual data.	Extracting sentiment and market signals from news, tweets, and financial reports to enhance forecasts.

Deep Learning	Uses multi-layered neural networks for hierarchical data representation.	Capturing complex patterns and time-dependent behavior in stock prices, particularly using LSTM, CNN, or RNN architectures.
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Table 2: Summary of Machine Learning Models Used in Stock Market Prediction

Model / Approach	Description	Application in Stock Market Forecasting	Key Reference(s)
Random Forest (RF)	Ensemble of decision trees; reduces overfitting and improves accuracy.	Detecting systemic risk factors (e.g., stock beta, volatility, ROE); risk prediction.	Kumar & K S, 2024; Yu & Zhao, 2020
Gradient Boosting Machine (GBM)	Sequential ensemble method focused on reducing residual errors.	Effective in capturing nonlinear relationships in financial indicators.	Kumar & K S, 2024
Logistic Regression	Statistical model used for binary classification.	Assessing capital reserve adequacy and systemic risk.	Yu & Zhao, 2020
Artificial Neural Network (ANN)	Inspired by biological neurons; capable of complex pattern recognition.	Predicting stock price trends using multi-layer structures like MLP.	Sharma et al., 2021; Ganser et al., 2021the more concise training methods that can be chosen. Several solutions already exist for this purpose in the tennis industry; however, none of them combine data generation with a wristband and classification with a deep convolutional neural network (CNN
Multilayer Perceptron (MLP)	Feedforward ANN with one or more hidden layers trained via backpropagation.	Stock market forecasting using structured input data.	Zhang et al., 2021we study the neural network learning algorithms in the field of capability assessment and index sensitivity. Aiming at the problem of overfitting and parameter optimization in neural network learning, the paper proposes an improved machine learning algorithm—the Ensemble Learning Based on Policy Optimization Neural Networks (ELPONN
Support Vector Machine (SVM)	Maximizes margin between data classes; used for classification and regression.	High-performance linear classification for financial data analysis.	Cortes & Vapnik, 1995; Srivastava & Bhambhu, 2010
Naïve Bayes (NB)	Probabilistic classifier based on Bayes' theorem.	Fast and scalable sentiment or price movement classification.	Rouf et al., 2021
Genetic Algorithms (GA)	Optimization algorithms inspired by natural selection.	Parameter tuning for rule-based or technical trading systems.	Rouf et al., 2021
Fuzzy Logic / ANFIS	Uses partial truth values for reasoning; ANFIS combines neural and fuzzy logic.	Market prediction using ambiguous or imprecise data inputs.	Rouf et al., 2021
Deep Neural Networks (DNN)	Multi-layer networks capable of deep feature learning.	Used for combining textual and numeric data for accurate stock price prediction.	LeCun et al., 2015; Wu et al., 2020

Convolutional Neural Networks (CNN)	Extracts spatial features from data.	Enhanced feature extraction for stock pattern recognition.	Aldhyani & Alzahrani, 2022 due to the high degree of correlation between stock prices, analysis of the stock market is made more difficult by batch processing approaches. The prediction of the stock market has entered a technologically advanced era with the advent of technological marvels such as global digitization. For this reason, artificial intelligence models have become very important due to the continuous increase in market capitalization. The novelty of the proposed study is the development of the robustness time series model based on deep learning for forecasting future values of stock marketing. The primary purpose of this study was to develop an intelligent framework with the capability of predicting the direction in which stock market prices will move based on financial time series as inputs. Among the cutting-edge technologies, artificial intelligence has become the backbone of many different models that predict the direction of markets. In particular, deep learning strategies have been effective at forecasting market behavior. In this article, we propose a framework based on long short-term memory (LSTM; Ratchagit & Xu, 2022) the convolutional neural network (CNN
Long Short-Term Memory (LSTM)	A type of RNN ideal for time-series forecasting.	Captures temporal dependencies in stock market data.	G. Kumar et al., 2022; Ratchagit & Xu, 2022 the convolutional neural network (CNN
CNN-LSTM Hybrid	Combines CNN's feature extraction with LSTM's temporal learning.	Improved prediction accuracy for stock closing prices.	Aldhyani & Alzahrani, 2022 due to the high degree of correlation between stock prices, analysis of the stock market is made more difficult by batch processing approaches. The prediction of the stock market has entered a technologically advanced era with the advent of technological marvels such as global digitization. For this reason, artificial intelligence models have become very important due to the continuous increase in market capitalization. The novelty of the proposed study is the development of the robustness time series model based on deep learning for forecasting future values of stock marketing. The primary purpose of this study was to develop an intelligent framework with the capability of predicting the direction in which stock market prices will move based on financial time series as inputs. Among the cutting-edge technologies, artificial intelligence has become the backbone of many different models that predict the direction of markets. In particular, deep learning strategies have been effective at forecasting market behavior. In this article, we propose a framework based on long short-term memory (LSTM
LSTM with PSO	Uses Particle Swarm Optimization to optimize weights in LSTM.	Accurate forecasting for major indices (S&P 500, Nifty 50, Sensex).	G. Kumar et al., 2022
Hybrid Approaches (HA)	Combines multiple ML models for improved performance.	Mitigates weaknesses of individual models; improves predictive reliability.	Cheng et al., 2012
Regression Algorithms (RA)	Models relationship between dependent and independent variables.	Predicting stock returns or price levels based on historical and macro data.	L. Zhang et al., 2013
Two-Delay Model (MLP, CNN, LSTM)	Introduces lag structures in deep learning architectures.	Forecasting stock data using temporal shift features.	Ratchagit & Xu, 2022 the convolutional neural network (CNN

10.3.5 Machine Learning Models

Machine learning (ML) is now central to financial forecasting, modeling systemic risk and stock behavior. Random Forest and Gradient Boosting Machines have proven effective for identifying key risk variables such as beta, volatility, and ROE (R. Kumar & K S, 2024). Logistic regression and Random Forest are also applied to capital adequacy assessments (J. Yu & Zhao, 2020). With the rise of big data, ML increasingly supports investment and risk management (Zhong & Enke, 2017). Early methods such as decision trees and Naïve Bayes have been surpassed by advanced approaches like Random Forest, logistic regression, and artificial neural networks (ANNs), particularly multilayer perceptions (MLPs) (Ballings et al., 2015; Zhong & Enke, 2017). Deep nonlinear architectures are especially effective in time-series forecasting (Bao et al., 2017). In practice, ML also supports fraud detection-PayPal reduced fraud to 0.32% of revenue using deep learning (Molina, 2021). Common ML models in finance include ANNs for complex patterns, SVMs for high-dimensional classification, Naïve Bayes for large datasets, Genetic Algorithms for optimization, Fuzzy Logic/ANFIS for uncertainty, DNNs for hierarchical learning, regression models for returns, and hybrid methods combining algorithms for greater accuracy (Cortes & Vapnik, 1995; LeCun et al., 2015; Cheng et al., 2012). Challenges include overfitting, mitigated through cross-validation and regularization (Rouf et al., 2021), and broader issues of volatility, uncertainty, and proprietary algorithms that complicate robustness testing (D. Shah et al., 2019). Despite these, ML remains a powerful tool for forecasting and risk management.

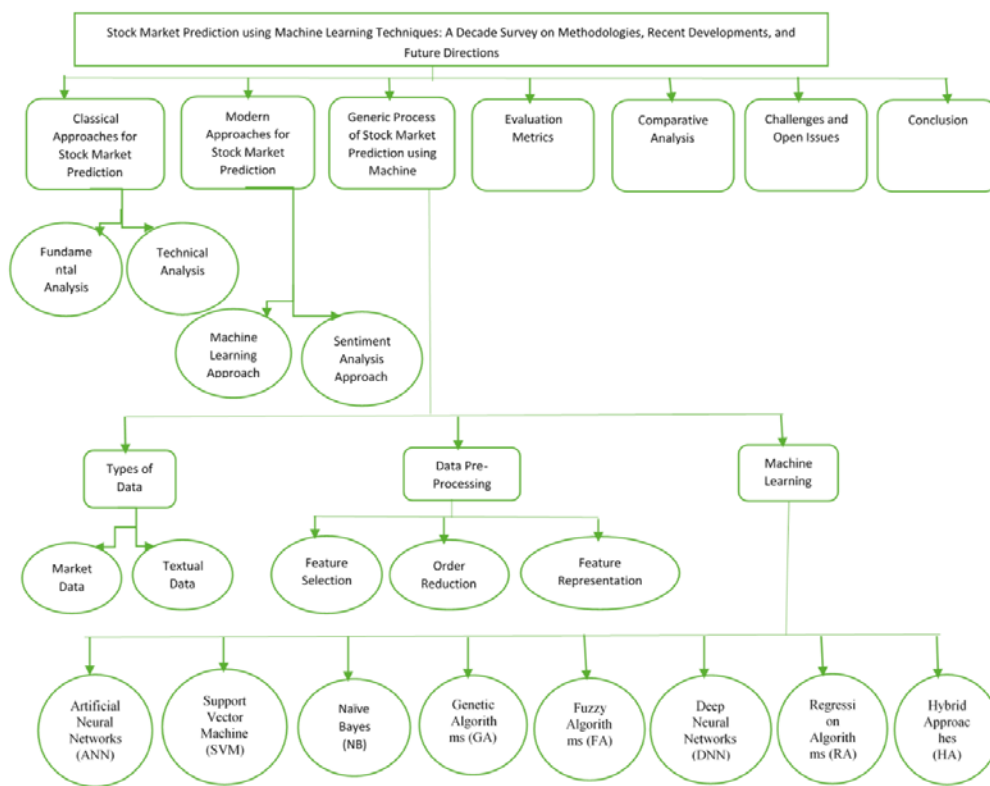


Figure 3. Stock Market Prediction using Machine Learning Techniques (Rouf et al., 2021)

10.3.6 Hybrid and Advanced Machine Learning Approaches

Hybrid deep learning models have shown strong potential for improving forecasting. G. Kumar et al., (2022) combined LSTM with Particle Swarm Optimization (PSO), achieving superior predictions for indices such as the S&P 500 and Nifty 50. Aldhyani & Alzahrani, (2022) due to the high degree of correlation between stock prices, analysis of the stock market is made more difficult by batch processing approaches. The prediction of the stock market has entered a technologically advanced era with the advent of technological marvels such as global digitization. For this reason, artificial intelligence models have become very important due to the continuous increase in market capitalization. The novelty of the proposed study is the development of the robustness time series model based on deep learning for forecasting future values of stock marketing. The primary purpose of this study was to develop an intelligent framework with the capability of predicting the direction in which stock market prices will move based on financial time series as inputs. Among the cutting-edge technologies, artificial intelligence has become the backbone of many different models that predict the direction of markets. In particular, deep learning strategies have been effective at forecasting market behavior. In this article, we propose a framework based on long short-term memory (LSTM integrated CNNs with LSTMs, outperforming stand-alone LSTMs on Tesla and Apple data. Ratchagit & Xu, (2022) the convolutional neural network (CNN introduced a two-delay mechanism to MLP, CNN, and LSTM models, improving forecasts for Microsoft and Pfizer stocks compared to linear benchmarks. Stock market prediction methods are generally classified into supervised (labeled data) and unsupervised (unlabeled data) learning. Common algorithms include SVMs, valued for accuracy in high-dimensional spaces (Cortes & Vapnik, 1995), kNN, which classifies based on historical similarity (Srivastava & Bhambhu, 2010), ANNs for nonlinear time-series modeling, Fuzzy Inference Systems (FIS) for handling uncertainty (Venugopal et al., 2009), and evolutionary algorithms for portfolio optimization. L. Yu et al., (2016) advanced this field with a mixed discrete-continuous differential evolution algorithm, scoring stocks by fundamental and technical indicators to construct profitable portfolios. Their Shanghai A-share study confirmed higher returns and robustness compared to benchmarks. Overall, hybrid deep learning and evolutionary optimization methods address limitations of traditional models, offering more accurate and realistic forecasting in dynamic financial markets.

10.3.7 Literature Review on Machine Learning

Machine learning (ML) has advanced financial forecasting by uncovering nonlinear patterns invisible to traditional methods. Studies consistently show ML outperforming classical approaches. You & Cao, (2021) demonstrated superior earnings prediction over analysts, while P. Chen et al., (2024) improved robustness by integrating FinBERT sentiment with LSTM models. Jing et al., (2021) combined CNNs for sentiment extraction with LSTMs for stock prediction, achieving higher accuracy, and Deep, (2023) emphasized multi-factor ML models combining fundamentals, technical, and sentiment. Hybrid designs, such as CNN-attention-LSTM-XGBoost (Shi et al., 2022) the research and prediction on the change of the stock price, can avoid the risk for the investors. The traditional time series model ARIMA can not describe the nonlinearity, and can not achieve satisfactory results in the stock prediction. As neural networks are with strong nonlinear generalization ability, this paper proposes an attention-based CNN-LSTM and XGBoost hybrid model to predict the stock price. The model constructed in this paper integrates the time series model, the Convolutional Neural Networks with Attention mechanism, the Long Short-Term Memory net-

work, and XGBoost regressor in a non-linear relationship, and improves the prediction accuracy. The model can fully mine the historical information of the stock market in multiple periods. The stock data is first preprocessed through ARIMA. Then, the deep learning architecture formed in pretraining-finetuning framework is adopted. The pre-training model is the Attention-based CNN-LSTM model based on sequence-to-sequence framework. The model first uses convolution to extract the deep features of the original stock data, and then uses the Long Short-Term Memory networks to mine the long-term time series features. Finally, the XGBoost model is adopted for fine-tuning. The results show that the hybrid model is more effective and the prediction accuracy is relatively high, which can help investors or institutions to make decisions and achieve the purpose of expanding return and avoiding risk. Source code is available at <https://github.com/zshicode/Attention-CLX-stock-prediction>. ”DOI”:”10.48550/ARXIV.2204.02623”, ”license”:”Creative Commons Attribution 4.0 International”, ”note”:”version: 2”, ”publisher”:”arXiv”, ”source”:”DOI.org (Datacite, further enhance accuracy. ML’s strength lies in integrating diverse data. Namdari & Li, (2018) merged fundamentals and technical via MLP, improving directional accuracy for NASDAQ technology stocks. Zhong & Enke, (2019) used deep neural networks with financial and economic indicators, boosted by PCA, for S&P 500 forecasts. Peng & Jiang, (2016) applied word embeddings with DNNs to financial news, outperforming price-only models, while Gálvez (2016) showed online sentiment improved forecasts in Argentina’s Merval exchange. Recent innovations focus on deep learning and NLP. Hung et al., (2024) embedded BERT for sentiment and GRU for time series into the Black–Litterman portfolio model, achieving 46.6% annualized returns. Vallarino, (2025) integrated RNN–LSTM with Transformers for Apple stock, surpassing price-only models. Lin et al., (2022) confirmed LSTM–GA optimization with hybrid datasets improved accuracy, and Wen et al., (2022) found Transformers enhanced forecasts by extracting relevance from financial news. Beyond forecasting, ML supports stock selection (Huang et al., 2021), risk culture assessment via clustering (Owusu & Gupta, 2024), and broader applications such as fraud detection and credit risk (Kour, 2024; Mittal & Sangwan, 2019). Challenges remain in interpretability, data quality, and regulatory compliance. Overall, ML demonstrates transformative potential in finance. Hybrid deep learning models that integrate fundamental, technical, and sentiment data consistently outperform traditional benchmarks, though transparency and robustness remain ongoing concerns.

10.3.8 Hybrid Neural Networks for Enhanced Forecasting

Hybrid neural networks (HNNs) integrate multiple architectures to improve predictive accuracy in nonlinear and volatile markets (T. Lin et al., 2017) ranging from resource allocation in data centers, load schedule in smart grid, and so on. Inspired by the recent successes of neural networks, in this paper we propose TreNet, a novel end-to-end hybrid neural network to learn local and global contextual features for predicting the trend of time series. TreNet leverages convolutional neural networks (CNNs). By merging linear and nonlinear models, HNNs overcome limitations of traditional approaches and better capture time-series dynamics. Bisoi & Dash, (2014) introduced a hybrid evolutionary dynamic network using Differential Evolution with the Unscented Kalman Filter, outperforming gradient-based and standalone methods in accuracy, noise resilience, and convergence—making it suitable for real-time forecasting. Similarly, Rather et al., (2015) combined linear models with recurrent neural networks (RNNs), showing that the hybrid reduced overfitting and improved generalization by capturing both trends and temporal dependencies. Srivinay et al., (2022) advanced this with a Prediction Rule Ensemble (PRE) plus Deep Neural Network (DNN) framework. PRE filtered technical indicators, while the DNN modeled

nonlinear patterns, lowering RMSE and MAE by 5-7% compared to standalone models. Although tested only with technical data, the framework is adaptable to fundamental and sentiment inputs. Overall, HNNs demonstrate strong potential in stock forecasting by integrating complementary methods, making them especially effective in data-rich and sentiment-sensitive markets such as the NASDAQ technology sector.

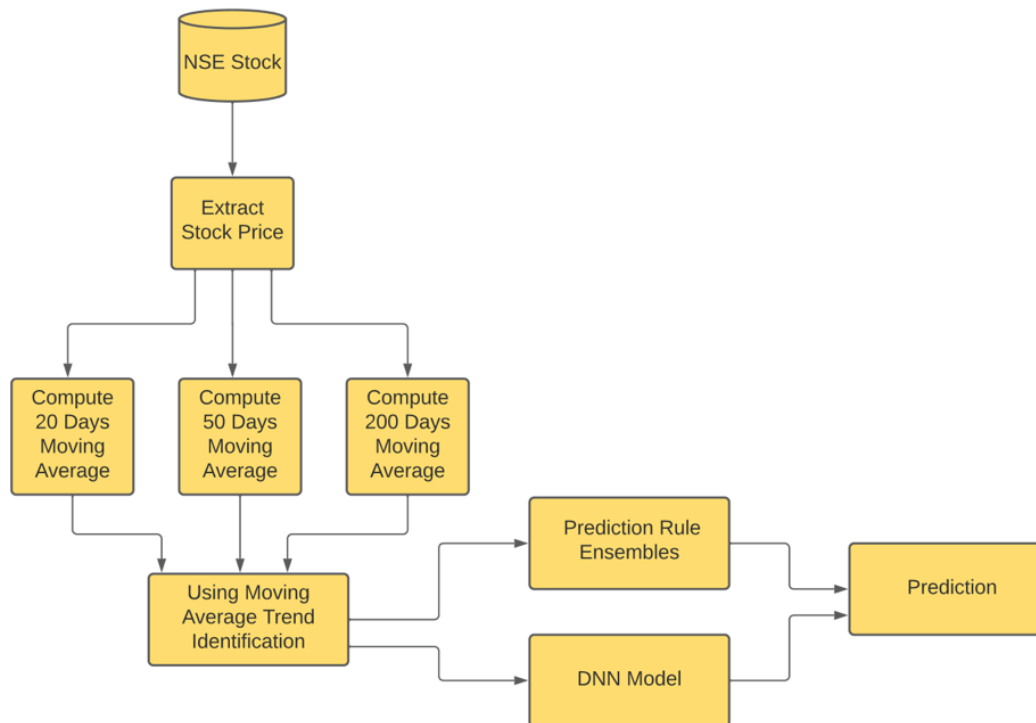


Figure 4. Chart: Srivinay et al., (2022) – overall work

10.3.9 Hybrid Approaches in Stock Market Forecasting

Hybrid approaches integrate statistical, machine learning, and pattern recognition methods to capture both linear and nonlinear market dynamics (D. Shah et al., 2019). Markowska-Kaczmar & Dziedzic, (2008) used feedforward networks with Perceptually Important Points to reduce dimensionality in time series. Tiwari et al., (2010) combined Hidden Markov Models with decision trees, achieving 92% accuracy on BSE SENSEX trends. Shen et al., (2012) blended statistical tools with SVMs to model inter-market correlations, reaching up to 85% accuracy for long-term DJIA forecasts. HNNs have been especially effective in combining financial and sentiment data. Wang et al., (2019) introduced the Hybrid Time-series Predictive Neural Network (HTPNN), integrating CNNs, LSTMs, and autoencoders, outperforming SVMs and feedforward networks. (J.-J. Wang et al., 2012) combined exponential smoothing, ARIMA, and backpropagation NNs, improving Shenzhen and DJIA predictions. Yoshihara et al., (2014) integrated RNN-RBM with Deep Belief Networks to capture news impacts, while Ding et al., (2015) used CNN-based sentiment modeling, achieving 64% directional accuracy for the S&P 500. Rather et al., (2015) blended ARIMA, Echo State Networks, and RNNs with genetic algorithms, lowering errors relative to standalone RNNs. Comparisons highlight context-specific strengths: Creighton & Zulkernine, (2017) found

hybrid models excelled in long-term horizons, while BPNNs performed better short term. T. Lin et al., (2017) ranging from resource allocation in data centers, load schedule in smart grid, and so on. Inspired by the recent successes of neural networks, in this paper we propose TreNet, a novel end-to-end hybrid neural network to learn local and global contextual features for predicting the trend of time series. TreNet leverages convolutional neural networks (CNNs advanced hybridization with TreNet, combining CNNs for local features and LSTMs for temporal dependencies, surpassing HMMs and other benchmarks. Arauco Ballesteros & Martínez Miranda, (2024) confirmed that adding sentiment to fundamental and technical inputs in MLP models improved prediction accuracy by 1.5% across S&P 500 firms. Overall, hybrid architectures demonstrate flexibility and improved accuracy by integrating diverse data sources.

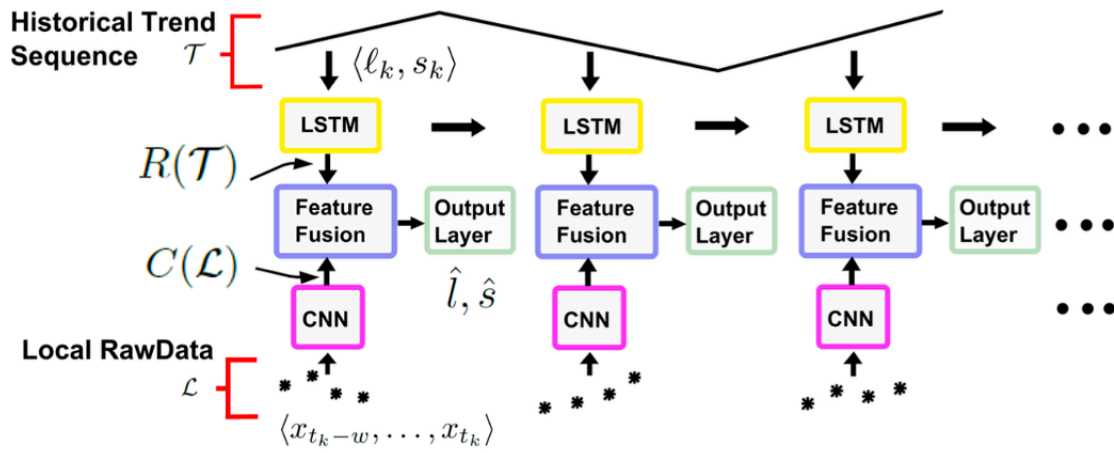


Figure 5. Illustration of the hybrid architecture of TreNet.

10.3.10 Hybrid Intelligent Systems in Financial Forecasting

Hybrid intelligent systems integrate neural networks, fuzzy logic, genetic algorithms, and optimization methods to improve forecasting in complex, uncertain markets. By combining complementary strengths, they address nonlinearities, ambiguity, and noisy data that limit traditional approaches. Tahmasebi & Hezarkhani, (2012) developed the Coactive Neuro-Fuzzy Inference System (CANFIS), optimized with genetic algorithms, improving learning in uncertain environments. Wermter & Sun, (2000) classified hybrid neural systems as unified, transformation, or modular, emphasizing adaptability and interpretability. Medsker, (1994) highlighted the integration neural networks with expert systems to blend learning and rule-based reasoning. Recent advances stress fuzzy logic and optimization. Bal et al., (2024) proposed modular neural networks for economic forecasting, while Lopez-Ramos et al., (2024) used type-2 and type-3 fuzzy logic to manage noisy data. Metaheuristic optimizers-artificial fish swarm and grey wolf (Barraza et al., 2024; Ochoa et al., 2024), Mayfly (Lizarraga et al., 2023), Flower Pollination, and particle swarm (Melin et al., 2023)- further enhance deep learning performance. Domain-specific studies show similar benefits. Psychogios & Ungar, (1992) combined first-principles models with neural networks for improved extrapolation, while (K. C. Lee et al., 1996) used statistical-neural hybrids for bankruptcy prediction. Hernández et al., (2020) introduced morphological-perceptron hybrids with higher accu-

racy and lower complexity. Senapati et al., (2018) improved stock forecasting by combining Adaline NNs with particle swarm optimization. Zhu et al., (2024) advanced deep hybridization with CEEMDAN-S-C-LSTM, integrating signal decomposition, filtering, CNNs, and LSTMs, reducing error by 65% on CSI 300 data. Overall, hybrid systems that merge neural, fuzzy, and optimization methods deliver superior accuracy, robustness, and interpretability, making them particularly valuable for volatile, sentiment-driven sectors such as the NASDAQ technology industry.

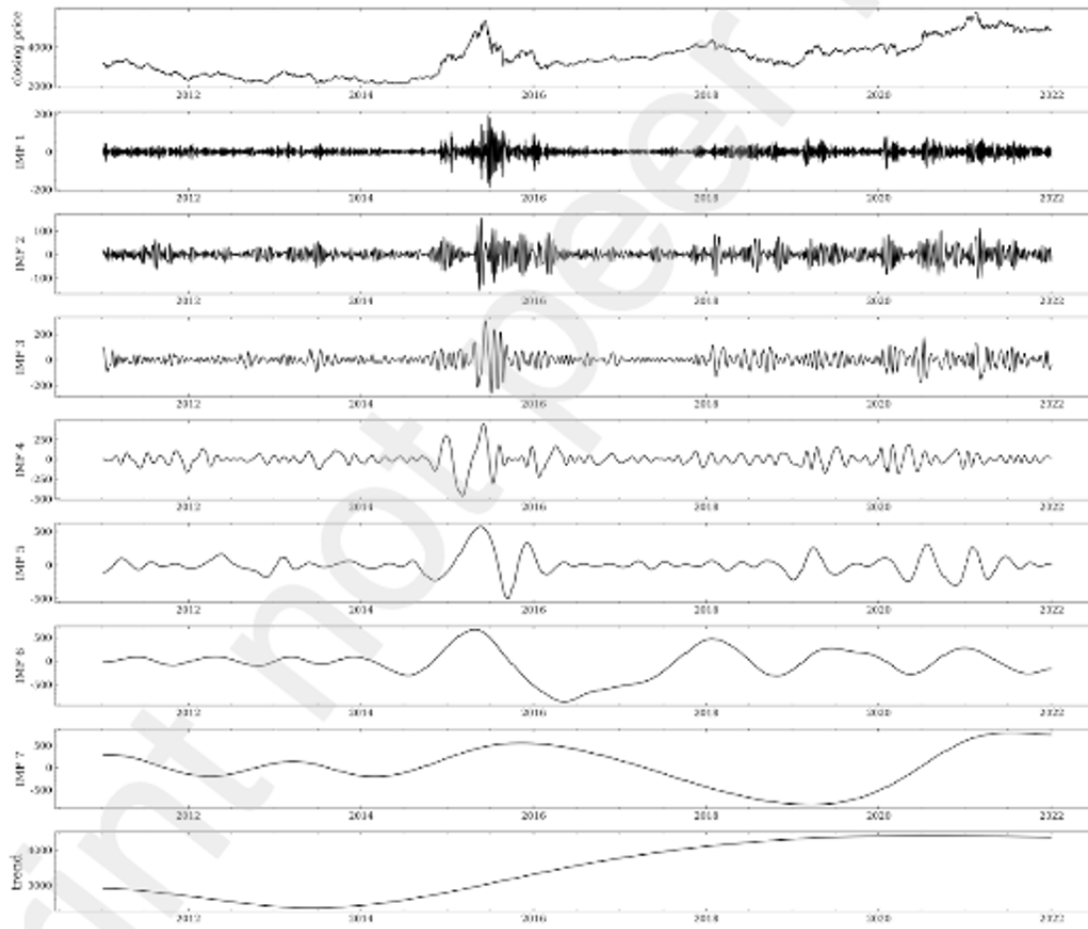


Figure 6. The decomposition result of the CEEMDAN algorithm. (Zhu et al., 2024)

10.3.11 Hybrid Neural Networks and Comparative Studies

Hybrid Neural Networks (HNNs) integrate deep learning with optimization algorithms to manage the noise and nonlinearity of financial data. Mousapour Mamoudan et al., (2023) developed a CNN–BiGRU model optimized with Firefly and Moth-Flame algorithms, achieving 96% accuracy on technical indicator signals, underscoring the value of evolutionary optimization in volatile markets such as the NASDAQ technology sector. Comparative studies highlight the limits of traditional models like ARIMA and exponential smoothing, which capture linear trends but fail with nonlinear dynamics (J.-J. Wang et al., 2012). Machine learning methods such as SVMs, Random Forests, and ANNs outperform these but risk overfitting and lack transparency (Ballings et al., 2015). HNNs bridge these gaps by combining diverse paradigms. Bisoi & Dash, (2014) and Rather et al., (2015) showed improved accuracy and faster convergence using neural networks with optimization algorithms. Srivinay et al., (2022) reduced RMSE and MAE by 5–7% by combining Prediction Rule Ensembles with Deep Neural Networks. Y. Wang et al., (2019) demonstrated that CNN–LSTM hybrids with autoencoders outperformed conventional classifiers in modeling technical and sentiment-driven features. Adding sentiment further strengthens models. Arauco Ballesteros & Martínez Miranda, (2024) found that including sentiment with fundamentals and technicals improved forecasts by 1.5% for most S&P 500 firms. Overall, HNNs consistently outperform both statistical and standalone ML models, with their multi-source integration making them especially effective for forecasting in complex, sentiment-sensitive technology markets.

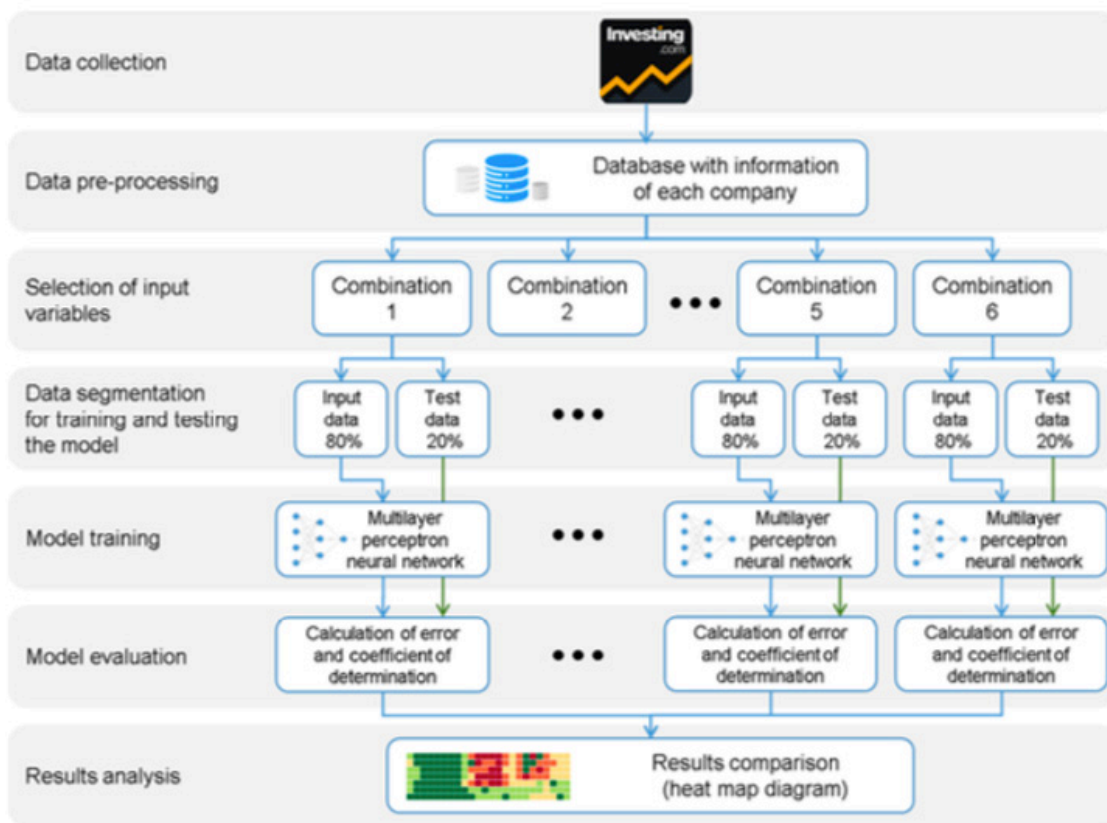


Figure 7. Proposed variables of interest. Source: (Arauco Ballesteros & Martínez Miranda 2024)

Overall, the literature shows that while traditional and standalone ML models remain useful in some contexts, hybrid neural networks more effectively capture the nonlinear and sentiment-driven dynamics of financial markets, making them especially promising for forecasting in the NYSE technology sector.

10.4 Conclusion

The paper has critically examined the literature on different forecasting models, encompassing fundamental analysis, technical analysis, sentiment analysis, and the growing role of hybrid models and machine learning. Each of the selected methods provides certain benefits: fundamental analysis measures intrinsic value through financial indicators, technical analysis tries to capture market trends and patterns, and sentiment analysis reflects behavioral and psychological drivers of the investor decision-making process. Each methods have its own advantages and drawbacks. However, these approaches have been used and applied in isolation, limiting their ability to explain or predict modern financial markets.

Recent advances in artificial intelligence and machine learning demonstrate the potential of integrated and hybrid forecasting models, which could operate on multidimensional datasets. Nonetheless, most of the existing techniques do not consider sector-specific characteristics. Hybrid models that merge technical and sentiment indicators have made notable progress in this field.

This paper discusses the gap in the literature regarding the development of hybrid neural frameworks that unify all these analytical perspectives while incorporating sectoral dynamics. Given the volatility in which we are living, innovation-driven growth, frequent economic imbalances, and sensitive investor psychology within the biggest financial markets, such an integrated approach would fill the gap.

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