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A Comprehensive Review on AI-Powered Stock Market Prediction Using Sentiment Analysis and Deep Learning Models

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Abstract
With the advent of the artificial intelligence (AI), natural language processing (NLP) and deep learning models, the financial stock market prediction has changed radically. The classical techniques of forecasting were based upon numbers of indicators such as price history, candlestick patterns and financial measurements but according to some of the research studies, market sentiments that are derived through financial news, tweets, reports and social behaviours are gigantic contributors to the fluctuation of the prices of the stocks. The more promising results with respect to both the trend forecasting and the risk estimation came from the models such as LSTM, GRU, BERT, FinBert, transformers, multimodal fusion network, and sentiment-aware hybrid architecture, etc. The main technological breakthroughs during 2019-2025, its relative strengths, benchmark dataset(s), limitations (e.g. explainable AI, adaptive transformer pipelines, multimodal trading agent, emotion-driven financial analytics), future direction of research etc. are collected together in this review paper. Utilizing sentiment signals along with machine learning models to improve their ability to predict in the future is an area of interest, and this paper aims to provide a detailed perspective to elicit the process of making better informed and accurate stock predictions and relieve stock forecasting systems of much of the burden.

Keywords- *Stock Market Prediction, Machine Learning, Sentiment Analysis, Natural Language Processing (NLP), LSTM, Financial News.*

1. Introduction
What is arguably one of the most tumultuous and uncertain financial conditions is a result of the risky economic times, as it happened in the global market, the impact of political forces, corporate financial reporting, social mood, and economic activities. The statistical prediction models were mainly the GARCH as well as the ARIMA, Linear Regression and Moving averages prediction models. These are cyclical or seasonal variation or stationary time series behaviour of markets estimated by these models. However, none of these traditional methods could be used to explain chaotic volume, non-linear behaviour, and variance depending on the emotions; which are significant in fulfilling financial forecasting today [4].As computational intelligence increased, machine learning models including the random forest, k-Nearest Neighbour (kNN), the decision tree and the support vector machine (SVM) were developed to offer flexibility and learn patterns. However, they were too reliant on manual searches of features at the time, they could not even understand the depth of psychology and behaviour as it influences investors behaviour [18] as events transpired.

1.1. Rise of Deep Learning in Financial Forecasting
One of these changes was a revolution in predictive analytics due to the development of deep learning models. Architectures, such as CNN, Long short-term memory (LSTM), gated Recurrent Unit (GRU), bi-LSTM are more accurate and display more consistent trends compared to traditional machine learning in identifying long-term relationships and hidden sequential dependencies in historical stock price data [4], [15]. Due to the fact that they preserved the memory of the past events and the sign of time, which is vital in predicting activities, LSTM-based

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systems emerged to be on the frontline.Even the deep learning models, though, started off lifeless by simplifying and idealising real-world financial behaviour by assuming that future values are only dictated by the previous numerical trends. The data anecdotes cannot be used to accurately predict any numbers because most stock events, such as earnings announcements, changes in regulations, global crises or intensive social media debates, tend to drive sentiment-related volatility [6].

1.2. Importance of Sentiment in Decision-Making

Stock markets are not only a question of mathematics since a human emotion, psychology, and mass mentality influence them. Sentiment has taken centre stage in the behaviour of investment as the digital financial ecosystems have risen. These eco-systems comprise stock trading platforms, web-based news report platforms like analyst reports, and microblogging platforms such as StockTwits and Twitter [2], [6].

Sentimental effects are becoming more pronounced in the important real-life trends:

- Even prior to the stabilisation of the numerical performance, the good-earnings news often triggers the bullish momentum.
- Speculative news, political unrest or rumours and fanatics can cause panic selling within a few minutes.
- Ordinary market principles can be suppressed by the reaction of individual investors in social networks (as in the GameStop rally or Tesla).

These incidences illustrate why reliable and realistic prediction systems need to incorporate the use of sentiment analysis and Natural Language Processing (NLP) in the prediction models [19], [22].

1.3. The Role of NLP and Transformer Models

Financial text sentiment signals are very high-context signals that are now extractable using recent developments in natural language processing (NLP), especially Transformer-based models such as BERT, FinBERT, GPT, RoBERTa, and XLNet. By means of the skill to understand the domain-specific lexis such as market correction, bearish outlook, downgrade, or profit margin erosion, which the traditional models falsely interpreted, FinBERT, which was only trained on the financial corpora, boosts the accuracy of sentiment polarity classification significantly [19]. Hybrid financial predictive control methods may be developed through combining mathematical stock signals with unstructured textual information to form algorithmic sentiment encapsulations [1], [3], [10].

1.4. Transition Toward Hybrid and Multimodal Predictive Systems

Multimodal architectures Multimodal forecasting models are experiencing increased popularity in research, in which forecasting models combine:

- Stock price trends in the past.
- Sentiment of financial news.
- Social media emotional scores.
- Analyst report and real-time events.
- Market volatility indices.

These hybrid frameworks accurately and effectively predict short-term movements, as well as inner-city stability, than single-source algorithms regularly and they are able to combine the merits of information deep learning and sentiment-mindful NLP pipelines [1], [3], [5], [10], [18].

1.5. Summary of Current Research Motivation

The motivation to write this review paper as developed upon by the literature existing in the area goes as:

- Statistical, to machine learning, to deep learning, to multimodal forecasting there has been a fast development.
- Sentiment is becoming increasingly important in real-life financial decision-making.
- Hybrid systems based on transformers are more predictive.
- Areas that should be studied further are interpretability, model reliability and real-time adaptiveness.

These advancements are summarised in this review, the existing research models are evaluated, and unexplored problems are identified, and future perspectives of the development of reliable systems of the integration of sentiment into financial forecasts are proposed.

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2. Background

With models such as the support vector machine (SVM), random walk theory, autoregressive integrated moving average (ARIMA), linear regression, etc. trying to predict future price patterns based on the historical trading the signals, stock price prediction in the past has been treated as a statistical forecasting problem. These rule-based machines struggled when trying to deal with the nonlinear patterns, noise and dynamic behavioural changes across markets that we normally see today, especially when it comes to dealing with periods of insertive high volatility such as financial crisis and geopolitics. Machine learning was the impetus for the evolution of adaptive learning capabilities, however, ML models in their early days were not able to capture the emotional effects of the market, which made them unsuitable for practical application [4]. The use of Natural Language Processing (NLP) to help predict stock prices was changed dramatically due to the introduction of opinions from analysts, social media activity, and financial news influencing quantitative systems. Models such as BERT, GPT and domain adapted FinBERT used to enable deep contextual understanding of financial text rather than just enjoy keyword polarity scores have made it possible to make accurate sentiment-based predictions [19], [22]. These days, many trading platforms and algorithmic systems offer sentiment scoring by natural language processing (NLP) as a feature for both long-term volatility prediction and short-term price movement prediction. [2] Since the hybrid architectures simultaneously compute numerical series patterns and linguistic financial sentiment patterns, it has been discovered that the combination of deep learning models (CNN, GRU, and LSTM) and sentiment embeddings is more accurate. These models are better than the traditional models because they are able to take into consideration the temporal dependencies, the semantic nuances, as well as the influence of the market context [6], [12]. The most sophisticated forecasting tools available today are multimodal architectures that combine financial variables, text sentiment, and price history.

3. Literature Review

The main goal of earlier studies on sentiment analysis and deep learning-based stock prediction is to lay the groundwork for this section of the work. Three key areas are used to categorize the literature

3.1 Methods of Sentiment Analysis

Sentiment analysis is crucial in modern stock prediction, where financial markets respond not only to simple mathematical calculations but also to news sentiment, public opinion, and emotional responses that can be deduced from financial journalism and social media posts. Research in the area of financial NLP unfolds in three major stages.Shows Figure 1 Workflow of Sentiment Analysis for Financial Text.

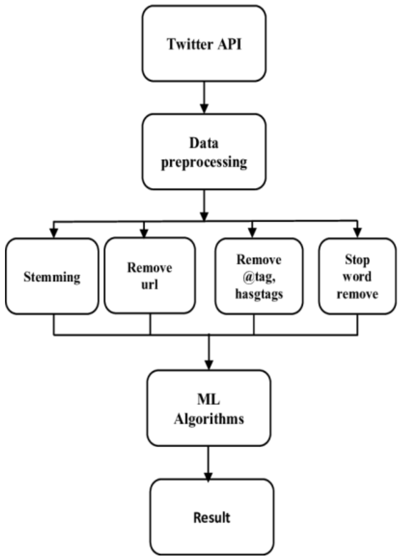

Figure 1 Workflow of Sentiment Analysis for Financial Text

3.1.1 Lexicon-Based Sentiment Classification

Lexicon dictionaries and keyword polarity matching were the major tools adopted in early sentiment-based stock prediction research. With predetermined word lists, these techniques have assified financial text as either positive, negative, or neutral. Lexicon-based approaches, although computationally light, often encountered the same issue of not being able to decipher ambiguous terms in financial texts such as "marginal decline" or "profit warning" and "market uncertainty", leading to inconsistent polarity detection and poor forecasting accuracy [6].

3.1.2 Machine Learning-Based Models of

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Sentiment

Learning features – social features that have been coded into the text based on labelled data – conventional machine learning classifiers of sentiment, such as logistic regression classifiers, SVM classifiers, and Naive Bayes classifiers, achieved moderate improvements. However, they relied mostly on manual feature engineering and could not capture the sequential language dependencies or learn the financial semantics context [11], [18].

3.1.3 Transformer-Based Financial NLP Models

BERT, RoBERTa, BERTweet, FinGPT and FinBERT are some examples of transformer-based models which have been brought along by recent NLP advancements. Among them, FinBERT was a domain-tuned model specifically trained on financial corpora with the ability to accurately analyse the context of sentiment, such as detecting uncertainty, vocabulary of market expectations and risk [19], [22]. Using data sets, like the Financial PhraseBank and FiQA datasets, shows that FinBERT and general-purpose language models revealed significant improvements in precision and recall for the financial sentiment classification [2], [19]. Due to the richer embeddings produced by transformer-based sentiment models that consider both the order meaning as well as the market intent, this research has given validation to the importance of transformer-based sentiment models, which produce richer embeddings that consider both order and market intent, for more sophisticated stock prediction systems [1][6].

3.2 Machine Learning and Deep Learning Models in Forecasting

The capacity of deep learning techniques to capture non-linear relationships, model sequential dependencies, and process vast amounts of temporal financial data has transformed stock trend forecasting.

3.2.1 Classical Machine Learning Limitations:

To be more specific, the previous models, SVM, Random Forest and Gradient Boosting, were good models for short-term forecasting but faced problems with long-term dependency and changing market signals. The main reasons hindering their widespread adoption were the dependence on feature engineering and their inability to adapt in unstable environments [4], [15], [18].

3.2.2 RNN-Based Sequential Learning Models

Recurrent Neural Networks (or RNNs) and their improved versions, such as GRU and LSTM, enabled greater flexibility in the model to remember the past patterns, which improved the forecasting accuracy. The ability of LSTMs to overcome gradient vanishing problems and detect long-range patterns in stock time-series data contributed to the particular popularity of LSTMs. According to research, LSTM-based systems have been shown to perform better than ARIMA and SVM models on a regular basis in terms of directional trend, RMSE and accuracy [4], [15].

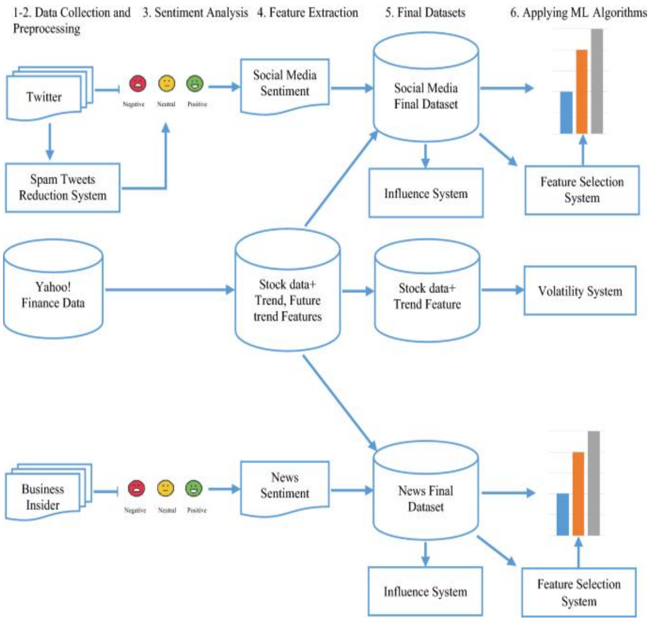

Figure 2 **Machine Learning Framework for Stock Market Prediction**

3.2.3 Transformer-Based Time-Series Models

Recent research efforts have produced new forecasting architectures, such as Autoformer, cross attention and Temporal Fusion Transformer (TFT). Without the need for repeated computation, such models have powerful modelling capabilities for predicting long-term sequences. In terms of their scale and accuracy, these architectures are more efficient than traditional RNNs and utilise self-

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attention to identify intertemporal relationships [3], [5], [16], [21].In the case of financial forecasting research, these developments mean highly scalable models are being incorporated with temporal dependency, network interpretability, and learning of cross-feature dependency [10][18].

3.3 Hybrid and Multimodal Architectures

Hybrid models make use of polyglot numbers in the stock and sentiment-driven linguistic embeddings by creating fully fledged predictive models based on either numerical trends or market sentiment.

3.3.1 Integration of Numerical Indicators and Sentiment Cues

Hybrid models are usually able to access stock price, volume, moving averages and historical volatility data as well as the sentiment embeddings from the news or social media texts at the same time. These models have acquired steady improvements in predictive accuracy as compared to the other traditional time series models or the sentiment-driven models [1], [3], [10], [18].

3.3.2 Cross-Modal Deep Neural Architectures

Recently, cross-modal attention and multimodal fusion transformers have been proposed and involve the dynamic interaction of neural network attention and sentiment cues in text during training. These models are more robust to noise and have increasing pattern recognition capabilities in order to cope with the market shocks or events [3], [5], [21].

3.3.3 Limitations and Current Trends

Despite improved performance, hybrid multimodal systems face challenges, including computational overhead, data imbalance, sentiment noise, lack of multilingual labelled datasets, and difficulty in model interpretability. However, recent models incorporating FinGPT and explainable AI (XAI) frameworks show potential in addressing real-time interpretability and financial compliance requirements [10], [18], [20].According to the literature, hybrid multimodal systems are the most promising area for intelligent financial prediction research since the best results are achieved when deep learning and financial sentiment modelling are combined.

4. Comparative Analysis Of Existing Approaches

Recent studies into deep learning and sentiment-based artificial intelligence (AI) powered stock prediction can be broadly subdivided into the following categories

- deep learning models that are purely numerical.
- models that are sentiment-only or text-based.
- Multimodal models that incorporate price data and sentiment embeddings.

Transformer and LSTM architectures have been proposed in some studies to model stock prediction with the closing price, high-low price and volume as input features as a sequence prediction problem. Although it has been proved that these models could better perform than the conventional ARIMA and machine learning models, they still cannot make the best use of the external market psychology, especially during event-driven stock crashes and peaks [4], [7], [15].However, sentiment-based models use FinBERT, BERTweet, and domain-specific language models to extract the polarity and emotional scores from financial news, tweets, financial news, and reports, which are the primary input features. When models are used singly, they do well, especially for long-term stock prediction tasks where price momentum and continuity of trend are of vital importance [2], [6], [19]. However, they have succeeded in drawing out the market sentiment. For deep learning models like LSTM, GRU, temporal fusion transformers, or cross modal attention models, hybrid multimodal models offer the most promising results by supplying text sentiment embeddings and numerical time series features. Better directional forecasts and more stable performance are given by these models in the turbulent environment by exploiting the contextual information of language models and the long-term dependencies in the price information [1], [3], [5], [10], [18].

5. Challenges And Research Gaps

Despite the great progress in the field of sentiment-aware stock prediction, there are still some challenges.

5.1.Noisy and Domain-Specific Financial Text

The financial text is very domain-specific, and it contains plenty of finance-related terms, risks hidden

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in plain sight, and sentiment changes. The traditional sentiment models, which have been based on non-financial text understanding, are unable to understand phrases like "downgrade", "underperform", "liquidity crunch" and "bearish outlook" and what they mean in a financial context. To overcome this, FinBERT models were introduced, which were trained on financial text corpora; however, even these models cannot understand financial text that consists of slang, tweets, and new financial instruments [2], [6], [19], [22]. One significant challenge that still exists is solid cross-domain adaptation, i.e., a sentiment model performing on a particular market, say on the stock market of the US, should be able to adapt well to another market, such as the cryptocurrency and Indian stock markets, without retraining [7], [18].

5.2. Few excellent labelled datasets are accessible

Most cutting-edge sentiment models rely on labelled sentiment data, such as Financial PhraseBank, FiQA and financial news data. However, financial sentiment annotation requires the knowledge of experts which is time-consuming and costly. Therefore, there are only a few high-quality, large numbers of multilingual labelled datasets, which impacts the generalisation ability of the sentiment models and the potential of overfitting to some specific domains [18], [19]. Semi-supervised, weakly supervised and distant supervision approaches have been suggested, but robust, standardised and well-developed financial sentiment annotation protocols still need to be explored [7], [10], [20].

5.3.Explainability and Interpretability of Models

The deep learning models, especially transformer models, are a "black box" since it is not at all clear how they work. This is a problem, especially with financial models, since they are a significant part of financial investment decisions or regulation. Many papers have been written on how to get better accuracy in predictions, but almost none have addressed how to get an explanation for why a certain feature or feeling is important for a particular prediction [3, 4, 5, 18]. There is a gap in XAI, especially in attention visualisation, feature attribution, counterfactual explanations, and rule extraction, especially for financial models that are based on sentiment analysis [7, 10].

5.4.Handling Extreme Situations and Regime Shifts

The financial market is exposed to sudden, drastic, or extreme changes like crises, pandemics, political issues, or even economic issues in the whole world. Models that are meant to be trained on "normal" financial data will behave alarmingly worse in these unusual but significant market regimes. While there have been a few recent papers that have used models that can handle volatility or have features that can help with event-driven models, there are few models that have been designed to be robust in sudden shifts in regimes [3, 5, 8]. Also, it is seen that the sentiment signals can change depending on the crisis situations that occur, especially since fear or panic is a significant factor in market behaviour in crisis situations. Designing models that can adapt to sudden shifts in regimes is a problem, especially for sentiment analysis models [1, 7, 18].

5.5.Criteria to Evaluate & The Gap in deploying them in the real world

The majority of the research has focused on using criteria such as "accuracy", "RMSE", "MAE", "F1 score", etc., which do not necessarily relate to the profitability of the model in the real world. Only a few research models have focused on using criteria that include "Sharpe ratio", "maximum drawdown", "transaction costs", etc., which are essentially the key criteria for a model to be deployed in the real world [1], [4], [13]. There is a huge "gap" that exists in the real-world application of the models, which has a "deeply rooted" need for a "deeper" understanding of the conclusions that can be made regarding how well a model can be treated, considering the level of constraints, which include "transaction costs", "risks", "regulatory issues", etc. [7], [10], [18].

6. Future Directions

Several possible research directions are identified for creating sentiment-driven, AI-based stock prediction models based on the aforementioned gaps.

6.1.Agentic Systems & Financial Large Language Models (FinLLMs)

Financial Large Language Models (FinLLMs), which can interpret regulatory filings, long-form earnings

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calls, unstructured reports, and multi-document narratives, are moving forward with FinGPT and other GPT-based models [10]. FinLLMs could be used as an engine in future models for:

- Event extraction (policy actions, lawsuits, mergers)
- Risk interpretation (credit rating downgrades, bankruptcies)
- Narrative-based market analysis

Another intriguing but little-studied field of study is agent-based models, in which an LLM functions as an autonomous trader or decision-support system with sentiment and numerical context [7], [10], and [18].

6.2. Scalable Multimodal and Multi-Source Fusion

In the future, sentiment-driven stock prediction models might incorporate multimodal fusion of sources other than news and tweets, such as:

- Technical indicator data, price, and volume
- News, social media, analyst reports
- Macroeconomic data

Advanced fusion models like temporal fusion transformers, cross-attention networks, and graph neural networks may be explored to connect entities & propagate sentiment information among relevant assets [1], [3], [5], [16]. Distributed training of models may be essential to handle the variety & scale of multimodal, high-frequency data streams.

6.3. Explanation of and Rules on AI for the Finance

While in the context of financial data, it is recommended that future research incorporate the direct incorporation of explanations and regulatory requirements in sentiment-aware financial forecasting systems. For instance, attention weights of the sequences of sentences, token contributions and interpretable surrogate explanations can create trust among financial practitioners and regulators in the case of AI-based financial forecasting [3], [7], [18]. Techniques that generate natural language explanations (e.g., "The prediction is bearish because of negative earnings outlook and regulatory risks") using FinLLMs have the potential to fill in the gap between articles or numbers and explanations [10].

6.4.Robustness Domain Adaptation Continual Learning

Future financial forecasting systems should be able to perform continual learning on different domains without being subject to catastrophic forgetting. Techniques such as domain adaptation, transfer learning from general LMs to FinLLMs, and fine-tuning using streaming data can help in improving the robustness of financial forecasting [6], [10], [16], [19]. Moreover, the adversarial training and stress testing on artificial financial crises can also help to enhance the robustness of the financial forecasting system.

Conclusion

This review article has given a comprehensive account of the application of AI in stock market prediction using sentiment analysis and deep learning models, with a focus on research work carried out from around 2019 to 2025. The move from classical statistical models to deep learning models, and then to sentiment analysis-based multimodal models clearly shows the move towards more complex representations of numerical data as well as sentiment analysis of sentence data [1] - [7], [18] - [20]. Transformer models like BERT, FinBERT and FinGPT have improved the science of sentiment analysis for monetary information, one in which the model can interpret complex declarations, as utilised in news articles, corporate declarations and social media. In conjunction to time series models, LSTM, temporal fusion transformers and other deep learning models, the entire model performance in stock direction prediction has shown enhanced performance over other state-of-the-art models [1]-6,10,16,19].There are still some problems that should be addressed, e.g., the availability of sentiment data, models/Language is not interpretable, robust, and correlated with the actual trading performance metrics [7], [10], [18].By analysing the existing literature, this review article will serve as a guiding light for developing new research in the area of sentiment analysis-based financial forecasting models that are not only efficient but also explainable, robust and in line with trading regulation.

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