A Future Trading System Using Ensemble Deep Learning

Usha Devi NSSSN[1] and Mohan R[2]

[1,2]*Computer Science and Engineering,NITT,Tiruchirappally, Tamilnadu*

Abstract: Stock price prediction is a challenging research problem due to various dependencies like news headlines, Twitter, microblogs, and price history. News headlines and price history are the most significant features for predicting stock prices, which help investors decide to sell, buy, or hold that maximizes the profits. The manual analysis of large amounts of news and price history information is impossible. Hence, automation is required to summarize the available data for wise trading decisions. We propose an ingenious Future Trading System Using Ensemble Deep Learning (FTSEDL) to improve the accuracy of the prediction. The objective is to develop FTSEDL that improves the Deep learning predictive model with a new context-based clustering, CbCA, and information fusion for an accurate stock price forecast. The CbCA filters the required features from the news datasets to generate quality datasets through context-based clustering. Information fusion combines the two vital features of stock price prediction: news headlines and price history. The present research experimented with six stocks, BHARATIARTL, SBIN, PNB, NXTDIGITAL, TCS, and WIPRO, covering possible up, down, and sideways trends to improve the predictive model evaluation. The experiment data considered the stock news and price history data from 8th August 2016 to 31th March 2023, i.e., 2427 trading days. CbCA achieved a homogeneity of 0.95, Completeness of 0.98, and Silhouette coefficient of 0.88. The proposed model, FTSEDL, achieved an accuracy of 91.693.09, RMSE of 13.14, and MAPE of 0.02, which outperformed the models in the recent literature. The FTSEDL has many advantages when compared with contemporary literature. In addition, there is vast scope to apply this concept in real time.

Keywords: Stock, Clustering, Feature Extraction, Fusion, Artificial Intelligence

1. INTRODUCTION

Stock price prediction with News sentiment analysis is an exciting research problem. The news media disseminates daily updates directly or indirectly, affecting the stock trader's decision [1]. News sentiment analysis became highly influential in stock market predictions, recommendation systems, and personal portfolio management. Therefore, the focus on news sentiment analysis substantially increases the portfolio profits. However, the performance of this analysis for stock price prediction depends on challenges presented in Natural Language Processing (NLP) and news processing.

The news contains various categories: business, profit or loss statements, stock price, business administration changes, policies, recruitment, achievements, welfare activities, etc. The features are classified into two groups based on their effect on stock price and domain knowledge. The features like profit, loss, and achievements correlate to stock price. In contrast, other features like welfare activities, celebrations, and recruitment are uncorrelated to the stock price. Analyzing these correlated features improves news sentiment analysis. Hence, there is a need for Feature Extraction in news sentiment analysis to extract prominent features that affect stock price prediction.

News sentiment analysis faces a polysemy problem. In polysemy, the word meaning changes with context. The domain-specific text analysis suffers from polysemy. For example, the meaning of "bull" changes with the context. In business-specific news, "bull" is a critical term that reveals the stock rise. However, this term would be classified as an animal in general. Hence, polysemy became a significant problem in news sentiment analysis. There is a need to incorporate context-based learning to solve polysemy and make news sentiment analysis reliable. Word2Vec is a popular method that improves news sentiment analysis by converting the sentences into meaningful embedding format [2].

Information fusion combines information from multiple sources to improve data quality and utilization. The stock price history and news headlines are essential in stock value prediction. We followed multi-source information fusion in the proposed system to consider both datasets [3]. The deep learning approach is robust and efficient for sentimental analysis applications. Deep learning uses primary Deep Neural Networks [4] like Convolutional Neural networks (CNN) and recurrent Neural networks (RNN) [5]. Moreover, most text analytics solutions use RNN. The two basic types of RNN are LSTM and GRU [6], and the GRU is suitable for short text processing [7].GRU understands

the input patterns and their correlation and determines the sentiments. The objective of the present research is to develop FTSEDL that improves the Deep learning predictive model with a new context-based clustering, CbCA, and information fusion for an accurate stock value forecast. Our Major Contributions:

1) Created news datasets with information fusion using news datasets and stock price history.
2) Proposed a new clustering algorithm, CbCA, for context-based clustering and compared it with baseline methods.
3) Modeled GRU Regressor for stock price prediction.
4) Integrated the CbCA with GRU for Feature Extraction.
5) The existing and proposed models were evaluated using RMSE, MAE, and MAPE metrics.

We organized the sections as follows: Section 2 explains the existing methods and their advantages and limitations. Section 3 describes the theory and implementation of the proposed work. The following section, i.e., Section 4, interprets the results and discussion. Further, the last section, i.e., Section 5, summarizes the results with the conclusion and scope of future work.

2. METHODS

A. News Sentiment Analysis for Forecasting Stock Price

News headlines disclose essential changes in the stock market. They are prominent in quickly identifying the market's flow and crucial in stock price movement prediction [8]. The stock price and business-specific news sentences are highly correlated [9]. The previous works considered all the business news for stock prediction without detecting every news sentence's significance by feature extraction. On the other hand, stock price history plays an essential role in forecasting the future price of a stock [10]. However, the previous works will consider either price history or news data for prediction. Consequently, these methods lead to unfruitful results in predicting the stock price. The present research incorporates close price and news data to improve prediction accuracy. They further incorporated a Feature Extraction method that extracts the essential news sentences that affect the stock price so that highly correlated features are included in input datasets.

The Sentiment analysis is used to deduct meaningful inferences from data. Ioannis Almalis et al. applied sentiment analysis to analyze the sector-wise stocks using news datasets [11]. The authors converted the sentences into an embedding format using Word2Vec to improve the quality of sentiment analysis. News sentiment prediction uses business-specific news articles to convert the news into statistical information [12], generating positive, negative, and neutral polarities. Dictionary-based sentiment analysis is also popular[13] for regional language news sentiment prediction.

The Sentiment analysis meets accuracy with Feature Extraction compared with predefined sentiment dictionaries like Vader [14]. However, analyzing the business headlines and clustering them based on context is challenging. In the present research, we selected English news, the most widely used in India for disseminating business news. The CbCA assigns the news item to the respective cluster, enhancing the news sentiment analysis with a deep learning model.

B. Feature Extraction

Feature Extraction is vital in obtaining the correlated features from the dataset. Feature Extraction enhances the news sentiment analysis by extracting the elements proportionately with the stock price. Identifying similar sentences and understanding their correlation is a challenging task [15]. Centroid similarity [16] is an approach for short text classification that uses the integrated framework of BERT, LDA, and CNN. These approaches help process generic English sentences. However, they suffer from polysemy problems, especially in news sentence sentiment analysis. Clustering plays a vital role in Feature Extraction. Shuang et al. have [17] explained the importance of nouns, adverbs, and verbs in Sentiment Analysis for generic data. Choudary et al. have expressed that identifying the parts of speech is necessary to understand the text [18]. Mehdi et al. proposed a matrix factorization method named RANMF [19] for High-dimensional text clustering. In the proposed clustering algorithm CbCA, the news sentences were clustered based on nouns and verbs that consider the sentence context.

C. Sentiment Analysis with Deep learning

The deep learning models are more accurate than the statistical models in stock value prediction [20]. The deep learning models are most suitable for Sentiment Analysis [21], and further, they are very useful models for stock value prediction [22] through sentiment analysis.

Anika Kanwal et al. applied LSTM, GRU, and RNN for stock value prediction using news sentiment analysis [23]. The approach yielded promising results, but the system considered the uncorrelated features in news data that would affect the system's reliability. The proposed FTSEDL uses GRU regression that learns the short phrases of news sentences and refines sentiments when integrated with CbCA.

3. THEORY AND IMPLEMENTATION

The proposed work explains how the prominent news feature extraction is helpful for stock price prediction. Fig.1 describes FTSEDL architecture. First, we present the system overview with modules, and then we go into the details of each module. The modules of the FTSEDL are as follows: Data Collection and Preprocessing, Feature Extraction, and Stock Price Prediction. First, We collected the news datasets for the stock BHARATIARTL, SBIN, PNB, NXTDIGITAL, TCS, and WIPRO from the Times of India, Bombay Stock Exchange, and National Stock Exchange websites. This news database contains 18,510 sentences. Further, we extracted the stock's historical data sets from the NSE website.Fig.2 illustrates the distribution
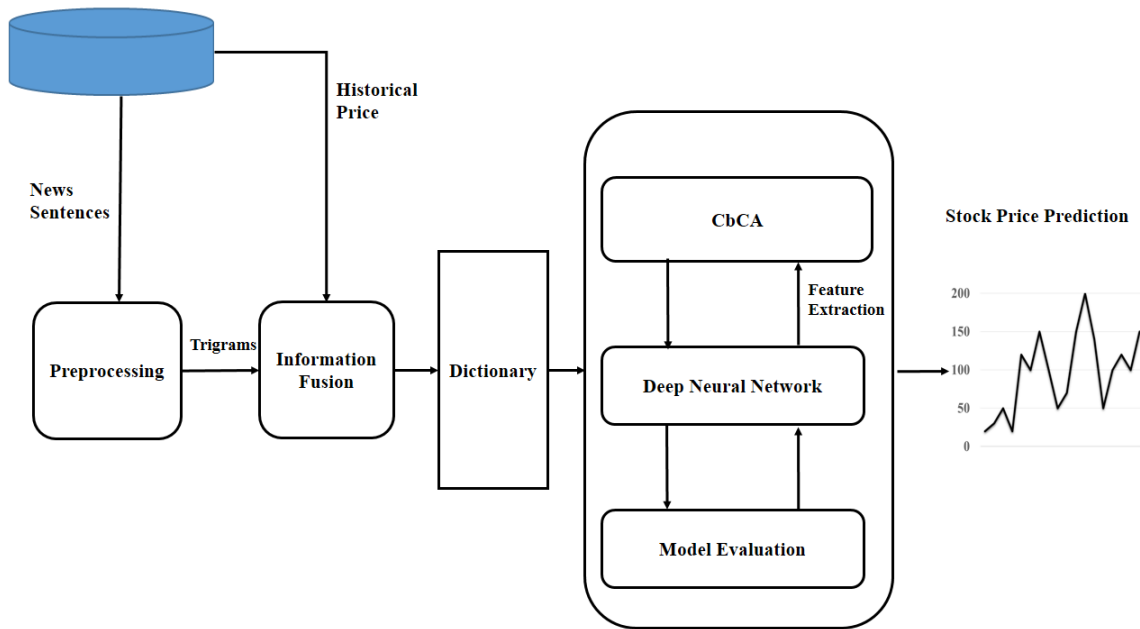
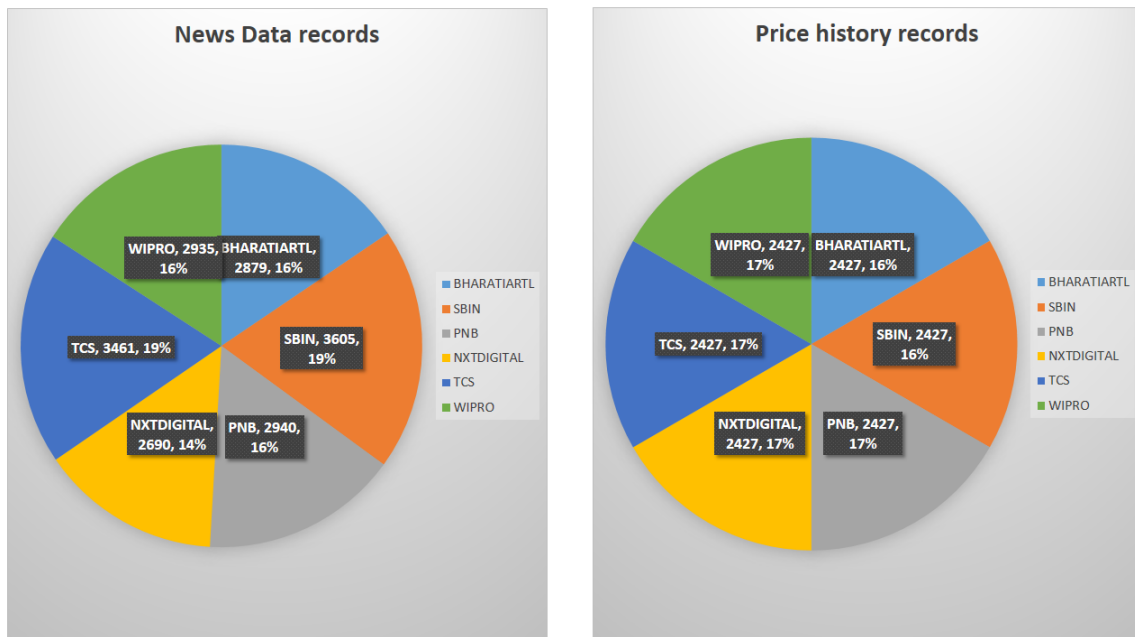Figure 1. Architecture of the proposed model.
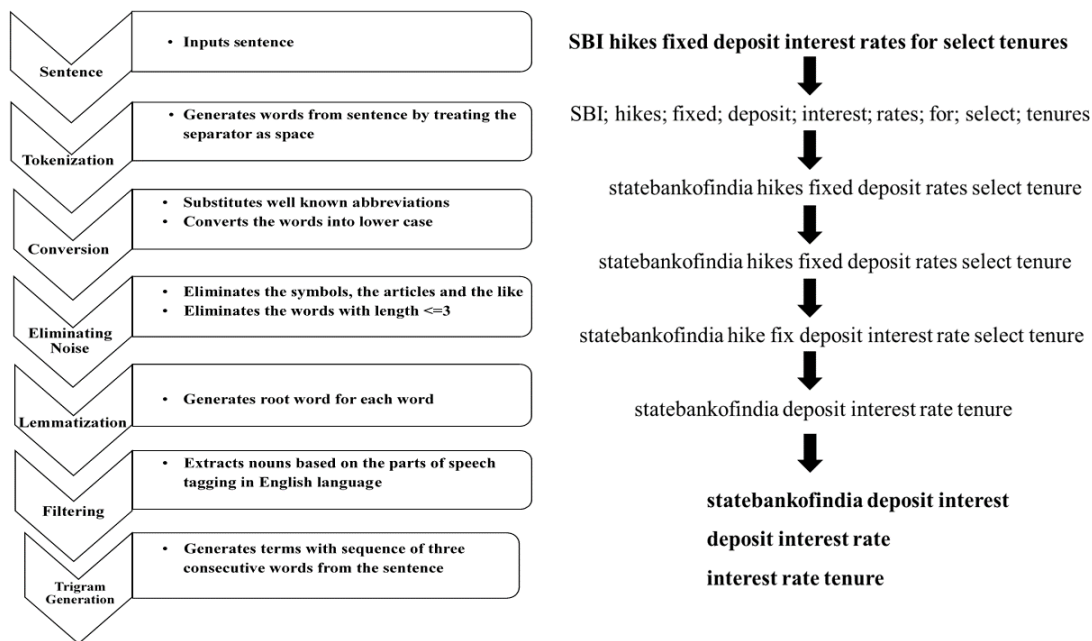

Figure 2. News and price history data distribution

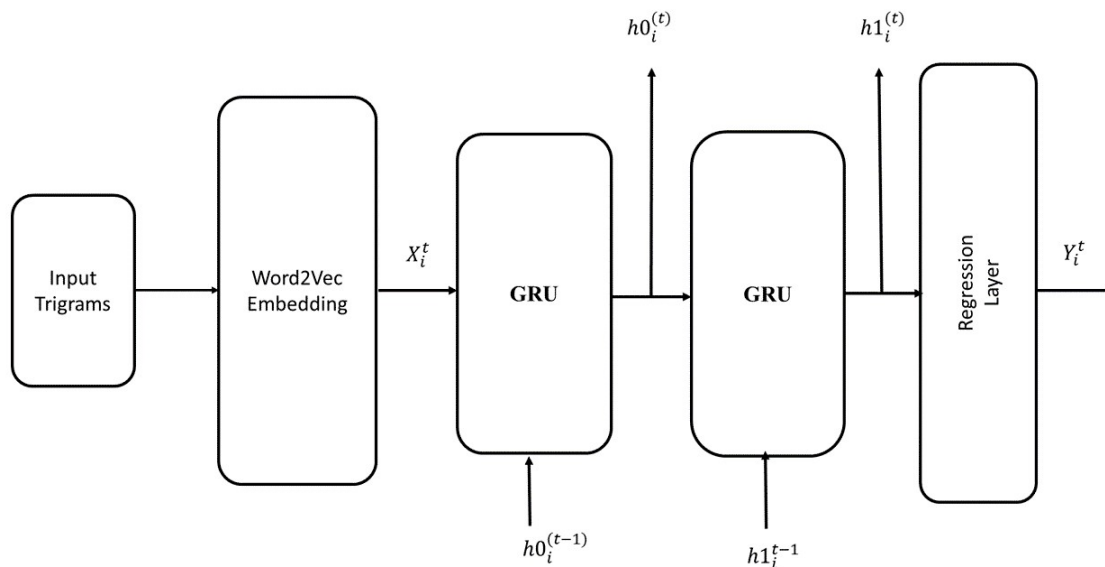Figure 3. News sentences preprocessing and trigrams generation.

Figure 4. 2-layer Gated Recurrent Unit model.

Algorithm 1 Context-based Clustering Algorithm

```
Input: Stock Database
Output: Set of Clusters
Begin
C₁=NULL
for each i in News_dict do
    for each j in News_dict do
        if NOV(Set(Cj).Issubset(s)) then
            s=set(News_dict[i])
            Cⱼ=set(Cⱼ).union(set (s)))
        end if
    end for
end for
End
```

of news and price history datasets. Next, the news and historical datasets were merged based on the Date and added to the news database. Next, Context-based clustering was performed on the datasets to separate different news items. Next, GRU regression was applied to news sentiments and stock prices to predict the future stock price. Next, if the model meets the Threshold accuracy, we consider the cluster and sentiment for stock price forecasting. Finally, the stock price was predicted using news sentiments and historical stock prices.

A. Information Fusion and Preprocessing

In the News database framing, we considered the stocks: BHARATIARTL, SBIN, PNB, NXTDIGITAL, TCS, and WIPRO. We collected historical close price data for 2427 working days of NSE, i.e., 8th August 2016 to 31st March 2023 with 14,562 records. In addition, we collected the news from the Times of India and the National Stock Exchange. Then the stock's historical price data is mapped with news data based on the new Date. Finally, the News database represents time series data with news and the stock price. The dataset size for six stocks is 18,510. Fig. 3 illustrates the process in each stage. After preprocessing, all the sentences were converted into trigrams to train the 2-GRU for context-based learning.

B. Context-based Clustering

The CbCA algorithm performs context-based clustering on the trigrams obtained from the preprocessing steps. After preprocessing, the trigrams consist of nouns, verbs, adverbs, adjectives, and the like. The CbCA algorithm checks for common parts of speech tags between sentences for grouping. Algorithm 1 explains the working of CbCA, generating clusters from a given news database and the result. The s denotes the trigram sentence in the news database. It checks for Set(C_j). Issubset(s). The statement results true if the C_j subset or equals to s; else, results false, Where the C_j represents the jth cluster and s represents the news sentence.

C. Gated Recurrent Unit

The GRU is the most suitable deep neural network for regression on textual data. Fig. 4 shows the layered architecture of GRU. The FTSEDL uses the stacked GRU with two layers as a learning model that trains and tests the trigrams to find the stock's price. The input vector is a set of trigrams converted into given dimension vectors using Word2Vec embedding, suitable for context-based learning. For example, the trigram "tcs hike fix" is represented in 3 X 100 for a given dimension of 100. Then, it is passed to the two layers stacked GRU layers. The X_i^t shows the input vector at time t, and Y_i^t Shows the predicted output vector at time t. The h_i^j Represents the hidden weights forwarding the intermediate outputs. The output vector from the GRU layers is passed to the Regression Layer. Then, the Regression Layer performs the multi-step prediction based on the given time step for the stock price prediction. Here, the time steps explain how often the GRU needs to look back to predict the future value.

4. RESULTS AND DISCUSSION

This section contains the experimental process, proposed model results, evaluation, and baseline model comparisons.

A. Experimental Process

The preprocessed datasets were given as input to the CbCA algorithm that produces clusters. These clusters were trained with GRU, and the GRU performance for each cluster was found. We repeated the experiment for 100 epochs and selected clusters greater than the threshold value. The threshold is considered to be 85% for choosing the models with considerable accuracy. Hence, we combined these clusters to predict the stock value.

$$Homogeneity = 1 - \frac{H(Y_{True} \mid Y_{Predicted})}{Y_{True}} \quad (1)$$

$$Completeness = 1 - \frac{H(Y_{Predicted} \mid Y_{True})}{Y_{True}} \quad (2)$$

$$Silhouette\ Coefficient = \frac{(MNCD - MICD)}{(Max(MNCD - MICD))} \quad (3)$$

where 　　MNCD: Mean Nearest Cluster Distance
MICD: Mean Intra Cluster Distance

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Actual_i - Predicted_i)^2}{N}} \quad (4)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Actual_i - Predicted_i| \quad (5)$$

$$MAPE = \sum_{i=1}^{N}\left|\frac{(Actual_i - Predicted_i)}{Actual_i}\right| \quad (6)$$
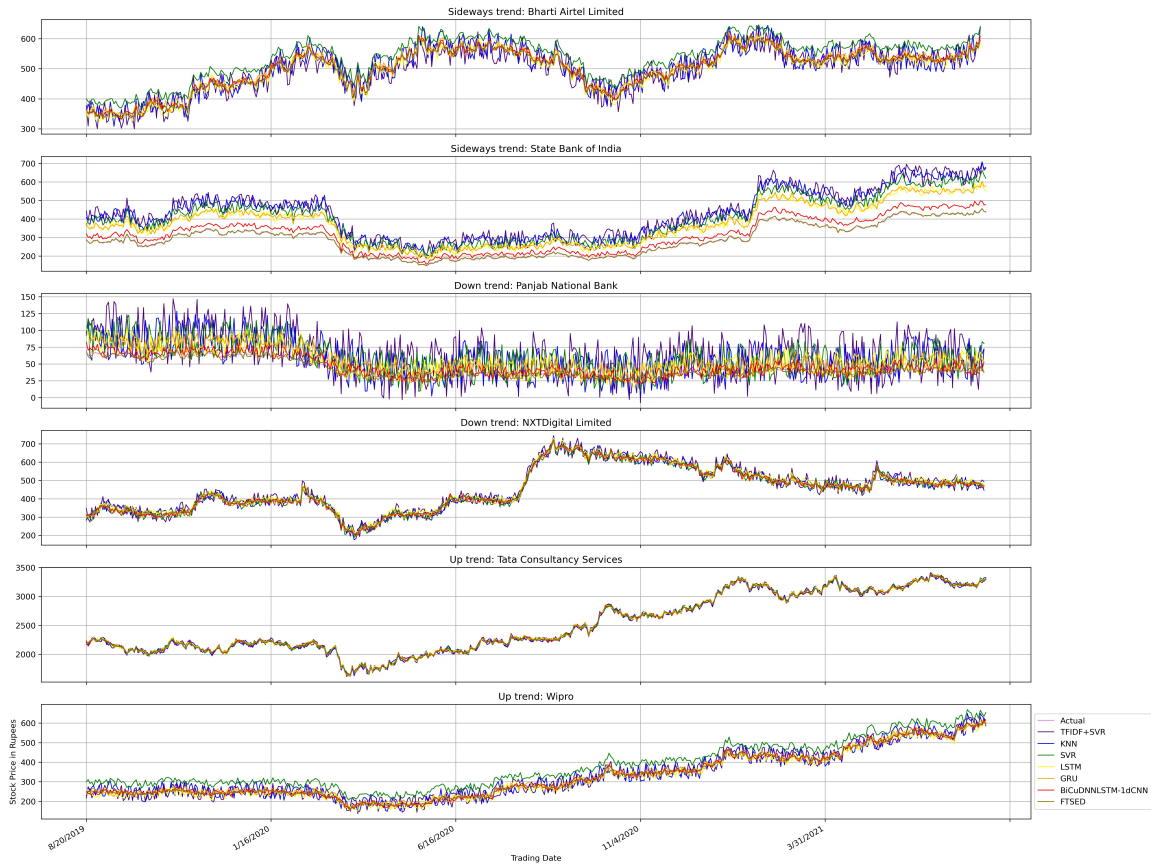
Figure 5. The predictive model performance for the six stocks with sideways, up, and down trends with the testing dataset.
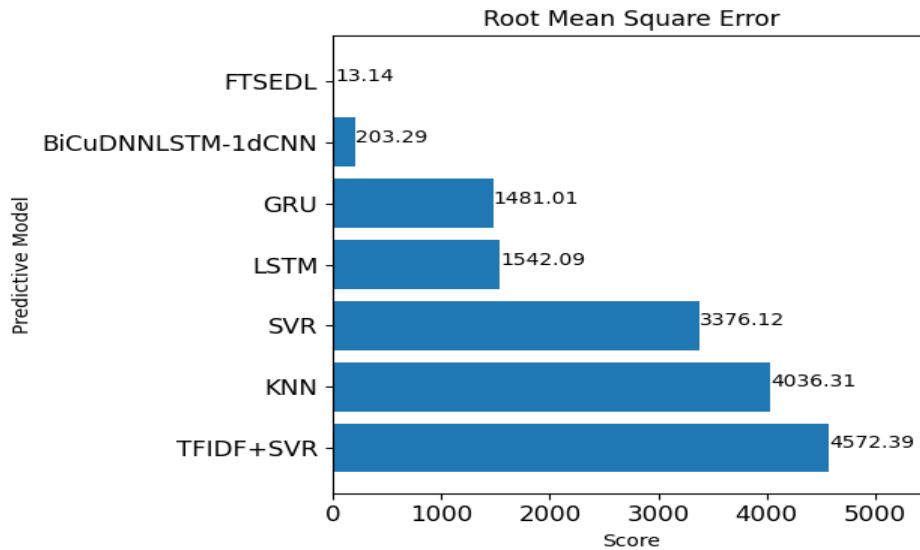

Figure 6. The predictive model's performance measurement using the RMSE metric.

TABLE I. An instance of fused information obtained from the news and price history datasets

| Date	Stock	Close price (Rs)	Trigrams
17-Apr-21	SBIN	339.9	statebankofindia private bank, private bank seen, bank seen race, seen race card, race card business
18-Apr-21	SBIN	339.9	statebankofindia pharmacist recruitment, pharmacist recruitment apply, recruitment apply online, apply online vacancy
20-Apr-21	SBIN	329.5	statebankofindia say charge, say charge zero, charge zero balance, zero balance account, balance account prior, account prior reasonable
24-Apr-21	SBIN	336.45	statebankofindia cut growth, cut growth vijay, growth vijay mallya, vijay mallya say,mallya say money, say money owes, money owes indian, owes indian bank, indian bank public, bank public money, public money cannot, money cannot made, cannot made bankrupt
25-Apr-21	SBIN	336.45	bihar suffer crore, suffer crore financial, crore financial loss, financial loss covid
27-Apr-21	SBIN	353.05	statebankofindia clerk exam, clerk exam registration, exam registration begin
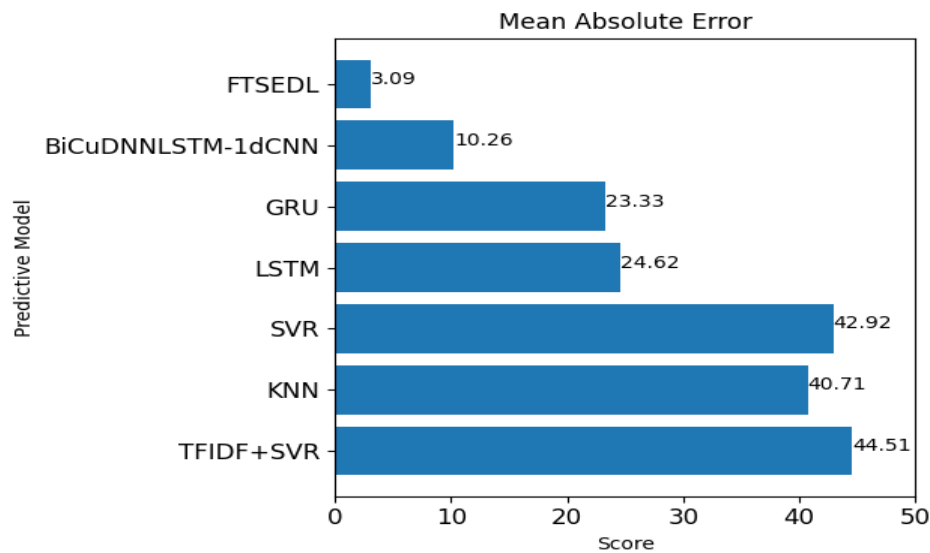
Figure 7. The predictive model's performance measurement using MAE metric.

TABLE II. Evaluation of Cluster models

Clustering Model	H	C	S
CbCA	0.95	0.98	0.88
RANMF	0.90	0.92	0.86
K-means	0.88	0.82	0.70
Agglomerative	0.31	0.34	0.58
Birch	0.44	0.48	0.52
Mini Batch K-means	0.4	0.42	0.60
MeanShift	0.3	0.55	0.52
OPTICS	0.72	0.57	0.44
Spectral	0.46	0.57	0.21
GMM	0.46	0.51	0.46

B. Metrics for Evaluation

The metrics Homogeneity, Completeness, and Silhouette coefficient are measured using 1 to 3 to evaluate the clus-tering and other baseline clustering methods. Homogeneity represents the closeness of a cluster. The resultant value one stands for 100% homogeneity. Cluster completeness determines that all the points that belong to the same cluster are assigned to the same class. The resultant value one stands for 100% labelling. To evaluate the existing and proposed models with metrics, accuracy, MAE, RMSE, and MAPE using 4 to 6.

C. Information Fusion

The news and price history datasets were combined to create the fused information. In this process, feature selection is applied to price history datasets to select the prominent features close price and Date. Feature extraction is applied to preprocess news data sentences to obtain trigrams, as shown in Fig. 3.In the next step, the close price and trigrams of specific stock were mapped with Date. This step results in datasets with (Date, Close price, Trigram)

TABLE III. The model performance on stock datasets

Model name	Phase/Stock	BHARATIARTL	SBIN	PNB	NXTDIGITAL	TCS	WIPRO	Average
	Training	85.66	87.46	74	78.63	80.91	79.45	81.09
CbCA+ GRU	Validation	77.23	74.55	72	72.45	78.39	71	74.27
	Testing	79.03	77.31	74.52	74.6	74	76.2	75.94
	Training	93.23	91.64	93.14	92.24	93.6	93.62	92.91
CbCA+GRU	Validation	89.55	88.47	90.56	89.22	89.29	89.65	89.46
2-Layers	Testing	91.21	90.81	92.18	91.61	91.27	93.09	91.69
	Training	86.23	86.15	78	75.12	80.38	79.22	80.85
CbCA+GRU	Validation	81.43	78.13	71.11	70.12	71.21	74.18	74.36
with 3-Layers	Testing	86.32	79.5	72.14	72	74.9	76.14	76.83

TABLE IV. The model performance on clustered datasets

Metric	Phase/Dataset	NC1	NC2	NC3	NC4	NC5	NC6
	Training	94.41	92.72	94.7	93.16	63.00	65.25
Accuracy	Validation	92.2	89.28	91.26	89.86	38.34	41.69
	Testing	93.34	91.8	92.18	92.19	46.78	57.13
	Training	-44.31	-39.13	-34.22	-36.05	-52.42	-69.46
Loss	Validation	-68.1	-55.44	-47.49	-62.44	72.68	35.92
	Testing	-73.24	-63.23	-58.91	-63.06	49.42	-2.24
Model Accuracy $\geq 85\%$		Yes	Yes	Yes	Yes	No	No

TABLE V. The model performance on stock datasets with and without feature extraction

Stock news dataset	Cluster size	Accuracy (%) without FE	Accuracy (%) with FE
BHARATIARTL	5	79.21	91.4
SBIN	6	83.82	92.04
PNB	6	87.40	91.11
NXTDIGITAL	6	83.70	91.89
TCS	6	86.82	90.6
WIPRO	7	78.52	93.09

pairs. Some example fused information is shown in Table I.

D. Comparing CbCA with Baseline Methods

The stock datasets were clustered using CbCA and Kmeans, Agglomerative, Birch, Mini Batch K-means, MeanShift, OPTICS, Spectral, and GMM. These methods were evaluated using cluster metrics, Homogeneity (H), Completeness(C), and Silhouette coefficient(S). Table II shows the summary of the methods. CbCA outperformed the baseline methods in clustering with a homogeneity of 0.95, Completeness of 0.98, and Silhouette coefficient of 0.88.

E. Prediction using Gated Recurrent Unit (GRU)

The GRU models were trained and tested with the stock datasets: BHARATIARTL, SBIN, PNB, NXTDIGITAL, TCS, and WIPRO. Table III summarizes the model's

performance for 100 epochs. Here, the testing accuracy does not fall beyond the training accuracy for all the models, showing that all three models performed without overfitting. The 2-GRU accuracy is 91.69%, i.e., GRU with two layers outperformed the GRU and 3-GRU. In 2-GRU, the number of layers selected reduced the system's complexity without compromising the learning model performance. 2-GRU is a quick learner compared with 3-GRU and performs better when compared with GRU and 2-GRU.

F. Feature Extraction Performance

The GRU models are trained with the news clusters. After careful observation, a Threshold value of 85% improved the model performance. Hence, we selected clusters greater than or equal to the Threshold value. Table IV describes the summary of these results. In this case study, the clusters NC1 to NC4 satisfied the Threshold value. Hence, these clusters were included in the training dataset to train the 2-GRU Regressor. We measured the model's performance with the original news database with and without feature extraction for six Indian stocks. Table V shows the summary of the results. The model performance significantly improved with feature extraction.

G. Performance Comparison

The FTSEDL performance was evaluated and compared with baseline models for the News database dataset. Fig. 5 illustrates the existing and proposed predictive model's performance in stock value prediction. Fig. 6 to 8 shows the evaluation models evaluated using metrics RMSE, MAE, and MAPE. The results showed that the proposed FTSEDL models outperformed the other baseline models with an
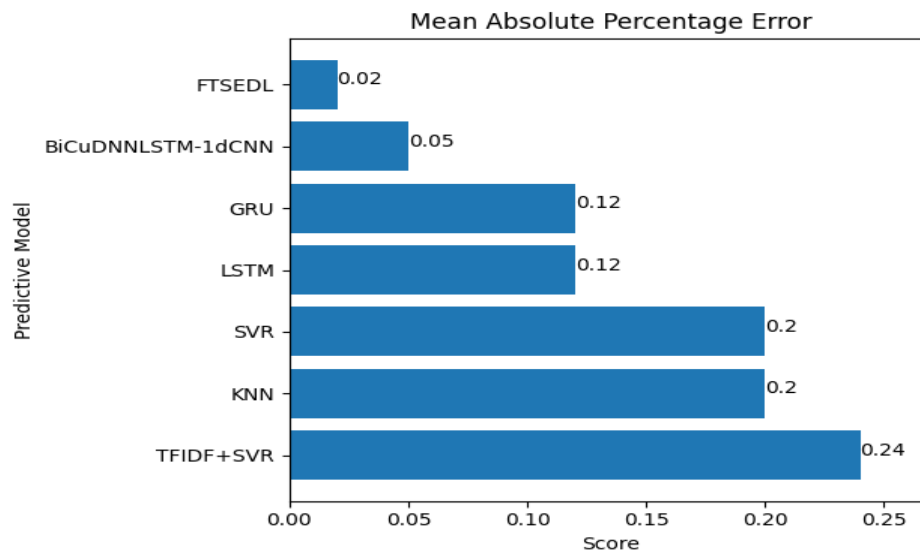
Mean Absolute Percentage Error

Figure 8. The predictive model's performance measurement using MAPE metric.

MAE of 3.09, RMSE of 13.14, and MAPE of 0.02. Extracting the sentences containing the prominent features that affect the stock price is crucial in enhancing the model's learning. The performance of the sentiment analysis is affected by the domain and the language.

5. CONCLUSION

The present work highlighted the trading model for future societal use. It emphasized the need for information fusion in stock value prediction. The experimentation is done with six stocks that cover three trends up, down, and sideways from 8th August 2016 to 31st March 2023. The information fusion improved the quality of the input news headlines and price history. The novel CbCA played a crucial role in clustering domain-specific data and outperformed the baseline clustering methods. CbCA achieved a homogeneity of 0.95, Completeness of 0.98, and Silhouette coefficient of 0.88. The proposed FTSEDL achieved an MAE of 3.09, RMSE of 13.14, and MAPE of 0.02.

The 2-layer GRU regression with feature extraction resulted in an excellent performance of 91.69% compared to other GRU models. Clustering the datasets for every new attempt increases the model's run time. Sometimes, the data availability is questionable due to changes in the website policies. Hence, clustered data requires the support of a dictionary so that correlated terms can be considered standard vocabulary that minimizes the computational complexity and reliability of the model. In the future, the FTSEDL can be extended with dictionary-based deep learning to enhance the performance of the stock value prediction model.

REFERENCES

[1] Q. Li, Y. Chen, J. Wang, Y. Chen, and H. Chen, "Web Media and Stock Markets : A Survey and Future Directions from a Big Data Perspective," *IEEE Trans. Knowl. Data Eng.*, vol. 30, no. 2, pp. 381–399, feb 2018.

[2] X. Chen, X. Ma, H. Wang, X. Li, and C. Zhang, "A hierarchical attention network for stock prediction based on attentive multi-view news learning," *Neurocomputing*, vol. 504, pp. 1–15, 2022.

[3] X. Chen, H. Xie, Z. Li, G. Cheng, M. Leng, and F. L. Wang, "Information fusion and artificial intelligence for smart healthcare: a bibliometric study," *Inf. Process. Manag.*, vol. 60, no. 1, p. 103113, 2023.

[4] M. Rahaman, M. Chowdhury, M. A. Rahman, H. Ahmed, M. Hossain, M. H. Rahman, M. Biswas, M. Kader, T. A. Noyan, and M. Biswas, "A deep learning based smartphone application for detecting mango diseases and pesticide suggestions," *International Journal of Computing and Digital Systems*, vol. 13, no. 1, pp. 1–1, 2023.

[5] A. J. Das, S. Choudhury, N. Saikia, and S. Rajbongshi, "Pedestrian detection in thermal and color images using a new combination of saliency network and faster r-cnn," *International Journal of Computing and Digital Systems*, vol. 13, no. 1, pp. 1–1, 2023.

[6] M. Zulqarnain, R. Ghazali, Y. M. M. Hassim, and M. Aamir, "An enhanced gated recurrent unit with auto-encoder for solving text classification problems," *Arabian Journal for Science and Engineering*, vol. 46, no. 9, pp. 8953–8967, 2021.

[7] L. xia Luo, "Network text sentiment analysis method combining LDA text representation and GRU-CNN," *Pers. Ubiquitous Comput.*, vol. 23, no. 3-4, pp. 405–412, 2019.

[8] N. Seong and K. Nam, "Predicting stock movements based on financial news with segmentation," *Expert Systems with Applications*, vol. 164, p. 113988, 2021.

[9] A. Thakkar and K. Chaudhari, "A comprehensive survey on deep neural networks for stock market: The need, challenges, and future directions," *Expert Systems with Applications*, vol. 177, p. 114800,

2021.

[10] S. Yang, "A novel study on deep learning framework to predict and analyze the financial time series information," *Futur. Gener. Comput. Syst.*, vol. 125, pp. 812–819, 2021.

[11] I. Almalis, E. Kouloumpris, and I. Vlahavas, "Sector-level sentiment analysis with deep learning," *Knowledge-Based Systems*, vol. 258, p. 109954, 2022.

[12] P. Das and A. K. Das, "Graph-based clustering of extracted para-phrases for labelling crime reports," *Knowledge-Based Syst.*, vol. 179, pp. 55–76, 2019.

[13] P. Jiao, A. Veiga, and A. Walther, "Social media, news media and the stock market," *J. Econ. Behav. Organ.*, vol. 176, pp. 63–90, 2020.

[14] A. Dey, M. Jenamani, and J. J. Thakkar, "Senti-N-Gram: An n-gram lexicon for sentiment analysis," *Expert Syst. Appl.*, vol. 103, pp. 92–105, 2018.

[15] S. Meshram and M. Anand Kumar, "Long short-term memory network for learning sentences similarity using deep contextual em-beddings," *International Journal of Information Technology*, vol. 13, no. 4, pp. 1633–1641, 2021.

[16] W. Liu, J. Pang, N. Li, F. Yue, and G. Liu, "Few-shot short-text classification with language representations and centroid similarity," *Applied Intelligence*, vol. 53, no. 7, pp. 8061–8072, 2023.

[17] K. Shuang, M. Gu, R. Li, J. Loo, and S. Su, "Interactive POS-aware network for aspect-level sentiment classification," *Neurocomputing*, vol. 420, pp. 181–196, 2021.

[18] A. Choudhary and A. Arora, "Linguistic feature based learning model for fake news detection and classification," *Expert Syst. Appl.*, vol. 169, p. 114171, 2021.

[19] M. Hosseinzadeh Aghdam and M. Daryaie Zanjani, "A novel regularized asymmetric non-negative matrix factorization for text clustering," *Inf. Process. Manag.*, vol. 58, no. 6, p. 102694, 2021.

[20] Y. Guo and X. Chen, "Forecasting the mid-price movements with high-frequency lob: A dual-stage temporal attention-based deep learning architecture," *Arabian Journal for Science and Engineering*, pp. 1–22, 2022.

[21] Z. Li, X. Li, H. Xie, F. L. Wang, M. Leng, Q. Li, and X. Tao, "A novel dropout mechanism with label extension schema toward text emotion classification," *Information Processing & Management*, vol. 60, no. 2, p. 103173, 2023.

[22] A. Kumar, A. Alsadoon, P. Prasad, S. Abdullah, T. A. Rashid, D. T. H. Pham, and T. Q. V. Nguyen, "Generative adversarial network (gan) and enhanced root mean square error (ermse): deep learning for stock price movement prediction," *Multimedia Tools and Applications*, pp. 1–19, 2022.

[23] A. Kanwal, M. F. Lau, S. P. Ng, K. Y. Sim, and S. Chandrasekaran, "BiCuDNNLSTM-1dCNN — A hybrid deep learning-based predic-tive model for stock price prediction," *Expert Syst. Appl.*, vol. 202, no. August 2021, p. 117123, 2022.

Usha Devi NSSSN She is a Ph.D. scholar in the Department of CSE, National Institute of Technology Tiruchirappalli. She holds an M.Tech. degree in Computer Science and Engineering from University College of Engineering Kakinada, JNTUK (2010), and B.Tech in Computer Science and Engineer-ing from JNTUH (2008). Her research in-terest includes Natural language processing with machine learning and deep learning, and cellular automata applications.

Dr. Mohan R is an Assistant Professor the Department of CSE, NIT Tiruchirappalli. He received a Ph.D. in High-Performance Com-puting at NIT Tiruchirappalli (2014), a Mas-ter of Engineering in Software Engineering at Jadavpur University, Kolkata(2004), and a Bachelor of Engineering in Computer Sci-ence and Engineering at Thiagarajar College of Engineering, Madurai Kamaraj Univer-sity (1998). He was awarded an "Honorable Mention" in ACM-ICPC Asia Region (Kanpur). He was on the academic council at various universities. He visited international universities for Academic Exchange Programme.

He is a visiting Faculty in Rajiv Gandhi Institute of Technology. He is an IEEE member and also a Life Member in ISTE. He has published books on the title "Impact of Artificial Intelligence on Bioinformatics" and "Artificial Immune System Based Clonal Classifiers" He is a reviewer for the Book Publisher, Tata McGraw Hill Education (India) Private Limited. He is a peer reviewer for "International Journal of Communication Systems", "International Journal of Cloud Computing" and "Future Generation Computer System." He published many National and International Confer-ences and Journal in his research area. His research area includes Text Analytics, High-performance computing, Graph theory, Im-age processing and Wireless networks.