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Towards Integrated Stock Market Forecasting: A Literature Review of Fundamental, Technical, and Sentiment-Based Approaches with Machine Learning

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Abstract

Stock market forecasting remains one of the most challenging and extensively studied problems in financial research, driven by its significant implications for investment decision-making and portfolio management. Traditional financial theories, such as the Efficient Market Hypothesis and the random walk model, suggest that stock prices are inherently unpredictable. However, a growing body of empirical evidence indicates that forecasting may be feasible when multiple sources of information are jointly considered. This study provides a comprehensive literature review of three primary analytical approaches, fundamental, technical, and sentiment analysis, and examines how their integration through machine learning techniques enhances predictive performance.

Fundamental analysis focuses on intrinsic value by evaluating financial statements, macroeconomic indicators, and firm-specific metrics such as profitability, leverage, and valuation ratios. While effective for long-term valuation, its limitations include difficulty in capturing nonlinear relationships and adapting to rapidly changing market conditions. Technical analysis, in contrast, relies on historical price and volume patterns to identify trends and trading signals, proving particularly useful for short-term forecasting. However, it often neglects broader economic and firm-level information. Sentiment analysis introduces a behavioral dimension by extracting investor mood and expectations from unstructured data sources such as news and social media, offering valuable insights into short-term market dynamics, though it faces challenges related to data quality and interpretation.

Recent advancements in machine learning and artificial intelligence have significantly transformed stock market forecasting by enabling the integration of these heterogeneous data sources into unified predictive frameworks. Models such as Random Forest, Support Vector Machines, Artificial Neural Networks, and deep learning architectures, including Convolutional Neural Networks and Long Short-Term Memory networks, demonstrate superior ability to capture nonlinear dependencies and complex interactions. In particular, Hybrid Neural Networks (HNNs), which combine multiple modeling techniques, have emerged as a highly effective approach, consistently outperforming standalone models and traditional statistical methods.

The literature reviewed in this paper highlights that integrated, multimodal forecasting models leveraging fundamental, technical, and sentiment inputs achieve higher accuracy and robustness compared to single-method approaches. These findings suggest that the future of stock market forecasting lies in hybrid machine learning frameworks capable of processing both structured and unstructured data while adapting to dynamic market conditions. Despite these advancements, challenges related to model interpretability, data quality, and market volatility remain, indicating important directions for future research.

Keywords: *Stock Market Forecasting; Machine Learning; Hybrid Neural Networks; Fundamental Analysis; Technical Analysis; Sentiment Analysis; Financial Prediction; Deep Learning; Multimodal Data Integration; Predictive Modeling*

1. Overview of Stock Market Forecasting

Stock market forecasting has long attracted researchers and investors due to its profit potential. Traditional financial theory, particularly the random walk hypothesis, suggests that stock prices are inherently unpredictable. Nevertheless, ongoing research indicates that forecasting may be feasible under certain conditions. The difficulty of prediction arises from numerous influencing factors, including economic indicators and investor psychology. In the short term, markets react strongly to sentiment and news, while in the long term, they tend to reflect intrinsic company value, implying that long-term forecasting may be more achievable.

Historically, two primary approaches have dominated market analysis: fundamental analysis, which evaluates intrinsic value using financial data, and technical analysis, which focuses on historical price and volume patterns (Nguyen et al., 2015; Park & Irwin, 2007). Both aim to identify profitable investment opportunities but are challenged by the complexity and noise of financial data. More recently, sentiment analysis has emerged as a third dimension, capturing investor behavior through news and social media data. Unlike classical finance models such as CAPM (Sharpe, 1964; Lintner, 1965), ICAPM (Merton, 1973), and the Fama-French model (Fama & French, 1992, 1993, 1996), modern research emphasizes the role of behavioral biases and market sentiment (Kumar & K S, 2024). Evidence shows that sentiment impacts sectors differently, enhancing performance in some while negatively affecting others.

Advances in artificial intelligence and machine learning have significantly transformed stock market forecasting by enabling the analysis of large, complex, and nonlinear datasets (Abu-Mostafa & Atiya, 1996). These models can integrate fundamental, technical, and sentiment data into unified frameworks (Shah et al., 2019a). Since market movements are driven by a combination of economic, political, and psychological factors (Zhong & Enke, 2017), hybrid approaches are increasingly considered essential for improving prediction accuracy. Current research broadly categorizes forecasting methods into statistical techniques, pattern recognition, machine learning, and sentiment analysis, with machine learning models increasingly combining all three analytical perspectives.

Finally, the rise of digital trading platforms and real-time data access has democratized investing and enhanced forecasting capabilities, allowing investors to leverage advanced tools in decision-making (Belton, 2021).

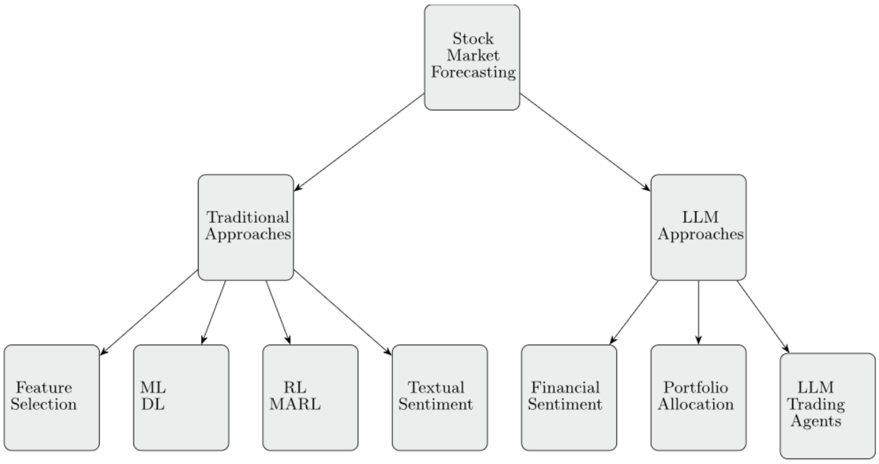

Figure 1: Taxonomy of stock-forecasting research areas: traditional numeric approaches versus LLM-centric approaches (Darwish et al., 2025)

2. Literature Review

2.1. Fundamental Analysis in Stock Forecasting

Fundamental analysis is a widely used approach for evaluating securities by examining intrinsic factors that influence their value. It incorporates both qualitative and quantitative elements, including financial statements, industry conditions, management quality, and macroeconomic indicators. The primary objective is to estimate intrinsic value and determine whether a stock is overvalued or undervalued (Christodoulaki & Kampouridis, 2022).

This approach typically consists of three components (Hu et al., 2015). Macroeconomic analysis evaluates indicators such as GDP and inflation to assess their impact on corporate performance. Industry analysis focuses on market structure, competition, and regulatory conditions. Company analysis examines financial and operational performance, including profitability, efficiency, and growth potential.

Empirical evidence supports the effectiveness of fundamental analysis. For example, Avijan Dutta et al. (2012) showed that financial ratios can distinguish between high- and low-performing stocks, achieving forecasting accuracy of 74.6%. Common valuation metrics include the Price-to-Earnings (P/E) and Price-to-Book (P/B) ratios. Lower P/E ratios are often associated with higher expected returns (Molodovsky, 1953), while P/B ratios help identify overvalued or undervalued stocks based on the relationship between market and book value.

Despite its strengths, fundamental analysis has limitations. It may struggle to capture nonlinear market dynamics and complex interdependencies (Deboeck, 1994), and its effectiveness depends on the availability and interpretation of large volumes of financial data. Nevertheless, it remains a core method for identifying fundamentally strong or weak companies (Namdari & Li, 2018).

Recent research highlights the importance of integrating fundamental analysis with machine learning techniques to improve forecasting performance. By incorporating variables such as revenue growth, profitability, and market conditions, investors can better assess financial health and competitive positioning. Valuation thresholds, such as those for P/E and P/S ratios, provide practical benchmarks for investment decisions (Viktorovich, 2024), helping identify undervalued or overvalued stocks.

Although fundamental analysis is essential for long-term valuation, it is generally less effective for short-term price prediction. Furthermore, the unstructured nature of many fundamental inputs makes automation challenging, though machine learning approaches are increasingly addressing this limitation (Haider Khan et al., 2011).

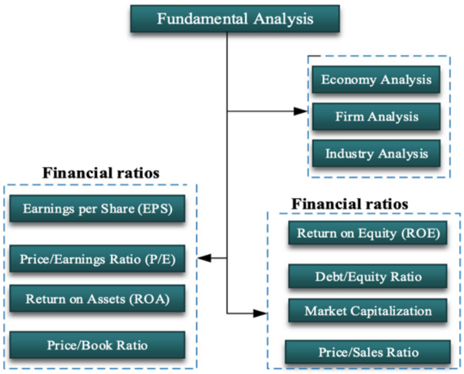

Figure 2: Fundamental Analysis (Haider Khan et al., 2011)

2.1.1. Relevant Financial Ratios in Fundamental Analysis

Nti et al. (2020) identify several key financial ratios commonly used in fundamental analysis to evaluate company performance and valuation:

Return on Equity (ROE) measures how efficiently a firm uses shareholders' funds to generate profits. A low ROE indicates inefficient capital utilization. It is calculated as net income after tax divided by shareholders' equity.

The Debt-to-Equity (D/E) ratio assesses financial leverage by comparing total liabilities to shareholders' equity. Lower values suggest underutilization of debt financing, while higher values indicate greater reliance on borrowed capital.

Market Capitalization (MC) represents the total market value of a company's outstanding shares and is calculated as share price multiplied by the total number of shares. It is commonly used to classify firms into small-, mid-, and large-cap categories.

The Price-to-Sales (P/S) ratio evaluates whether a stock's price reflects its revenue generation, while the Price-to-Book (P/B) ratio compares market value to book value, helping identify overvalued or undervalued stocks.

Earnings per Share (EPS) measures firm profitability on a per-share basis and is calculated as net income divided by the number of outstanding shares, with adjusted versions accounting for dividends.

The Price-to-Earnings (P/E) ratio is a widely used valuation metric that reflects how much investors are willing to pay per unit of earnings. Higher P/E ratios may indicate expectations of future growth. Dunne (2015), analyzing 456 companies between 2000 and 2014, examined the relationship between P/E ratios and subsequent stock performance, highlighting its relevance in forecasting returns.

Return on Assets (ROA) measures how efficiently a firm utilizes its assets to generate earnings. It is calculated as net income divided by total assets, or alternatively adjusted by including interest expenses when ignoring debt costs.

Overall, these ratios provide essential insights into profitability, valuation, and financial stability, forming the quantitative foundation of fundamental analysis.

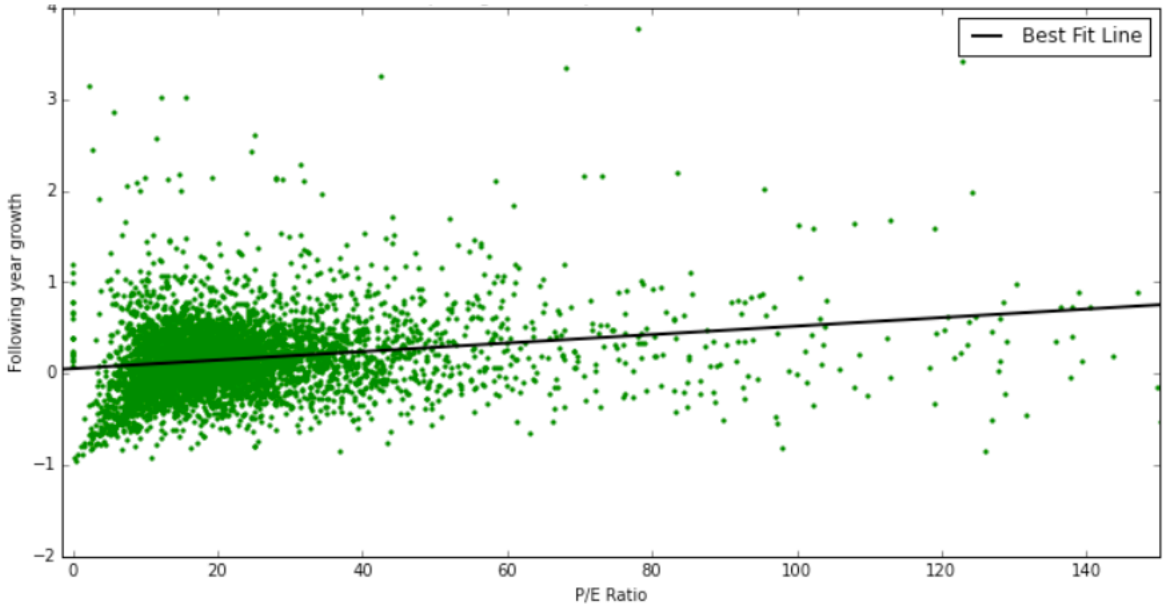

Figure 3: Relationship between P/E Ratio and the following year's growth (Dunne, 2015)

2.1.2. Literature Review in Fundamental Analysis

Phan & Chang (2024) examined the use of machine learning models: Long Short-Term Memory (LSTM), one-dimensional Convolutional Neural Networks (1D CNN), and Logistic Regression (LR), for stock trend prediction based on fundamental analysis. Using financial statement data from 269 firms (2019–2023), they constructed two prediction tasks: Annual Stock Price Difference (ASPD) and the gap between market price and intrinsic value (DCSPIV). Their findings show that Logistic Regression outperformed CNN and LSTM, achieving accuracies of 74.66% and 72.85%, respectively.

Recent studies increasingly integrate fundamental analysis with machine learning techniques. Huang et al. (2021) applied models such as Feed-forward Neural Networks, Random Forest, and ANFIS to S&P 100 data, demonstrating that these approaches can outperform the market when sufficient data are available, with Random Forest showing the best performance. Bekiros & Georgoutsos (2005) found that neuro-fuzzy models outperform neural networks and buy-and-hold strategies during bear markets, although buy-and-hold performs better in bull markets.

Ftiakas & Vlahavas (2021), analyzing 1,353 NASDAQ stocks, concluded that no single model consistently dominates, highlighting the need for multiple approaches. Similarly, Cao & You (2020) showed that machine learning methods such as Random Forest, Gradient Boosting, and Artificial Neural Networks outperform traditional techniques by capturing nonlinear relationships in financial data.

Overall, the literature demonstrates that combining fundamental analysis with machine learning enhances forecasting accuracy and provides deeper insights for investment decision-making.

2.2. Technical Analysis and Its Applications

Technical analysis is a widely utilized approach in financial markets for analyzing and forecasting price movements by examining historical market data, particularly price and trading volume. Unlike fundamental analysis, which evaluates economic and financial fundamentals, technical analysis operates on the premise that historical price and volume patterns can reveal insights into future market behavior. This approach is especially popular among short-term and day traders who use it to guide their entry and exit decisions. Technical analysts employ a variety of tools and methodologies, including price charts, trendlines, chart patterns, volume analysis, and technical indicators, to identify potential trading opportunities (Murphy & Murphy, 1999). The underlying assumption is that market prices reflect all known information and that behavioral patterns in price movements tend to repeat over time. Technical analysis is primarily focused on short-term forecasting and typically disregards external macroeconomic factors. According to Viktorovich, (2024), it centers on the repetition of historical patterns and assumes that these patterns are meaningful for predicting future price directions.

2.2.1. Technical Indicators Used in Technical Analysis

Nti et al. (2020) identify several key indicators commonly used in technical analysis for predicting stock price movements:

The Simple Moving Average (SMA) calculates the average of recent closing prices over a defined period, smoothing short-term fluctuations to identify trends. The Exponential Moving Average (EMA) extends this concept by assigning greater weight to recent prices, making it more responsive to new information.

The Moving Average Convergence Divergence (MACD) is a momentum indicator derived from the difference between short-term (12-day) and long-term (26-day) EMAs, helping identify trend direction and potential reversals.

On Balance Volume (OBV) uses trading volume to predict price movements, with rising OBV suggesting upward trends and declining OBV indicating potential price decreases.

The Relative Strength Index (RSI) measures whether a stock is overbought or oversold by comparing average gains to average losses, providing signals for potential trend reversals.

Although technical analysis has traditionally dominated stock price prediction, relying on historical price and volume data, it has limitations. Li et al. (2015) argue that quantitative indicators alone cannot fully capture a firm's financial condition. As a result, incorporating unstructured data such as news and social media has become increasingly important for improving predictive accuracy.

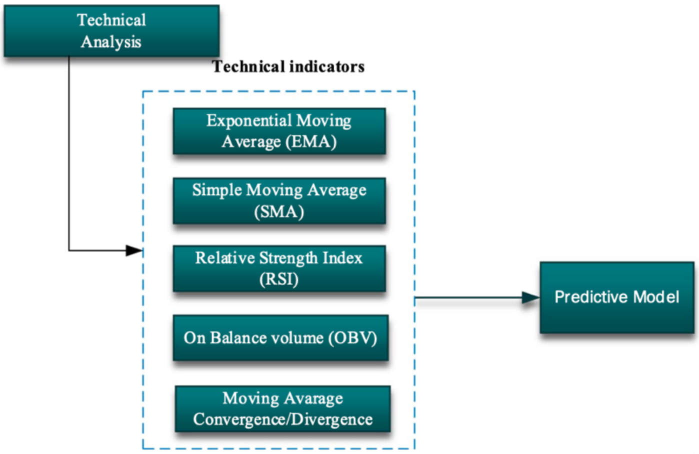

Figure 4: Technical Indicators (Nti et al., 2020)

2.2.2. Literature Review on Technical Analysis

Ding et al. (2023) argue that publicly available information, such as historical prices and trading volumes, is largely reflected in asset prices, supporting the efficient market hypothesis. However, empirical evidence suggests that technical analysis can still generate economically meaningful returns, despite concerns such as data snooping (Park & Irwin, 2007). Studies have shown that technical strategies can produce significant profits across both individual assets and market indices (Brock et al., 1992; Avramov et al., 2015; Osler, 2003).

Technical analysis relies on the assumption that past price patterns can predict future movements (Namdari & Li, 2018). It focuses on price and volume data rather than intrinsic value, using tools such as moving averages, MACD, candlestick charts, and momentum indicators. Its theoretical foundation lies in Dow Theory, which posits that prices reflect all available information, move in trends, and exhibit recurring patterns. Despite its popularity, the approach has limitations, including reliance on static rules and limited consideration of external economic or geopolitical factors (Deboeck, 1994).

Recent research has increasingly combined technical analysis with machine learning techniques. Dash & Dash (2016) developed a hybrid system integrating technical indicators with neural networks, outperforming traditional models such as SVM, Naïve Bayes, and decision trees. Similarly, Hu et al. (2015) identified key domains of technical analysis, including sentiment, volume, trend, momentum, and volatility, which together provide a comprehensive framework for market interpretation.

Further studies highlight the interaction between technical analysis and market sentiment. Ding et al. (2023) constructed a sentiment indicator based on technical trading strategies, finding that it predicts short-term returns and generates abnormal profits, although these effects tend to reverse over time. Detzel et al. (2021) provide a rational equilibrium explanation for technical analysis, while Zhu & Zhou (2009) emphasize behavioral factors, suggesting that noise traders create inefficiencies exploitable through technical strategies. Evidence from hedge fund performance also indicates that technical analysis can improve returns and timing, particularly during high-sentiment periods, though its effectiveness may diminish in low-sentiment environments (Smith et al., 2014).

Overall, the literature suggests that while technical analysis has theoretical limitations, it remains a valuable tool, especially when combined with machine learning and sentiment-based approaches, to enhance forecasting accuracy and trading performance.

2.3. Role of Sentiment Analysis in Financial Markets

Sentiment analysis (SA), or opinion mining, is a Natural Language Processing (NLP) technique used to identify and quantify the emotional tone in textual data such as news, social media posts, and online comments. Its primary goal is to classify content as positive, negative, or neutral, providing insights into public opinion and investor behavior. Despite its usefulness, SA faces challenges such as interpreting context, sarcasm, and cultural differences, with effectiveness largely dependent on data quality and algorithm sophistication (Liu, 2015).

Investor sentiment reflects optimism or pessimism regarding future returns and risks, often deviating from purely rational expectations (Baker & Wurgler, 2007). As a result, sentiment analysis has become increasingly important in financial research. Studies show that stock prices are strongly influenced by web-based information and events, leading to the development of event-driven prediction models that utilize data from platforms such as Twitter and financial news sources (Ding et al., 2014). Incorporating sentiment data has been shown to improve predictions of stock price movements and volatility (Chen & Chen, 2016).

Unlike fundamental and technical analysis, sentiment analysis focuses on the psychological and behavioral aspects of markets. It captures the "wisdom of crowds," enabling the aggregation of diverse investor opinions to enhance forecasting accuracy (Devi & Bhaskaran, 2015). This makes it a valuable complementary approach when integrated with quantitative data.

Market sentiment represents the aggregate mood of market participants and is reflected in observable trading behavior. While related to investor sentiment, it captures the collective outcome of individual beliefs and actions. Generally, rising prices indicate bullish sentiment, while declining prices reflect bearish sentiment (Sohangir et al., 2018).

Overall, sentiment analysis provides an additional layer of insight into market dynamics, complementing traditional approaches and improving the predictive performance of modern financial models.

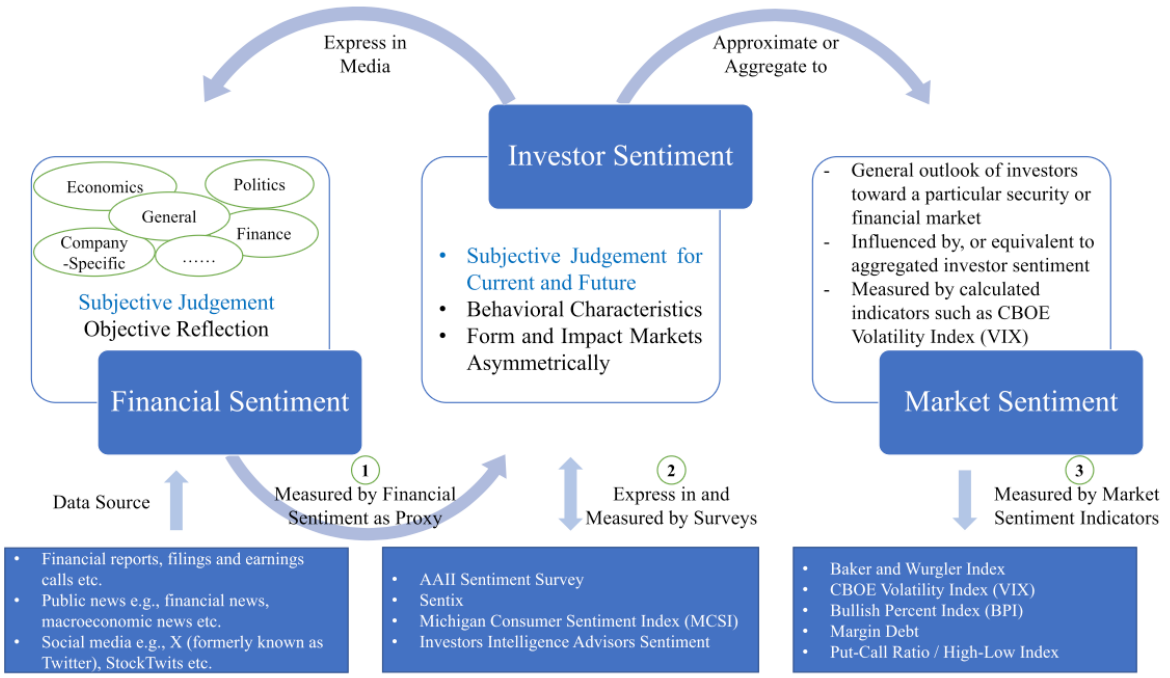

Figure 5: Financial sentiment, investor sentiment, and market sentiment. (Du et al., 2024)

2.3.1. Market Sentiment Indicators Used in Sentiment Analysis

Investor sentiment influences financial markets asymmetrically, with effects varying across different market conditions. It is often measured using proxy indicators derived from historical data, such as price movements and volatility, which are inherently backward-looking.

However, unstructured information, such as political events or breaking news, can trigger sudden market reactions. For instance, a major tariff announcement by U.S. President Trump in April 2025 led to a sharp 4.8% decline in the S&P 500 the following day, highlighting the limitations of relying solely on structured data and the importance of incorporating unstructured signals into forecasting models (Kim & Park, 2025).

One of the most widely used sentiment indicators is the Volatility Index (VIX), which reflects expected market volatility over the next 30 days based on S&P 500 options pricing. High VIX levels indicate increased fear and uncertainty, while low levels are associated with stable or bullish markets (Du et al., 2024).

Other commonly used indicators include the Equity Market Sentiment Index (EMSI), High–Low Index, Bullish Percent Index (BPI), and the Baker–Wurgler Index. The latter combines multiple market-based variables, such as IPO activity, trading volume, and dividend premiums, into a single sentiment measure (Baker & Wurgler, 2006).

Importantly, market-based sentiment differs from semantic sentiment derived from news text. While the former reflects actual market reactions embedded in prices, the latter captures linguistic tone. Empirical evidence suggests that market-based sentiment indicators generally have stronger predictive power for stock price movements (Ma et al., 2023).

2.3.2. Literature Review on Sentiment Analysis

Recent advancements show that sentiment analysis, combined with natural language processing and text mining, provides valuable insights into market behavior that traditional models may overlook (Deep, 2023). It has become a key tool for capturing public emotion and forecasting asset prices (Alsing & Bahceci, 2015). Empirical evidence suggests that sentiment affects portfolio returns differently across sectors, positively influencing some industries while negatively impacting others, with additional interactions observed with macroeconomic variables such as interest rates (Kumar & K S, 2024). However, the lack of a standardized definition and measurement of investor sentiment limits its predictive consistency across industries.

Sentiment is particularly important in explaining short-term market fluctuations, often causing deviations between market prices and intrinsic values. Over the long term, however, prices tend to realign with fundamentals, as demonstrated by Shiller (1980). Early applications of sentiment analysis in finance, such as Bollen et al. (2011), used textual data from news and social media to forecast market trends, establishing a foundation for subsequent research. Sentiment classification methods are typically divided into machine learning and lexicon-based approaches (Bhardwaj et al., 2015), with studies confirming that sentiment signals significantly improve predictions of volatility and short-term price movements (Seng & Yang, 2017; Shah et al., 2019).

Recent research increasingly integrates sentiment analysis with advanced machine learning models. Approaches such as FinBERT have been developed to address domain-specific language challenges and improve classification accuracy (Chen et al., 2024). Hybrid models combining sentiment data with deep learning techniques, such as LSTM, ARIMA, and transformer architectures, have demonstrated superior performance compared to standalone models (Shankar et al., 2024; Vallarino, 2025). Similarly, integrating sentiment with fundamental and technical data enhances predictive accuracy and supports more robust investment strategies (Jing et al., 2021).

Several studies highlight the importance of diverse data sources. Social media sentiment, including Twitter-based indicators, provides real-time insights into investor behavior (Sarmiento, 2017; Zhao & Yang, 2023), while ESG-related sentiment and multilingual data have further improved forecasting performance (Lee et al., 2024; Lin et al., 2022). Additionally, large-scale event-driven analyses, such as those conducted during the COVID-19 pandemic, confirm that sentiment extracted from multiple online sources significantly influences market predictions (Das et al., 2022).

Overall, the literature demonstrates that sentiment analysis is a powerful complement to traditional approaches, particularly for short- to medium-term forecasting. Its integration with machine learning and multimodal data sources continues to enhance the accuracy and depth of stock market prediction models.

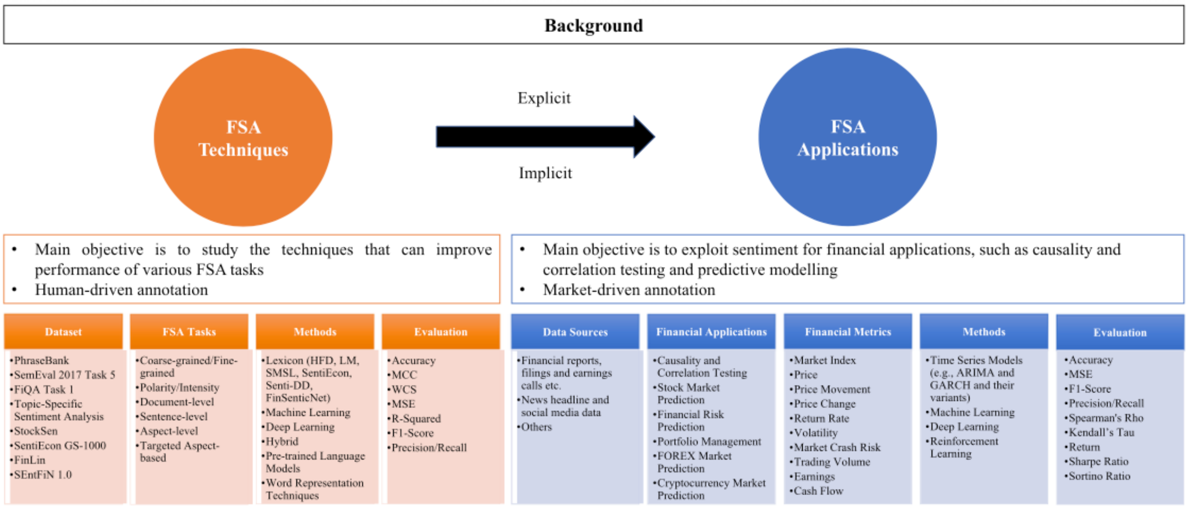

Figure 6: Financial Sentiment Analysis Framework (Du et al., 2024)

2.4. Machine Learning

Machine learning (ML), a subfield of artificial intelligence, enables systems to learn from data by identifying patterns and adapting algorithms without explicit programming (Hurwitz & Kirsch, 2018). Its ability to process large, complex, and nonlinear datasets makes it particularly valuable for stock market forecasting, where traditional models often struggle due to volatility and uncertainty (Rouf et al., 2021).

ML models are generally categorized into three main types. Supervised learning uses labeled data to predict outcomes such as stock prices or returns. Unsupervised learning identifies hidden patterns in unlabeled data, supporting tasks such as clustering and anomaly detection. Reinforcement learning learns optimal strategies through interaction with an environment and is commonly applied in algorithmic trading.

A major advancement within ML is deep learning, which uses multi-layered neural networks to model complex relationships and hierarchical data structures (Nielsen, 2015; Sherstinsky, 2020). These models, inspired by the human brain, are particularly effective for capturing nonlinear dependencies in financial data. Foundational work by Hopfield (1982) demonstrated how neural networks can perform pattern recognition and memory retrieval even with incomplete or noisy inputs, a property highly relevant for financial forecasting.

In stock market applications, a wide range of ML models is employed. Ensemble methods such as Random Forest and Gradient Boosting improve predictive accuracy by combining multiple models. Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Naïve Bayes are widely used for classification and regression tasks. Deep learning models, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, are particularly effective for capturing temporal and structural patterns in financial data. Hybrid models, such as CNN-LSTM combinations or LSTM optimized with evolutionary algorithms, further enhance performance by leveraging the strengths of multiple techniques.

Additionally, text data analytics has become increasingly important, enabling the integration of unstructured data such as news and social media into forecasting models. Overall, machine learning provides a flexible and powerful framework for stock market prediction, particularly when combining multiple data sources and modeling approaches.

2.5. Machine Learning Models

Kumar & K S (2024) applied machine learning models to identify systemic risk factors, highlighting Random Forest and Gradient Boosting as particularly effective, with variables such as stock beta, volatility, and return on equity (ROE) serving as key predictors. Similarly, Yu & Zhao (2020) used logistic regression and Random Forest to assess capital adequacy in financial institutions, improving risk prediction accuracy. Despite these advantages, machine learning models often face challenges related to interpretability and the complexity of financial markets (Deep, 2023).

Machine learning applications in finance are typically divided into supervised and unsupervised learning (Shah et al., 2019a). While early approaches relied on simpler models such as decision trees and Naïve Bayes, more advanced techniques, including Random Forest, logistic regression, and artificial neural networks (ANNs), have demonstrated superior performance (Ballings et al., 2015). Deep learning models, particularly those based on neural networks, are increasingly used due to their ability to capture nonlinear relationships in time-series data (Zhong & Enke, 2017; Bao et al., 2017).

ANNs, including Multilayer Perceptrons (MLP), are widely applied for pattern recognition and forecasting tasks. Support Vector Machines (SVM) offer strong classification performance in high-dimensional datasets, while Naïve Bayes provides efficient probabilistic classification. Optimization techniques such as Genetic Algorithms (GA) are used to fine-tune model parameters, and fuzzy logic systems (e.g., ANFIS) handle uncertainty in financial data. Deep Neural Networks (DNNs), including CNN and LSTM architectures, enable advanced feature extraction and time-series modeling, particularly when combining structured and unstructured data.

Hybrid approaches have gained significant attention, combining multiple models to improve predictive accuracy. For example, LSTM models optimized with Particle Swarm Optimization (PSO) and CNN-LSTM architectures have demonstrated superior forecasting performance compared to standalone models (Kumar et al., 2022; Aldhyani & Alzahrani, 2022). Similarly, enhanced architectures incorporating time-delay mechanisms further improve prediction accuracy (Ratchagit & Xu, 2022).

Despite these advancements, challenges such as overfitting, market volatility, and rapidly evolving trading algorithms remain significant. Techniques such as cross-validation and regularization are commonly used to improve model generalization (Rouf et al., 2021). Additionally, the proprietary nature of many algorithmic trading strategies limits transparency and reproducibility.

Overall, machine learning models, particularly deep learning and hybrid approaches, have significantly advanced stock market forecasting by capturing complex patterns and integrating diverse data sources, though challenges related to robustness and interpretability persist.

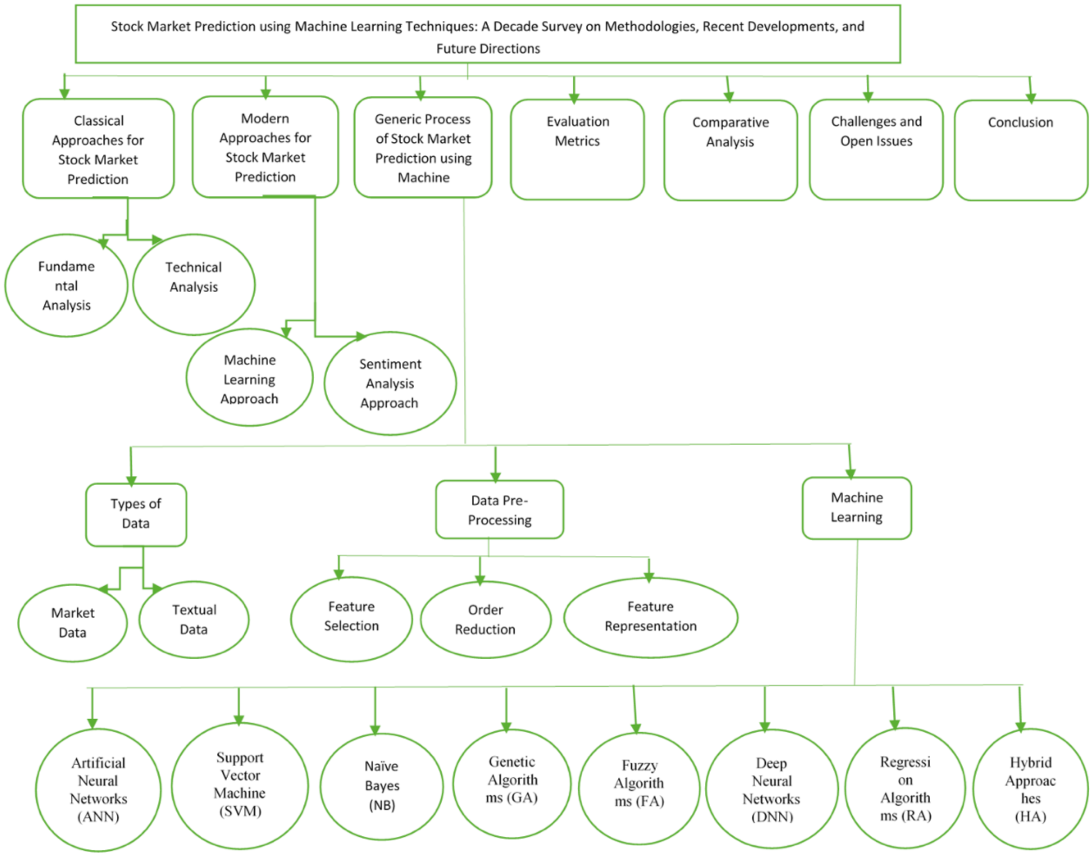

Figure 7: Stock Market Prediction using Machine Learning Techniques (Source: Rouf et. al., 2021)

2.5.1. Literature Review on Machine Learning

The application of machine learning (ML) in stock market prediction represents a major advancement, enabling the detection of complex nonlinear patterns that traditional models cannot capture. Studies show that ML models consistently outperform conventional approaches in various forecasting tasks.

You & Cao (2021) demonstrated that both linear and nonlinear ML models outperform traditional methods and analyst forecasts in predicting corporate earnings. Similarly, Chen et al. (2024) highlighted the effectiveness of deep learning models, particularly LSTM networks, in capturing temporal dependencies, proposing a multimodal framework combining FinBERT-based sentiment analysis with time-series modeling. Jing et al. (2021) further confirmed that hybrid CNN-LSTM models improve prediction accuracy by integrating sentiment and technical data.

Recent research emphasizes the value of integrated approaches. Deep (2023) developed a multi-factor model combining fundamental, technical, and sentiment data with ML algorithms, achieving superior performance. Similarly, Shi et al. (2022) proposed a hybrid architecture integrating CNN, LSTM, attention mechanisms, and XGBoost, significantly improving forecasting accuracy. Namdari & Li (2018) also showed that combining fundamental and technical indicators within an MLP model outperforms single-method approaches.

Deep learning models have demonstrated strong performance across various applications. Zhong & Enke (2019) applied Deep Neural Networks with dimensionality reduction techniques to forecast S&P 500 movements, achieving improved results over traditional benchmarks. Peng & Jiang (2016) and Gálvez (2016) showed that incorporating textual sentiment data enhances prediction accuracy compared to models based solely on historical prices. Similarly, Hung et al. (2024) integrated NLP and deep learning into portfolio optimization, achieving superior returns and risk-adjusted performance.

Hybrid and multimodal approaches continue to dominate recent research. Lin et al. (2022) demonstrated that combining structured and unstructured data using optimized LSTM models improves forecasting accuracy, while Vallarino (2025) showed that integrating transformer-based sentiment analysis with LSTM reduces prediction error and challenges the efficient market hypothesis.

Despite these advancements, challenges remain. Issues related to data quality, interpretability, and regulatory considerations persist (Kour, 2024; Mittal & Sangwan, 2019). Additionally, the inherent volatility of financial markets limits predictive reliability (Manjunath et al., 2024).

Finally, the emergence of Transformer architectures (Vaswani et al., 2017) has further enhanced NLP capabilities, enabling more accurate extraction of sentiment and contextual information from financial texts, thereby improving forecasting performance (Wen et al., 2022).

2.6. Hybrid Neural Networks for Enhanced Forecasting

Hybrid neural networks (HNNs) combine the complementary strengths of different neural architectures to improve predictive accuracy and learning performance (Lin et al., 2017). In stock market forecasting, they are especially valuable because financial time series are nonlinear, volatile, and nonstationary. By integrating diverse modeling approaches, HNNs can capture both short-term fluctuations and long-term dependencies more effectively than standalone methods.

Bisoi & Dash (2014) proposed a hybrid evolutionary dynamic neural network that combined infinite impulse response filters with dynamic neurons and trained the model using Differential Evolution and the Unscented Kalman Filter. Their hybrid framework outperformed traditional gradient-based and standalone methods in forecasting accuracy, robustness to noise, and convergence speed. Rather et al. (2015) similarly showed that blending linear models with recurrent neural networks improved stock return prediction, since linear models captured broad trends while RNNs modeled temporal dependencies and nonlinear market dynamics.

Recent studies reinforce the strength of hybrid models. Srivinay et al. (2022) combined Prediction Rule Ensembles with Deep Neural Networks, reducing RMSE and MAE by 5–7% compared to standalone ANN and DNN models. Wang et al. (2019) developed the Hybrid Time-series Predictive Neural Network, integrating CNNs for financial news features, LSTMs for temporal dependencies, and sparse autoencoders for dimensionality reduction. Their model exceeded benchmark accuracy by nearly 5%, demonstrating the benefits of jointly learning semantic and temporal representations. Likewise, Wang et al. (2012) combined exponential smoothing, ARIMA, and backpropagation neural networks into a hybrid forecasting system that outperformed its individual components.

Other hybrid approaches have incorporated textual data and sentiment. Yoshihara et al. (2014) combined an RNN-RBM with a Deep Belief Network to include the long-term impact of news events, while Ding et al. (2015) used a CNN-based event-driven sentiment model trained on millions of news events to forecast the S&P 500 and individual stocks. These studies show that hybrid architectures are particularly useful when integrating technical, statistical, and sentiment-based information.

The literature also highlights the value of optimization and fuzzy-neural systems. Tahmasebi & Hezarkhani (2012) demonstrated that combining neural networks, fuzzy logic, and genetic algorithms improved prediction accuracy in uncertain environments. Similarly, Senapati et al. (2018) integrated Adaline neural networks with particle swarm optimization, while Mousapour Mamoudan et al. (2023) combined CNN-BiGRU architectures with metaheuristic optimization and feature selection, achieving an accuracy of up to 96%. These findings suggest that optimization techniques enhance the adaptability and robustness of HNNs.

Recent work has further extended hybrid architectures through advanced preprocessing and modular design. Zhu et al. (2024) proposed a CEEMDAN-S-C-LSTM model that integrated noise reduction, convolutional layers, and LSTM networks, significantly outperforming benchmark models. TreNet, introduced by Lin et al. (2017), combined CNN and LSTM components through a fusion layer and achieved better results than standalone CNN, LSTM, and conventional methods, highlighting the value of jointly modeling local and global temporal features.

Comparative studies consistently show that hybrid neural networks outperform traditional statistical models such as ARIMA and ESM, as well as many standalone machine learning models, in capturing the nonlinear and sentiment-sensitive nature of financial markets. Models that integrate fundamental, technical, and sentiment indicators have demonstrated measurable improvements in accuracy, including gains of up to 1.5% in S&P 500 company forecasting when sentiment variables were added (Ballesteros & Miranda, 2024). Overall, the literature confirms that HNNs provide one of the most promising approaches for stock market prediction, particularly in complex sectors such as NASDAQ technology stocks.

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