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A Review of Sentiment-Driven Intelligent Systems for Analyzing the Influence of News Media on Stock Market Prediction

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***Abstract*— This review presents the field of intelligent system that enquires sentiment-driven stock prediction, an area of research that aims to predict market direction combining traditional financial analysis tasks and sentiment generated by investors and the community. This paper explains hypothesis that incorporating sentiment analysis into stock price prediction can enhances intelligent system prediction performances. This article summarizes various ways of sentiment-based stock prediction by reviewing various research articles and highlights increase in performance of predictive model which incorporate sentiment analysis in their algorithm.**

***Index Terms*— Financial market, News media, Social media, Predictive modelling, Sentiment analysis, Stock price prediction.**

I. INTRODUCTION

Prediction of stock prices is one of the cornerstones for financial decision making, in order to maximize the returns for investors in this ever-changing market. Traditional financial predictive models mostly depend on stock price data and technical indicator, which are not able to capture dynamic market forces generated through investor sentiments and real time news events.

The whole investment decision-making process can benefit greatly from the merging of investor emotions with traditional financial analysis. This innovative mix allows market participants to do well in capitalizing on emerging trends in technology, going ahead to exploit the vast experience of leveraging sentimentally social media analytics. By utilizing different sentiment news data platform like Twitter, Stocktwits, and news media outlets like Alpha Vantage, Moneycontrol predictive models can enhance their ability to predict dynamic stock price trends. This paper aims to provide a review of sentiment driven stock prediction pipeline, involving data acquisition and preprocessing, financial news sentiment analysis and sentiment score generation, feature engineering and predictive modelling.

This review tries to cover prominent studies published between 2018 to 2024 which examine various approaches of sentiment driven stock prediction across various global stock market. The main consideration is to evaluate hybrid model that involves machine learning (ML) and deep learning (DL) for sentiment analysis and later for stock price prediction. Various research exemplifies how an easier and probably faster methodology of sentiment-based stock prediction models gives rise to enhanced financial profits.

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For instance, Li Jiahong et al. [1] uses naïve bayes for sentiment analysis from news forum post and then obtained predictions from Long Short-Term Memory (LSTM) leading to an astonishing prediction accuracy of 87.86% with respect to the CSI300 index outperforming other benchmark models by 6%. Guo Li et al. [2] have shown how the twitter sentiment score model was able to forecast trending for the FTSE 100 index by accuracy of 67.22%, outperforming traditional econometric models. The combination of sentiment analysis, stock exchanges' historical data, and modern machine learning techniques has led to enhanced prediction accuracy. Among these hybrid models are CNNs for sentiment classification and LSTMs for technical analysis, which performed even better than models without such features and even single models in forecasting stock prices on the Shanghai Stock Exchange, according to work from Jing et al. (2021) [3]. This adds credence to the use of sentiment-based models to increase predictive ability for those who approve of predicting future trends in the stock market.

II. Literature Review

The review on sentiment driven stock price prediction organized into three themes based on the technique used for sentiment analysis i.e., Lexicon (Dictionary) based approaches, ML based approaches, DL and hybrid-based approaches. This section examines key studies, methodologies used, their performances and limitations of every approaches. Lexicon based approaches basically involves predefined dictionary which have sentiment classification for set of financial text as either positive or negative with their associated degrees of sentiment which helps to derive sentiment score, these dictionary offers interpretability but remain static over time providing limited adaptability to financial text. ML-based approaches utilize the strength of statistical techniques to classify the financial text such as SVM, Naïve Bayes, Logistic regression (LR) etc. These models can efficiently derive sentiments from text as they excel in handling structured features and also are efficient in computation and interpretability. DL and hybrid-based models harness the power of neural network to captures the complex intricacies pattern and temporal dependencies of stock market movements.

D. Shah et al. [4] aim to determine how news sentiments affect stock market movements of pharmacological industry in Nifty Pharma Index namely NSE: ALEKM, NSE: LUPIN, and NSE: SUNPHARMA. Stock data contains intraday (30 min gap) from Investing.com and six-month news article were analyzed from moneycontrol.com. It entails building a 100-word customized pharmaceutical specific dictionary and the predictive model take decision of 'buy', 'sell', and 'hold' based on threshold value of sentiment score derived through customized dictionary. The model achieves directional accuracy of 70.59% for short term prediction. It suffers from limited scalability due to manually created customized dictionary, which can be overcome by employing more advance statistical or ML models for sentiment analysis. X. Li et. al. [5] studies twelve stock data of Hang Seng Index(Hong Kong) across four sectors (Commerce, Utilities, Finance, Properties) and also utilize the technical indicators (moving averages, MACD, RSI, and MFI) and the news article from FINNET aligned with stock data analyzed through four different type of sentiment dictionary .Then build a DL model(2-layer LSTM) to incorporate stock and sentiment data predicting stock price trend(fall, rise, horizontal).Base line models(SVM, MKL) was outperformed by DL model attaining 83.8% accuracy. This comparison study reveals that Loughran-McDonald financial dictionary perform better than remaining dictionaries. It does not contain any event-specific sentiment analysis which can be implemented for broader validation. N. Das et. al [6] studied how public sentiment influenced stock market predictions of the Corona virus pandemic using LSTM architectures. The study employs Nifty50 stock data from Yahoo Finance and VADER, LR, Loughran-McDonald, Henry, and other seven sentiment analysis tools on scraped data from stock headline, tweets, financial news, Facebook comments etc. The research finds that Linear SVC-based sentiment scores derived from Facebook comments achieve 98.11% accuracy. When sentiment scores were integrated within the stock data, the prediction accuracy of 98.32% was achieved, marking the extreme effect emotions have on the movements of the stock market.

J. Huang et al. [7] utilizes HHPIC (Taiwan stock market) stock data chip indicators like Trading volume, stock price change, margin buy loan etc. Sentiments of social media related to HHPIC was taken from Taiwan's PPT bulletin board system and processed using CKIP parser and NTUSD dictionary to calculate sentiment score. Finally Binary logistic regression induced with backward elimination was used to measure the change extend of stock prices at three levels of p-value (0%, 0.5%, 1%) which subsequently improved accuracy by 4.05 %, 1.35%, 2.70% respectively. It was also concluded that stock price change was negatively correlated with sentiment score suggesting the contrarian market attitude (e.g., selling when others buying and vice-versa) A. Kanavos et al. [8] focuses on the relationship between Twitter tweets sentiments and stock price data of Microsoft and Apple leveraging sentiment analysis of Stanford CoreNLP induced with Naïve Bayes Classifier. Lambda architecture with three layers (Batch, Serving, Speed) have been used to perform sentiment analysis to correlate tweet sentiments with stock prices. Highest accuracy has been achieved by Bigrams, tweet polarity has association with the price movements of Apple and Microsoft stocks. It solely relies on Twitter data, potentially missing broader sentiments from another platform like stockTwits, Reddit etc. M. Kesavan et al. [9] collect historical Infosys stock (NSE) data from Moneycontrol and web scrape sentiment data from Facebook posts, Twitter, News headlines and subsequently sentiment scores are generated through NLTK, GloVe embeddings and a lexicon-based sentiment classification. The sentiment induced stock dataset fed to LSTM network with ADAM optimizer, variable lookback period to predict next day closing price percentage change for predicting price fluctuations (decreases, increases, and stagnation). This predictive model achieved accuracy of 96.95 % confirming inducing sentiment data to predictive model results in close alignment with predicted and actual prices. Limitation may include reliance on limited types of stock, focusing on single stock, challenges in detecting sarcasm.

I. K. Nti et. al. [10] analyzed stock data from the Ghana Stock Exchange (GCB, MTNGH, TOTAL) with tenure ranging from Jan 2010 to Sep 2019 to predict future stock prices over various timeframes (90, 60, 30, 7) days. Investor's sentiment was obtained from Twitter, forum discussion(sikasem.org), headlines from news portals of Ghana and Google Trends, later they all were analyzed through NLTK for polarity and subjectivity score. Multilayer ANN was employed to predict binary movement(rise/fall) of stock prices for 1-90 days ahead. Combined dataset with sentiments from all sources has highest accuracy of 77.12 %, among all sources Twitter outperforming others in accuracy (up to 60.05%) when combined with stock dataset. The results also emphasize the existence of a strong correlation between social media and stock market activities which indicates that investors can make use of online data to better predict the market and make informed investment choices. Limitations include focus on single market, challenges with cultural specificity and short-term sensitivity.

Y. Huang et. al. [11] called for the construction of a multichannel collective network for stock price forecasting using social media sentiment analysis and representing the results in candlesticks chart. Sentiment features were extracted from Twitter using natural language processing (NLP) tools, while historical stock data was converted into candlestick charts to capture price movement patterns. The model integrates both data types using two CNN branches: 1-D CNN for sentiment classification and 2-D CNN to predict binary movement(increase/decrease) of stock prices over look ahead of 4,6,8,10 days. When tested on five major stocks: Google, Tesla, Apple, IBM, and Amazon, the approach outperformed single-data-source models, achieving a 75.38% accuracy (10 day look ahead) for Apple. Longer prediction periods yielded better results than shorter ones with Apple and Tesla showing stronger performances. W. J. Liu et. al. [12] set forth a model that considers seven major stock indices (NYSE, FTSE 100, SSEC, Nikkei, NASDAQ, S&P 100, DJI) from Yahoo Finance alongside financial news from website Investing. Financial news was processed with LSTM-CNN model suing Word2vec embeddings and the Financial PhraseBank dataset for sentiment classification achieving 8.3% higher accuracy then standalone LSTM. Combination of sentiment attention mechanism and TrellisNet (SA-TrellisNet) uses the news and stock sentiment index, to predict closing prices which outperformed other models like RNN-LSTM and CNN-GRU, showing lower MSE, MAE, RMSE, MAPE and higher R-squared. The architecture is assessed with seven major stock indices, including NASDAQ, and S&P 500, and it competes with existing prediction methods.

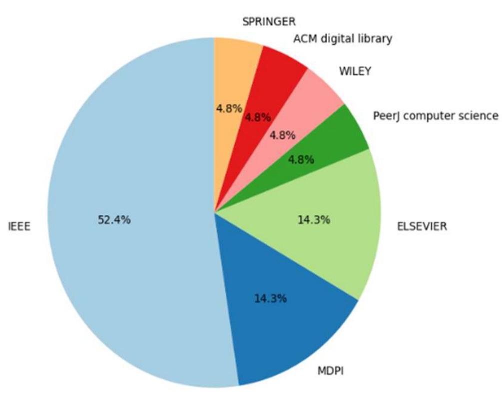

Figure 1. Publisher Distribution

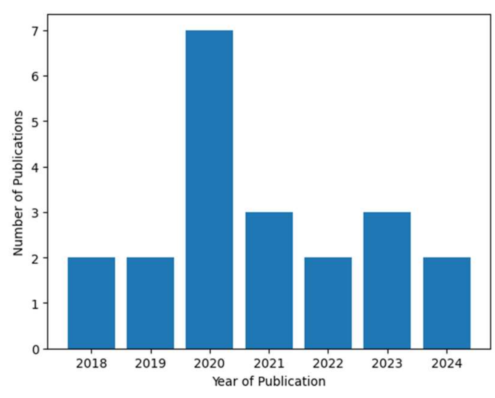

Figure 2. Year-wise publication

R. Chiong et. al. [13] take stock price data from German ad hoc announcements and include feature as abnormal and normal returns, with five-day lagged AbnormalReturnSign and also include financial news text from same dataset, derive polarity and subjectivity using TextBlob. Predictive model contains an ensemble RNN model, LSTM, GRU, SimpleRNN fusion, for stock price binary classification (up/down) movement. Ensemble RNN outperform baseline like PSO-SVM, Kraus and Feuerriegel's model achieving highest accuracy of 59.71%, while incorporating sliding window enhances balanced accuracy by 15.84% compared to sentiments only model. Fig.1 shows publisher- wise distribution of research papers used in this review paper, IEEE is the most prominent publisher, followed by MDPI and ELSEVIER. Fig.2 depicts year wise distribution of research paper used in review paper.

III. Motivation

Incorporating sentiment analysis into stock prediction models significantly improves accuracy, which eventually provides appropriate financial returns to investors making financial market more resilient. This review of sentiment driven stock prediction will empowers retail and institutional investors to capitalize on emerging trends in volatile market using data-driven strategies.

IV. Problem Domain and Definition

Problem domain of this review focuses on financial market prediction, sentiment analysis, and AI which integrate NLP, ML, DL to solve the problem of traditional stock prediction model that uses historical price data and technical indicators which often fails to capture dynamic behavior of stock market as it is unable to include economic indicators, corporate performance, investor's behavior etc.

V. Statement

Inclusion of real-time news events which capture investor sentiments through various platforms like Twitter, StockTwits, and financial news outlets can increase prediction accuracy which significantly drives the market movements.

VI. Problem Formulation and Solution Methodologies

The problem is to formulate a model that integrate financial and sentiment data as shown in fig. 3 and goes through following stages: data collection, preprocessing, sentiment analysis, feature integration, predictive modelling and evaluation. We outline key solution methodologies stage by stage aligning them with problem formulation and justifying their use by giving supporting examples from this review.

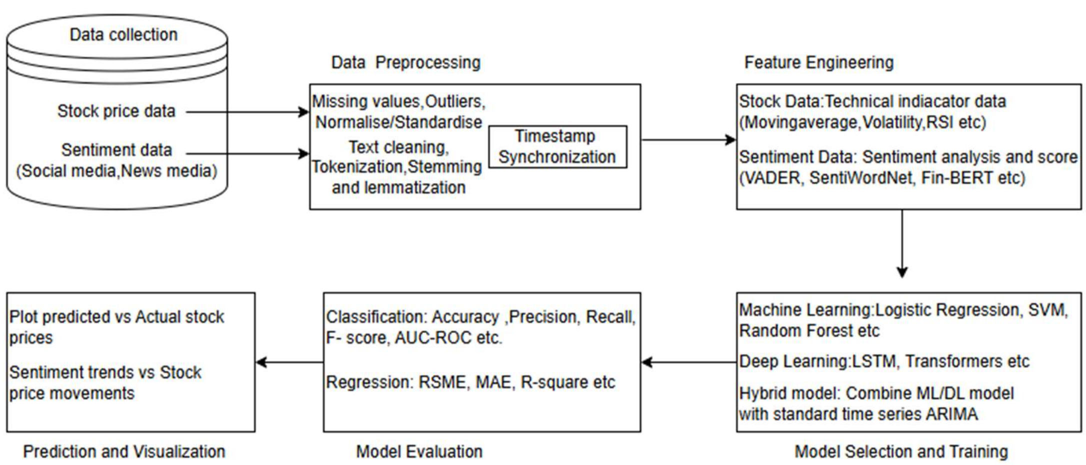

Figure 3. Steps for sentiment-based stock prediction

Initially stock data and sentiment data is collected from Application programming interface (API) like Twitter API and platform like StockTwits and from news portals like moneycontrol, Livemint financial etc. as D. Shah et. al. [4] uses Moneycontrol news for Nifty Pharma stocks and A. Kanavos et al. [8] utilized Twitter news for Apple and Microsoft. The next stage is to process the data which is essential since text data is usually disorderly and requires sorting and structuring. Data preparation is used for tokenization, stop-word removal, stemming, and lemmatization.

TABLE I. DESCRIPTION FOR PROMINENT RESEARCH PAPERS FOR SENTIMENT-BASED STOCK PREDICTION

Ref.	Stock Data	Sentiment Data	Time Period	Sentiment analysis	Predictive model	Model evaluation and Key findings
[14]	National Stock Exchange (NSE): Stocks of BOB, PNB, HDFC, ICICI	NDTV, Livemint, Financial Express, Moneycontrol and Business Today.	August 2018 and September 2018	NAIVE BAYES	KNN, SVM, NAIVE BAYES, NN	KNN outperformed SVM, Naïve Bayes, and neural network achieving accuracy upto 91.2%
[15]	Colombo Stock Exchange: ASPI, S&PSL20	Twitter API	Three time periods: Sep-Dec 2009, Jan-Mar 2015, and May-Jul 2020.	LR, NAIVE BAYES, KNN, Decision tree	Sentiment differences correlated with daily stock index movements	LR (72.35%) and Naïve Bayes (71.76%) have most effective accuracy
[16]	Historical stock data: SPDR S&P 500 Index ETF (SPY)	Stocktwits	April 1, 2020, to February 28, 2022	FinBERT, VADER, 2-class sentiment model	(Original SVM, Ensemble SVM) + (FinBERT, VADER, 2-class sentiment model)	FinBERT with Ensemble SVM achieve highest F1-score (65.30 %)
[17]	Yahoo Finance: StockNet, NASDAQ stock exchange.	Twitter API	1 January 2014 to 1 January 2016	Neutro-sophic Logic (NL) integrated VADER	LSTM	Improved accuracy to 78.48% by integrating NL
[18]	Yahoo Finance, for Apple stock	StockTwits	January 2010 to March 2017	SVM with linear kernel	SVM	SVM stock prediction accuracy (76.86%)
[19]	Yahoo Finance, stocks analyzed - Microsoft (MSFT)	Twitter, StockTwits	16 July 2020 to 31 October 2020	TextBlob, VADER	MLP, SVM, KNN, LR, DT, RF, NB,	Twitter+VADER improved stock movement prediction (76.3% F1 score)
[20]	Yahoo Finance API: Microsoft (MSFT), Amazon (AMAZ), and Tesla (TSLA)	The New York Times	January 1, 2015, to August 13, 2020	TextBlob, VADER	(Sentiment+ without sentiment) with LSTM	With sentiment outperformed without, AMAZ shows max improvement (MSE reduced from 0.01112 to 0.00109)
[21]	Yahoo Finance, Stocks: Microsoft (MSFT).	Twitter, StockTwits	16-07-2020 to 31-10-2020	TextBlob, VADER	SVM and LR	Twitter with VADER improved prediction (76.3% F-score, 67% AUC) compared to stocktwits. SVM outperformed LR across all dataset
[22]	6 stocks from the Chinese stock market	East Money forum	July 1, 2016, to June 30, 2022	Customised financial dictionary	MS-SSA-LSTM (Multisource sparrow search algorithm optimized LSTM) LSTM	MA-SSA-LSTM achieve highest accuracy with average R^2 improvement of 10.74% over LSTM
[23]	9 high volume stocks in BIST 100 (Istanbul Stock Exchange)	Twitter, Mynet Finans, Public Disclosure Platform (KAP), Bigpara	September 1, 2018, to September 1, 2019	Turkish specific BERT	(Word2Vec, GloVe, FastText) + (CNN, RNN, LSTM)	Accuracy of FastText+LSTM (86.39%) and Word2Vec+LSTM (80.61%) are top performer.

Text is represented in numbers using Bag of Word, term frequency inverse document frequency techniques as used by S. Kalra et al. [14] Some advanced techniques also involve using model embeddings such as Word2Vec or GloVe embeddings to capture word semantics as done by M. Kesavan et al. [9]. Rahul et. al. [24] shows that stock market data alone is sufficient to project stock valuations, but it lacks sentiment and performs very inefficiently. Advanced machine learning tools like web scraping (BeautifulSoup, Scrapy) and APIs streamline data collection, enabling effective integration of structured stock price data and unstructured sentiment data for predictive modelling. After this sentiment analysis is done, there are basically following categories of sentiment analysis: lexicon, machine learning, deep learning, and hybrids as depicted in the Fig.4. D. Shah et al. [4]

employs customized pharmaceutical dictionary (lexicon based) to assign sentiment scores, Wen jun Gu et al. [25] integrate FinBERT and StockTwits to enhance the sentiment extraction process. Then sentiment integrated stock data will be fed into these algorithms for model selection and training after data processing. Random Forest (RF)and XGBoost are just a couple of examples of some of these traditional techniques that are interpretable and generally efficient in modelling structured data, they are however preferred in time series analysis as they understand the temporal dependencies and more complex patterns shown by financial market behavior. Non-linear patterns may be addressed through the hybrid models that integrate and use both deep and machine learning as shown by G. Mu et al. [22] through MS-SSA-LSTM. The model can finally be assessed with classification metrics such as accuracy, F1-score as shown by J.X Liu et al. [16] or regression metrics such as MAE, and RSME as shown by W. J Liu et al. [12]. Table 1 depicts details of the predictive model and evaluation technique used in this review paper.

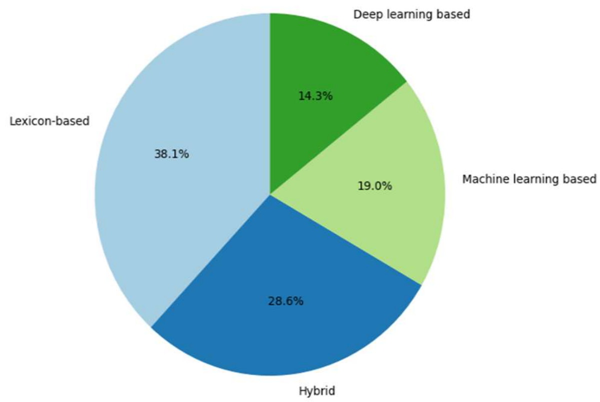

Figure 4. Distribution of sentiment analysis technique used in this review paper.

VII. Results and Sensitivity Analysis

Results shows that classification prediction (rise/fall/stagnant) are most commonly used by the Intelligent Systems, with accuracies often exceedingly more than 80%. Regression task (price prediction) also showed reduced error when advanced models are used like MS-SSA-LSTM, TrellisNet. The sensitivity analysis shows that evaluation results varies when there is change in inputs and other various parameters like sensitivity to data sources, time periods, sentiment analysis method, model complexity, and market conditions. Multi-sources sentiment models are more robust getting high accuracies (70- 80%) as compared to single source sentiment model accuracies (60-70%), because single source sentiment dataset captures platform-specific noise. Long-term prediction (60-180 days) have more accuracies (75-98%) as compared to short-term prediction (1-30 days) as it captures noise and unable to integrate sustained sentiments. DL and hybrid methods attaining maximum accuracies (above 80%) for large, diverse dataset followed by ML methods (70-90% accuracies) if sufficient training data is provided. Lexicon-based perform with least accuracies (60-80%) because they are limited by static vocabularies. Complex model can handle high-dimensional data effectively, but require more data to obtain results as well as computational resources as shown by W-J Liu et al. [11] by employing SA-TrellisNet. Models performs more efficient when market are volatile (90-98% accuracies) as compared to normal market conditions (60-80%) because volatile markets amplify sentiments effects, as seen by N. Das et al. [12].

VIII. Data Models and Comparative Results

To provide an exhaustive list of data models and their comparison, we analyse performance of sentiment driven stock prediction models across following dimensions: data sources, sentiment analysis techniques, predictive models and their evaluation metrics results in Table 1.

IX. Conclusion and Future Work

Much recent work in stock forecasting has turned to sentiment analysis using high-tech NLP models, with the addition of multimodal fusion and hybrid methods. It is evident that models based on transformers such as BERT and FinBERT have greatly improved the accuracy of sentiment extraction from financial texts and social media posts. Research directions to investigate in the future include the development of domain-specific sentiment models, multimodal data integration (including news, social media, and videos), and enhancing AI-driven prediction interpretability. More specifically, the other exciting avenues would involve coupling large language modelling (LLM) on model decision-making and using federated learning for the secure and decentralized analysis of data. The latest innovations in sentiment scoring, merging dynamic sentiment over time with real-time price reactions, are, too, worthy of doing further research upon.

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