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Original Article

Enhanced Context-Based Stock Recommendation Integrating News Classification and Technical Indicators

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Abstract *- This paper presents a method for predicting stock price trends by leveraging online textual news as a contextual factor. Incorporating both historical stock prices and online news data, the cognitive process involves extracting Context Features (CF) from news sources to provide recommendations for traders. Utilizing a Naïve Bayes classification algorithm, news sentiment is efficiently categorized as positive or negative, yielding a News Sentiment Weight (NSW). A News Sentiment Weight (NSW) is then computed for the news, and its impact on a specific stock is assessed to predict the trend. Additionally, the quality of the stock concerning technical is evaluated using different financial technical methods(Indicators), forming the Technical Weight of Stock (TWoS). The combination of NSW and TWoS with weights is utilized to predict the price of the stock trend and offer recommendations to traders. The paper predicts stock trends by combining NSW and TWoS and delivers tailored recommendations to traders. Comparative analysis showcases the superior performance of this contextual approach over traditional recommendation systems, highlighting its efficacy in accurate stock signal prediction.*

Keywords *- Cognitive Process Stock recommendation, Naïve Bays algorithm, News Sentiment Weight(NSW), Technical Weight of Stock (TWoS).*

1. Introduction

Knowledge Discovery in Data (KDD), also called knowledge extraction from extensive databases, involves extracting valuable hidden knowledge from large datasets. This process requires analysing data from diverse sources and condensing it into useful information to identify patterns beneficial for activities that enhance business and decision-making. The problem in the existing literature is some of the research work is based on the classification of textual news with various classification algorithms, and some are based only on technical indicators. However, in the proposed work, an attempt will be made to design and develop a hybrid model that will use the classification of textual news published online as contextual information and technical information about the stock to predict the exact price. The different AI and ML techniques are applied particularly due to the dynamic and highly fluctuating form of stock prices. Investors must make swift and cautious decisions in this domain, as an erroneous move could result in significant losses. This research seeks to address this challenge by generating promising recommendations and facilitating well-informed decision-making for investors. The paper is organized as follows: Section 2 explores a literature review of data mining, machine learning, recommendation systems, and the market. And also provides information about the background of recommendation systems, technical parameters that are frequently leveraged for stock scripts, and text mining for news analysis. Section 3 outlines the methodology employed in the research. Section 4 contains detailed experimental results with graphs. Finally, Section 5 contains concluding remarks about the work done and gives a way for future work.

2. Literature Survey

Forecasting in the stock market remains a prominent subject of interest for data mining researchers. Numerous studies have focused on anticipating the most accurate and robust rules. Widely employed methods for stock price prediction include Neural Networks, Genetic Algorithms, Association, Decision Trees, and Fuzzy systems. Text mining stands out as a straightforward technique among these approaches. In research work [1], the authors provide a focused exploration of Support Vector Machine (SVM) based classifiers, particularly different variations of SVM classifiers, in the context of multi-category text classification, specifically applied to News data. The research article [2] uses NLP techniques that try to detect the news sentiment of various

companies whose news is published on Reuters for a particular period, find the effect of such emotions on stakeholders of the company, and compare the reactions of the market in terms of price of a stock and volatility. The work reported in [3] The proposed method for price movement prediction of a particular script appears to be a promising approach integrating various data sources for accuracy enhancement. Using mathematical indicators and sentiments extracted from the news is a thoughtful combination, acknowledging the multi-faceted nature of factors influencing stock prices. The survey work done in [4] is to present the latest detailed review of current works on ML and DL models for price prediction of a particular share. The work done in the paper [5] is based on time series data. A hybrid model is designed and developed to use time-series financial data as input and predict accurate results with excellent performance. In the survey paper [6], a detailed survey was conducted using a systematic approach for the ten years from 2011 to 2020. It considers the research papers that used hybrid techniques to develop stock prediction systems and classify them. In the research article [7], they built up a stock price recommendation application and found a way to denote pricing information calculated by technical indicators and classify news text by analysis of sentiments and how stock prices are predicted. The paper [8] shows investment ideas based on analyzing sentiments of news on finance that are functional to the stock market of Brazil. The paper [9] suggests separating the AI stage and identifying pattern stage, enabling the trading system to produce a more accurate set of thoroughly validated trading suggestions. The research conducted by [10] introduces an enhanced sine and cosine algorithm. The algorithm incorporates extra criteria of sin and cos functions to adjust the errors in BPNN, i.e., back propagation neural networks. Paper [11] introduces a method to improve stock trend prediction by incorporating index analysis and learning. The approach accounts for the influence of market trends on individual stock behaviour, utilizing the market key to distinguish between the effects of overall market trends and fundamental movements of individual stocks. In [12], a pioneering network based on feature-enhanced LSTM joined with residual-driven SVM, is employed to generate stock recommendations. Meanwhile, [13] focuses on a model that is based on the mining of opinions. This model introduces a part of the speech to excerpt the users' opinions and conduct tests. In [14], researchers analyze the news content of online social networks in China. They extract features in sentiment and features in LDA (Latent Dirichlet allocation), which are part of these accounts and input them, along with technical parameters, into a new proposed model entitled RNN-boost for predicting changes in stock markets. Lastly, the paper [15] formulates a function for time series prediction using multivariate data, aiming to capture the impact of temporal effect and transformation information of the data of the time series under consideration. In [16], a ground-breaking model named the DIMG (Deep Implicit Memory Gaussian) Network is introduced. This model incorporates a kernel process that is bidirectional with deep memory and employs features that are implicit in nature. This method is used to enhance predictions in time series data. The research work [17] presents an innovative system for predicting stock prices based on integrating random forest and LSTM. [18] details the development of a correlational graph and LSTM prediction system. The model described in [19] utilizes a genetic algorithm for optimizing the points of variable mode decomposition. Researchers then employ an LSTM network to predict future data using inputs generated through VMD. [20] introduces a CNN model designed to classify the investors' emotions hidden in many stock portals and forums. Subsequently, a hybrid R&D-based model based on the LSTM and Neural Network approach is proposed to analyze technical indicators in the stock market along with the emotion analysis output obtained in the previous step. The survey papers [21, 22] provide a detailed examination of various algorithms and methods for stock recommendation systems. In contrast, paper [23] introduces a hybrid model called eTrend that integrates long-term and short-term strategies by combining TF strategies and XCS, i.e. extended Classifier Systems. The research outlined in the paper [24] focuses on evaluating price predictability in the financial Tehran market using the neural network and the PCA analysis method. Meanwhile, studies in [25, 26, 27, 28] delve into country-specific stock prediction systems based on artificial neural networks tailored to their respective stock exchanges. However, a common limitation across these works is the absence of consideration for the real-time impact of news alongside technical analysis using statistical indicators. The paper [29] illustrates a stock recommendation system based on users' requirements and interests. In the paper [30], the authors introduced a new way of investment through a recommendation describing how AI and automation can be used and how a system is developed and tested, giving robust and accurate results. Market dynamics often witness immediate or delayed effects on certain stocks following news releases. Hence, a crucial need arises to explore the combined influence of online news and stocks' technical aspects for effective stock market trading.

3. Materials and Methods

This section throws light on system architecture and how the system is implemented. The detailed system architecture is shown in Figure 1. Data Extraction is done from online news publishing sites as RSS feeds and text datasets are prepared. Text Preprocessing is done for Tokenization, in which the news sentences are broken into separate words. The data set is deprived of the stop words (common words like “to,” “the”, “and,” etc.) to highlight the relevant content. Stemming is the process of getting the root words. It shortens words to their most fundamental meaning, for example, converting "increased" and "increasing" to the stem word "increase". Named Entity Recognition (NER): A script name mentioned in the news text will be extracted. The importance of this step lies in the sense of associating stock script with news. An

algorithm classifies the text in news as either positive or negative. In this step, the system uses labeled data for supervised training to a machine-learning model that predicts a sentiment. News Sentiment Weight (NSW) Calculation: After the news categories are done, the NSW is computed. The sentiments of the news articles related to a given stock, aggregated, could produce a single measure of sentiment for this NSW. The main aim of this system appears to analyze news items about stocks, recognize and extract essential information, and determine the attitude attributed to the news. NSW could then be viewed as a measure to assess public perception. During the system's second phase, the company currently in the news has its historical stock prices retrieved from the web portal. Technical analysis is then performed on the downloaded data, leading to the Technical Weight of Stock (TWoS) calculation. By amalgamating the News Sentiment Weight (NSW) with the Technical Weight of Stock (TWoS), decision-making rules are devised to determine recommendations. Following these rules, recommendation signals like BUY, HOLD, and SELL are produced and subsequently transmitted to the users.

3.1. Implementation

Different modules are designed, developed, and tested in the developed system.

3.2. Raw Data Extraction Module

It involves extracting Really Simple Syndication (RSS) feeds containing news text from various sites. A custom software agent is developed to retrieve raw text present in news data that is published on selected news platforms like Moneycontrol, Yahoo Finance, Moneyworks4me, CNBCTV18.com, Reuters, etc.

A selected news is then organized into a table accompanied by timestamps. The historical stock prices of the news selected for further consideration are downloaded from the NSE site and stored in a separate table.

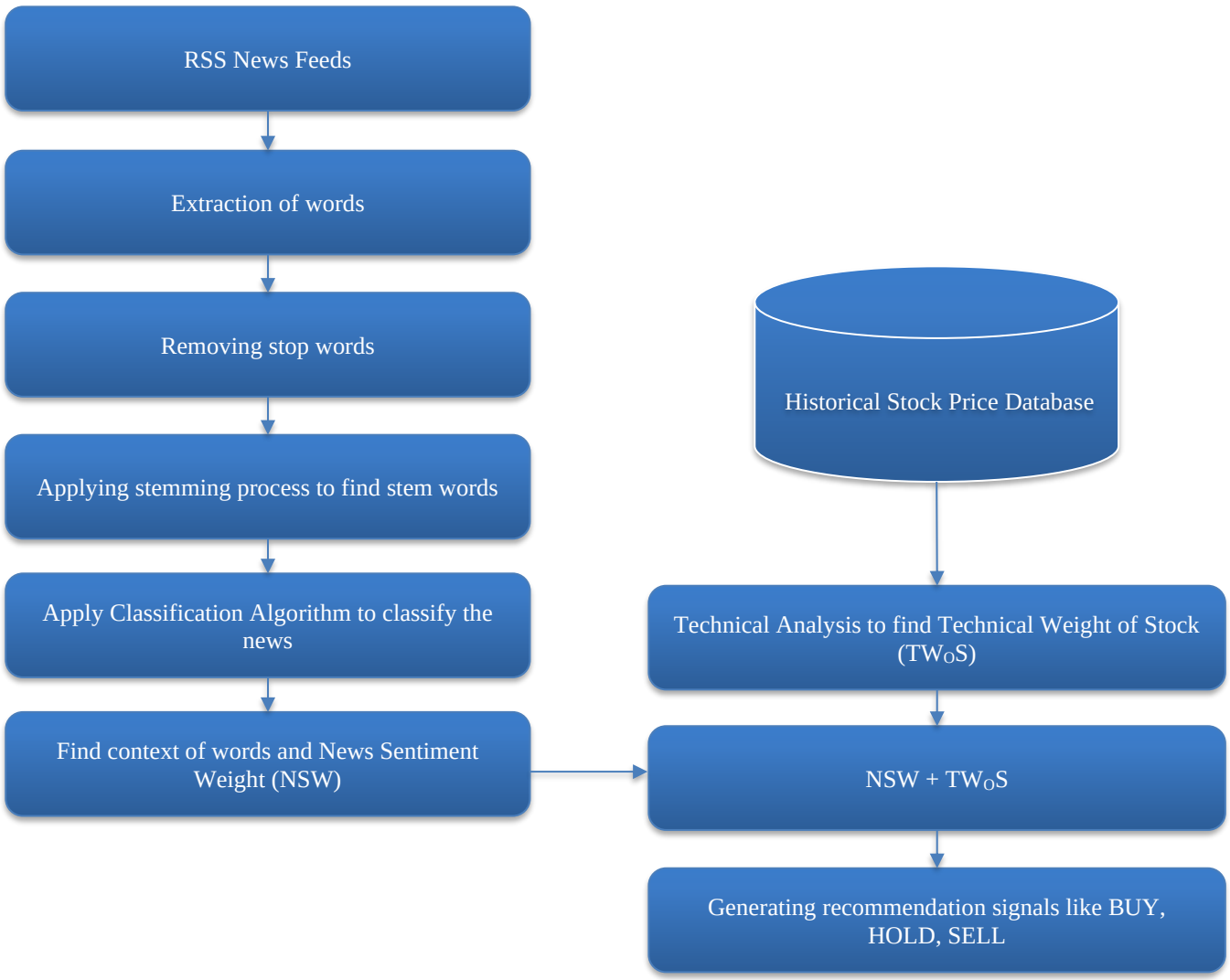

Fig. 1 System architecture

Table 1. News text data extracted with date, portal, and opening price of stock

Sr.No.	News Text	Date	Portal	Opening Price on Date in Col '3'
1.	Infosys Net Sales increased at Rs 37,441.00 crore, up 16% Y-o-Y for March 2023	21/04/2023	MoneyControl.com	1228
2.	Tata Consultancy Services March 2023 Standalone Sales at Rs 49,780.00 crore, up 17.24% Y-o-Y	20/04/2023	MoneyControl.com	3090
3.	Q4 PAT up 26% YoY for Rs. 5,279.7 cr for ITC	20/04/2023	MoneyControl.com	400
4.	Indian Oil Corporation June 2023 Net Sales down 11.92% Y-o-Y at Rs 197,526.57 cr.	28/07/2023	MoneyControl.com	96
5.	Eicher Motors' motorcycle arm reports 7% rise in sales in March 2023	03/04/2023	moneyworks4me.com	3050
6.	IGL shares fall 5% on Delhi electric vehicle policy draft	20/10/2023	CNBCTv18.com	447
7.	BEL Q4: Beats street estimates, Strong order book position at Rs 60,690 crore	22/05/2023	CNBCTv18.com	108

3.3. Creating Dataset

During this phase, the training dataset is assembled, encompassing labels for a class, such as positive or negative. Let's examine the provided dataset (D1), which comprises five news items—four being positive and one negative. The Preprocessing Module serves to preprocess the obtained data. Text news preprocessing involves sentence tokenization, stop word removal, and stemming. Certain entries contain missing values for the stock data extracted from BSE that feature stocks highlighted in the news. Addressing this missing value issue in stock market data, one effective solution involves replacing the missing values with those of the nearest neighbor.

Additionally, when encountering missing dates in the dataset, the approach taken is to substitute the stock prices on those dates with the previous day's price for the respective company. In this phase, stop words are eliminated from every news article. Stop words, such as "a," "an," "the," "is," "of," "can," "in," "into," etc., are excluded. Utilizing stemming, a stemmer is employed to identify the base word of an identified term in the text. Extraction of stock name to compute the probability of the stock name being extracted. The stock name is also essential for retrieving the dataset needed for Technical Analysis.

3.4. Text Classification Module

Text classification is accomplished through the utilization of the Naïve Bayes Algorithm, undergoing thorough testing for validation. Text classification employing the Naïve Bayes Algorithm is based on probabilistic principles. The algorithm calculates the probability of a given document belonging to a particular category by considering the frequency of words within that category. Despite its simplicity, Naïve Bayes effectively handles large datasets and is known for its speed and efficiency. The system is provided with comprehensive training to enhance its ability to predict future test cases efficiently. The training process encompasses the following steps:

3.5. Identifying Distinct Terms

At this phase, distinct words are singled out from the dataset. These exclusive words are then saved in a vector known as the Unique Vocabulary (UQV). Determining the positive occurrences of individual unique words involves calculating the frequency of each word in positive instances. Specifically, it entails counting the number of times a term appears in positive news and subsequently storing this information in a vector known as PV. It is determined how often each unique word appears in negative instances, and these occurrences are in a vector known as NV (Negative Vector).

Determining the likelihood of each distinct word being positive involves the computation of the positive probability for each unique word, employing the following formula in this phase:

Consider n to be a count of terms in positive news.
Consider nk, the frequency of the term k occurring in positive news.
Consider nw, the count of unique terms appearing in news text.

Then,

$$p\left(\frac{Wk}{pos}\right) = \frac{nk+1}{n+nw} \tag{1}$$

The finding of negative probability of all unique words in news text is as follows :
Consider n is a count of terms of a negative news text.
Consider nk, the frequency of the term k present in negative news cases.
Consider nw, which is the count of unique terms.

$$p\left(\frac{Wk}{neg}\right) = \frac{nk+1}{n+nw} \tag{2}$$

Calculating the probability of a positive case

$$p_{pos} = \frac{n_{pos}}{n_{total}} \tag{3}$$

Calculating the probability of a negative case:

$$p_{neg} = \frac{n_{neg}}{n_{total}} \quad (4)$$

NSW and TWoS calculation modules will be used to design the Weight of News Sentiment (NSW) and Technical Weight of Stock (TWoS). The NSW mathematical formula is as follows:

$$\partial(P)_{pos} = \frac{(p(pos) - p(neg))X\ 100}{p(pos)} \quad (5)$$

$\partial(P)_{pos}$ is the percentage difference between +Ve and -Ve probability,
(Pos) the probability that the news text is positive,
(Neg) the probability that the news text is negative

After the above calculation of $\partial(P)_{pos}$, various conditions are defined to give the weights to each range of $\partial(P)_{pos}$ value to find NSW_{pos}

NSW_{pos} = 2 ∈ ($\partial(p)$ between 0 to 25)

NSW_{pos} = 4 ∈ ($\partial(p)$ between 26 to 50)

NSW_{pos} = 6 ∈ ($\partial(p)$ between 51 to 75)

NSW_{pos} = 8 ∈ ($\partial(p)$ > 75)

Similarly, the NSW_{neg} is found with the formula below.

$$\partial(P)_{neg} = \frac{(p(neg) - p(pos))X\ 100}{p(neg)} \quad (6)$$

NSW_{neg} = 2 ∈ ($\partial(p)$ between 0 to 25)

NSW_{neg} = 4 ∈ ($\partial(p)$ between 26 to 50)

NSW_{neg} = 6 ∈ ($\partial(p)$ between 51 to 75)

NSW_{neg} = 8 ∈ ($\partial(p)$ > 75)

Technical Weight of Stock (TWoS) is designed by combining the TWoS of the moving average, the TWoS of RSI, and the TWoS of stochastic. The formula is developed which is as follows:

$$TWoS_{SMA} = 1, \text{ if Closing Price > SMA of TWoS}; \ 0, \text{ else} \quad (7)$$

$$TWoS_{RSI} = 1, \text{ if TWoS RSI is > 50}; \ 0, \text{ else.} \quad (8)$$

$$TWoS_{Stochastic} = 1, \text{ if Stochastic of TWoS < 80}; \ 0, \text{ else} \quad (9)$$

Following is the explanation of how a Technical Weight of Stock(TWoS) is calculated, which will be used in the recommendation module.

$$TWoS = TWoS + TWoS_{RSI} + TWoS_{Stochastic} \quad (10)$$

The recommendation module will make use of the NSW_{pos}, $NSW_{pos,}$ and TWoS.

$$R_{s1} = NSW_{pos} + TWoS \quad (11)$$

$$R_s = 1 \text{ if } R_{s1} \geq 8; \ 0, \text{ otherwise.} \quad (12)$$

$$R_{s2} = TWoS - NSW_{neg} \quad (13)$$

$$R_s = -1 \text{ if } R_{s2} \leq -4; \ 0, \text{ otherwise.} \quad (14)$$

Finally, generate Recommendation Signals (R_s) the following rules are developed. If R_s = 1, then the BUY indicator is produced for the script appearing in the context of news. If R_s = 1, then the SELL indicator is produced, and if R_s = 0, then the HOLD indicator is produced for the script, which appears in the context of the news text.

4. Results and Discussion

The experimental stage encompassed extensive testing on a dataset gathered from diverse news sources, such as moneycontrol.com, CNBCTV18.com, oneyworks4me.com, finance.yahoo.com, and others. The dataset consisted of around 1906 news articles, each meticulously labeled with either a positive or negative sign through classification.

By implementing the described techniques, recommendation signals were generated. The evaluation process included scrutinizing prediction accuracy and comparing it with the actual closing prices, measured by the gain value at the end of 30 Days. Notably, it was observed that relying solely on TWoS or NSW did not consistently produce accurate recommendation signals.

However, adopting a combined approach of NSW+TWoS resulted in accurate signals in the maximum cases. Table 2 shows the results of the various stocks with open and closed prices. It also shows the signals generated by NSW, TWoS and a combination of NSW+TWoS. The last column of Table 2 reflects the gain in percentage in the short-term period.

The example graph is shown in Figure 2 for the Infosys stock with open and close prices from 21/04/2023 to 31/05/2023 after the news “Infosys Net Sales increased at Rs 37,441.00 crore, up 16% Y-o-Y for March 2023” came online sites.

Figure 3 shows the ITC stock with open and close prices from 20/04/2023 to 31/05/2023 after the news “Q4 PAT up 26% YoY for Rs. 5,279.7 cr for ITC” came online. Figure 4 shows the stock of Eicher Motors when the news is published on the news websites: “Eicher Motors’ motorcycle arm reports 7% rise in sales in March 2023”.

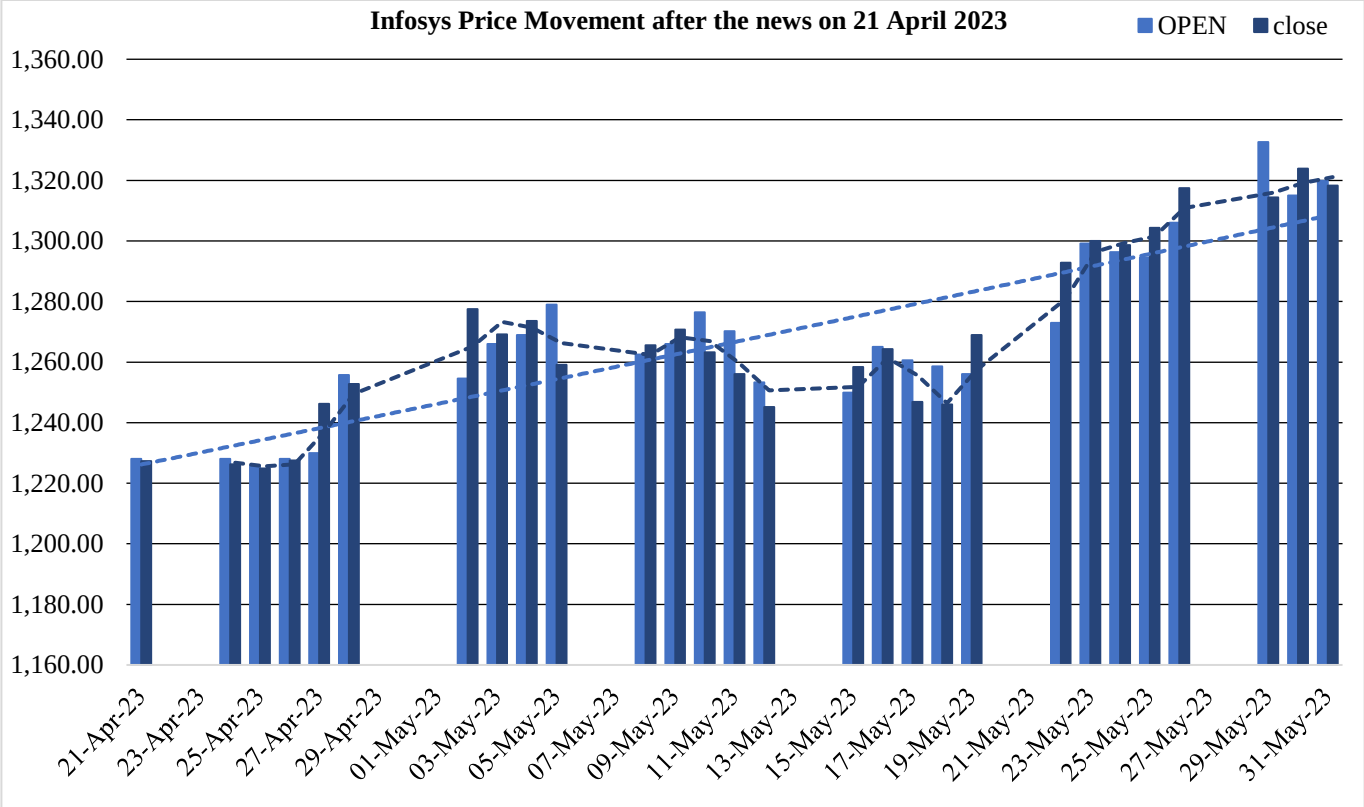

Fig. 2 Graph showing open and close price movement of Infosys stock after the news on 21/04/2023

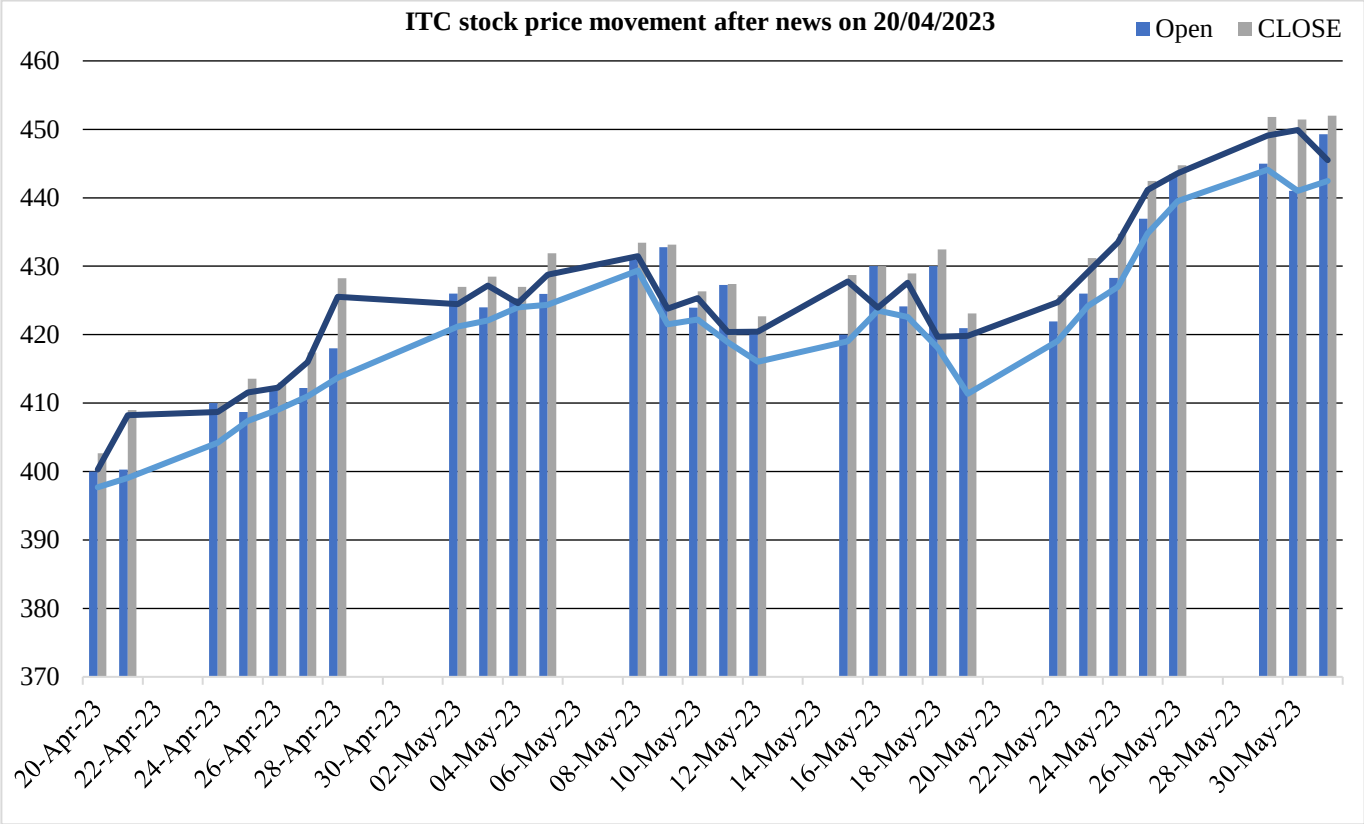

Fig. 3 Graph showing open and close price movement of Infosys stock after the news on 21/04/2023

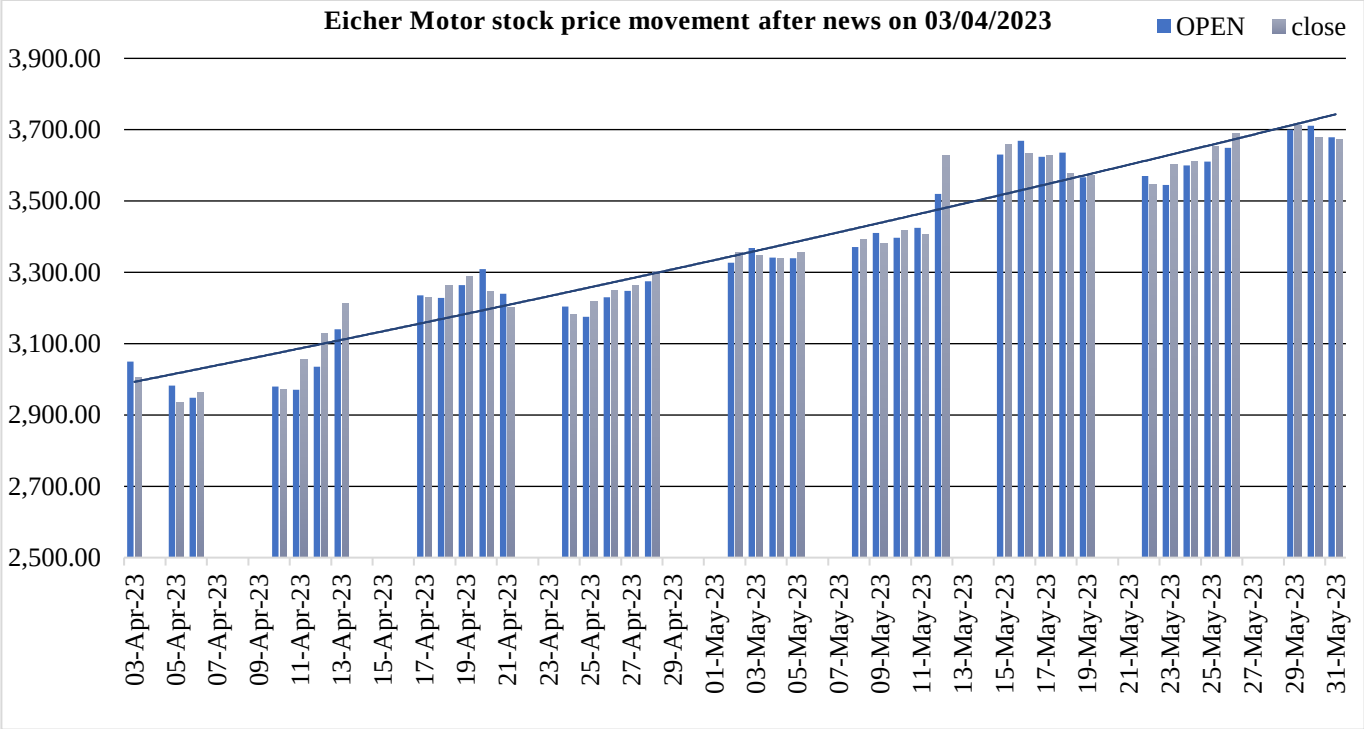

Fig. 4 Graph showing open and close price movement of Eicher Motors stock after the news on 03/04/2023

Table 2. Prediction results of NSW, only TWoS and NSW+TWoS both

Stock Name	Date	Open	NSW	TWoS	NSW + TWoS	Actual Close	Date	Gain in %
Infosys	21/04/23	1228	BUY	SELL	BUY	1319	31/05/23	7.41
TCS	20/04/23	3090	BUY	BUY	BUY	3309	31/05/23	7.08
ITC Ltd.	20/04/23	400	BUY	SELL	BUY	449	31/05/23	12.25
IOC	28/07/23	96	SELL	HOLD	SELL	90.75	31/08/23	5.78
Eicher Motors	03/04/23	3050	BUY	BUY	BUY	3678	31/05/23	20.59
IGL	20/10/23	447	SELL	HOLD	SELL	390	30/11/23	14.61
BEL	22/05/23	108	BUY	BUY	BUY	121	30/06/23	12.03

Technical data from last year was used as training data to validate the method. The algorithm was then implemented, and its results were compared with stock prices. The findings demonstrate that the approach produces impressive results, providing investors with valuable insights into potential stocks for investment. The results are shown in Table 2 with different methods such as NSW, TWoS, and a combination of NSW and TWoS, i.e. NSW+TWoS, which has given a very good outcome on performance in achieving the consistent gain percentage in a short-term period. The gain percentage is shown in the last column of the table, ranging from 5% to 20%. The short-term period considered is 15 to 60 days. In the experiments, the lowest gain was 5.78% for IOC Ltd. from 28/07/2023 to 31/08/2023 in 30 days. The highest gain is for the stock Eicher Motors, which is approximately 20.59% from 03/04/2023 to 31/05/2023 in 56 days.

5. Conclusion

In summary, this research has explored the impressive capabilities of the developed system in evaluating the financial gains associated with stocks highlighted in news articles. The results indicate that integrating online textual news with historical stock price data, as part of a cognitive process, proves to be effective and efficient for predicting stock performance.

The methodology involves applying sentiment analysis and technical analysis to online stock market news articles, with technical analysis employing predefined rules on stock data. These extraction methods yield two valuable indices: the News Sentiment Weight (NSW) and the Technical Weight of Stock (TWoS). Experimental findings reveal that combining features such as NSW and TWoS enhances forecasting accuracy compared to the individual utilization of these features.

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