International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-12 Issue-5, June 2023

An Aggregator Framework for Transforming Big Data in Real-Time using PT-INDRNN

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Abstract*: The prediction of stock market prices based on the financial text sentiment classification using Machine Learning (ML) and Deep Learning (DL) models is becoming popular among researchers in the era of Big Data (BD). Nevertheless, owing to the lack of extensive analysis, most of the developed ML and DL models failed to achieve better classification results. Thus, for the real-time prediction of the polarity of the stock price, a Probability Tanh-Independently Recurrent Neural Network (PT-IndRNN)-based classification of the sentiment of the financial text data of Twitter is proposed to solve this problem. Primarily, by employing the corresponding API, the real-time financial data and Twitter data are extracted and stored in the MongoDB database using Apache Flume. This stored data with the historical big datasets are taken and pre-processed. Next, by deploying the proposed Hadoop Distributed File System (HDFS) clustering, the pre-processed stock market data and Twitter data in real-time, as well as the historical dataset, are combined separately. After that, the features are extracted from the clustered sentences. Then, by utilizing the SentiWordNet, the sentences chosen using Linear Scaling-Dwarf Mongoose Optimization Algorithm (LS-DMOA) are converted to negative and positive scores. In the end, the sentiment of the financial texts is classified by the PTh-IndRNN, which is proved by obtaining reliable result values.

Keywords*: Hadoop Distributed File System (HDFS), Probability Tanh-Independently RNN (PTh-IndRNN), Application Programming Interface (API), Linear Scaling-Dwarf Mongoose Optimization Algorithm (LS-DMOA), financial text sentiment analysis.

I. INTRODUCTION

The act of forecasting the future value of company stock or else other financial instruments traded on an exchange is termed the Stock Market Prediction (SMP). If the SMP is performed effectively, it could be paramount for the investors. Investors might be guided for making suitable decisions on whether to buy or sell shares by the effectual SMP (Nousi& Tjortjis, 2021, [1]). As per the Efficient Market Hypothesis (EMH), predicting the market with a hundred percent accuracy is not possible. However, the researchers have not stopped the effort to enhance the methodologies for surpassing the stock price random walk pattern (R. Gupta & Chen, 2020, [2]). For ages, an active area of research is to design robust and accurate predictive models for stock price prediction (Mehtab& Sen, 2020, [3]). ML and text data mining implemented to data extracted from social networks are famous techniques to detect the future value of the stock market.

Useful information like public government policies, decisions, political events, investors' opinions, etc. is encompassed in the web content of social networks, namely Facebook, Twitter, Instagram, and reviews (Kesavan et al., 2020, [4]). The performance of the forecasting stock price could be effectively improved by regarding fundamental analysis data like financial web news or posts on social networks (Lin et al., 2022,[5]). Social networks are characterized by the 5Vs of BD like velocity, volume, value, variety, and veracity. Thus, BD analytic techniques and frameworks in Social Networks are commonly exploited (Bazzaz Abkenar et al., 2021, [6]).

Sentiment analysis grounded on financial texts, which has a significant effect on perceiving the emotions of the crowd and predicting the financial or else economic situation trends is termed the usual BD analytic technique (Shao & Chen, 2022, [7]). When it comes to the interpretation and analysis of sentences, words, phrases, and statements, data mining requires all kinds of text-mining tools as the information is represented in textual form (Hassani et al., 2020, [8]). In text, mining of large data, Apache Spark, and Hadoop map-reduce have played a very vital role in BD analytics. Spark applications could be written rapidly and Hadoop has flexible scalability (Y. K. Gupta & Sharma, 2020, [9]). Next, the financial text sentiment can be classified as positive, negative, or neutral with the features of the extracted text. A few methodologies like Support Vector Machine (SVM), Generative Adversarial Network (GAN), and Domain Adaptation are developed for the classification of financial text sentiment (S. Dong & Liu, 2021, [10]). Nevertheless, owing to the unstructured data, those techniques possess some limitations. Thus, this paper proposed a reliable DL-based PTh-IndRNN-based financial text sentiment classification for real-time BD analysis on Twitter.

A. Problem Statement

There are certain limitations due to the following problems even though several ML models are developed for the prediction of the market trend based on sentimental analysis.

Manuscript received on 02 May 2023 | Revised Manuscript received on 09 May 2023 | Manuscript Accepted on 15 June 2023 | Manuscript published on 30 June 2023.

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- The efficient representation, access, and analysis of unstructured or semi-structured data are still challenging considering the variety of datasets in BD.
- A dataset with high dimensionality may not be minable causing ML algorithms to over fit data or generate incomprehensible rules.
- To perform mapping, shuffling, and reducing tasks, MapReduce in HDFS requires a lot of time; thereby increasing latency.

By analyzing these problems, the contribution of the proposed framework is given as,

- A novel HDFS MapReduce model is proposed for solving unstructured data problems and time complexity problems in existing HDFS.
- Feature Selection (FS) based on the LS-DMOA algorithm is proposed to solve the high dimensionality in the datasets.

The remaining part is arranged as follows: the related works of the proposed framework are elucidated in section 2; a detailed explanation of the approaches leveraged in the proposed framework is described in section 3; the experimental results of the proposed framework are expounded in section 4; the paper is winded up with the future work in section 5.

II. RELATED WORKS

(Xiaofeng et al., 2021, [11]) done research on sentiment classification of future predictive texts. Here, grounded on Bi-directional Encoder Representations from Transformers (BERT), the sentiment classification was done. As per the outcomes, the sentiment measurement's accuracy was augmented. Nevertheless, since the stock's closing price was neglected, the prediction was not reliable.

(Jaggi et al., 2021, [12]) constructed a system centered on historical stock prices and financial-related messages for detecting stock movement. The system was presented with Fin-A Lite BERT (FinALBERT). For training the FinALBERT, the dataset was labeled with '3' methodologies. The percentage change methodology with '2' labels depicted the superior outcomes among the labeling methodologies. Nevertheless, a huge amount of time was taken for training FinALBERT; moreover, in the system's performance, there was no considerable enhancement.

(Achyutha et al., 2022, [13]) exhibited a user classification and stock market-centric recommendation engine. For the sentimental analysis of tweets, the engine was developed with Naïve Bayes (NB). The final prediction recommended which company was nice to invest in. But the recommendation outcomes might deteriorate with unstructured data.

(Rodrigues & Chiplunkar, 2022, [14]) examined a BD system for topic classification and sentiment analysis of Twitter data. Next, a sentiment analysis model with the Hybrid Lexicon-NB Classifier (HL-NBC) was presented. The sentimental analysis was done by the HL-NBC technique with superior accuracy. However, performance deterioration could be caused by unstructured data by the Hive constructed on Hadoop.

(Demirbaga, 2021, [15]) developed HTwitt for the analysis of the streamed Twitter data. On top of the Hadoop ecosystem and a set of ML methodologies embedded within a BD analytics platform, the HTwitt was constructed. As per the outcomes, high-quality outcomes were offered. Nevertheless, the sentiment of text in continuous values could not be detected accurately with the NB.

(J. Dong, 2020, [16]) recommended a financial investor sentiment analysis grounded on Field Programmable Gate Array. The fusion of a multi-window Convolutional Neural Network (CNN)-LSTM and a multi-window CNN was utilized. As per the outcomes, the CNNs' accuracy was better. Still, the accuracy of CNN could not be reliable without the regularization of missing values.

(Bourezk et al., 2020, [17]) employed '2' techniques of sentiment classification centered on online stock market news articles for detecting the movements of stock prices. Lexicon-centric and NB classifier-centric sentiment analysis was the '2' deployed techniques. As per the outcomes, the negative mood had a huge effect on stock market indices' fluctuations. But just some companies' stock prices were evaluated, which caused the system prone to overfitting problems.

(Dubey et al., 2021, [18]) developed an Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO)-centric system for data pre-processing and data classification in the BD environment. As per the outcomes, the PSO-SAW's efficacy was depicted on accuracy level. However, an update procedure was required as the content information of attributes varied; thus, the system was limited.

(Khan et al., 2022, [19]) built an SMP grounded on ML classifiers and social media news. For the stock market prediction, twelve ML classifiers were appraised. In the performance of the individual classifiers, enhancements were depicted by the ensemble of predictions. But it was difficult to afford the time overhead in the prediction model with the multiple ML classifier analysis.

(Deepika & Nirupama Bhat, 2021, [20]) presented an efficient SMP centered on the Kalman filter. The Kalman filter predicted the stock market value to smoothen noise and the Accelerated Gradient LSTM (AG-LSTM). The AGLSTM attained 90.42% accuracy with the Kalman filter. The model could not improve the accuracy of prediction with an outlier or missing data even with the Kalman filter.

(Aasi et al., 2021, [21]) designed a sentiment and public engagement analysis for stock price prediction. For offering a 1-week prediction on the stock close value for the technology company "Apple Inc", a Multivariate Multistep output LSTM (MMLSTM) was presented. The LSTM models were surpassed by the MMLSTM. However, the system was presented for detecting only a single company's stock value.

(Nti et al., 2021, [22]) recommended a multi-source information-fusion system for accuracy enhancement in stock market prediction. The fusion was presented with CNN and LSTM. As per the outcomes, enhanced prediction accuracy was attained on the gathered dataset. Still, for the fusion model, it was challenging to afford the essential memory footprint.

(Yasir et al., 2020, [23]) developed a DL-centric system for detecting the interest rate with Twitter sentiment. Twitter sentiments of '6' mega-events were deployed as input. As per the outcomes, when event sentiment was integrated, the system's error was minimized. However, the utilized DL model takes more time to train its parameters with the large dimensionality of the features.

(Zhao et al., 2021, [24]) presented a sentimental analysis and key entity detection approach for online financial texts developed centered on the BERT. For enhancing the presented system's performance, ensemble learning was leveraged. As per the experiments, the BERT-centric systems' performance was superior. But the system's performance might deviate if no significance is offered to the neutral, positive, and sarcastic sentences.

(Xu et al., 2020, [25]) employed a Stock Movement Prediction Network (SMPN) grounded on the tweet and historic prices. An incorporative attention system that merged the local and contextual attention schemes for offering information was employed by the network. As per the outcomes, the system depicted superior performance on tweet and historic price datasets. Nevertheless, the accuracy level might be degraded since the system's low-learning efficiency was wielded for extracting contextual information.

III. PROPOSED FINANCIAL TEXT SENTIMENT CLASSIFICATION METHODOLOGIES

The fluctuations in the stock market are influenced since the financial texts are more readily available as BD. Thus, the investor is aided by the prediction of the financial text polarity to invest money in the share market. Thus, for classifying the polarity of Twitter texts for the prediction of stock price, a DL-based PTh-IndRNN with LS-DMOA is proposed to overcome this limitation. In Figure 1, the proposed framework is shown.

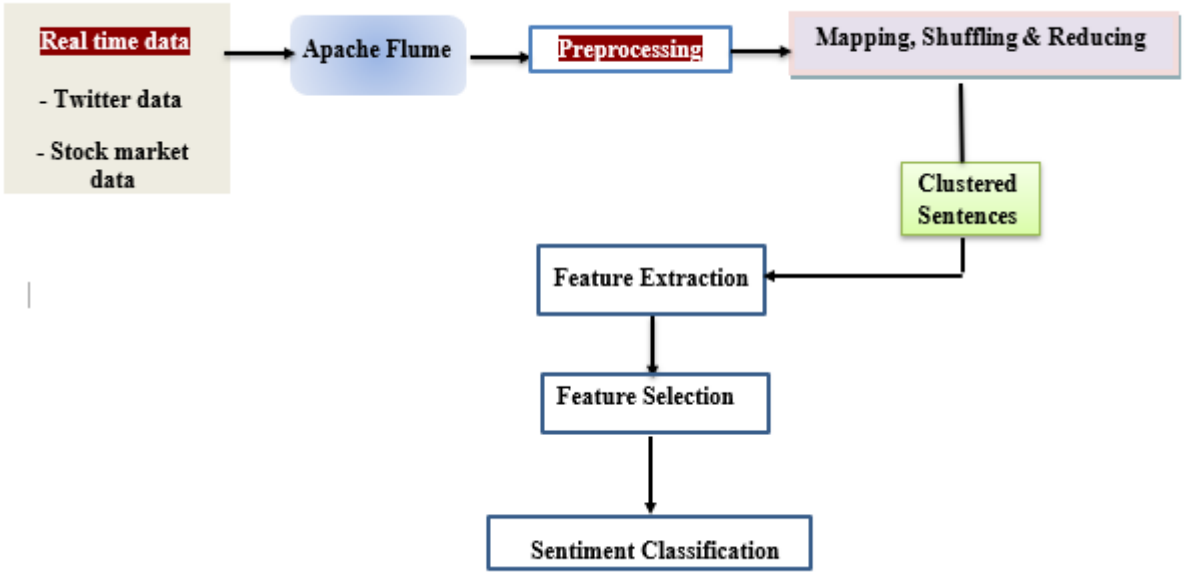

Figure 1: Architecture of the proposed framework

A. Input Data

Primarily, in the proposed model, the real-time big-data, and historical big-data of financial data of Twitter and the stock market are taken.

Real-time data: The real-time Twitter data with financial tweets are extracted with the Twitter API. By employing the External API, the real-time stock market data are extracted from external websites.

Storing Real-time data: In the Mongo DB with NoSQL, the extracted real-time data are stored as a database with the help of Apache flume. An open-source, powerful, reliable, and flexible system used to collect, aggregate, and move large amounts of unstructured data from multiple data sources into MongoDB with a NoSQL database is termed the Apache Flume. The stored database (D) is denoted as,

$$D = [d_T, d_S] \quad (1)$$

Here, the Twitter and the stock market datasets are signified as d_T, d_S.

Datasets: For enhancing the system's accuracy, the publicly available datasets of Twitter tweets and nifty-50-stock-market datasets are taken with D. The historical dataset set (H) is equated as,

$$H = [h_T, h_S] \quad (2)$$

Here, the historical Twitter and stock market dataset is depicted as h_T, h_S.

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B. Pre-processing

To restructure the data for a better classification process, pre-processing is performed. The Twitter and the stock-market datasets are pre-processed separately in the proposed model.

1) Twitter Data Set

The financial texts in d_T, h_T are pre-processed separately with the following steps:

Tokenization: During tokenization, the financial texts are split into words.

URL removal: Here, the URL present in the financial texts is removed.

Stop word removal: In this step, the unnecessary words (is, was) are removed from the text.

Word Stripping: The elongated words (ngggg, …..) and Short words (gd,gn) are reframed.

Stemming: Next, the words are reduced by neglecting the prefixes, suffixes, and affixes such as ed, ing, en, etc.

The pre-processed d_T, h_T is denoted as a_T, b_T.

2) Stock-Market Data Set

The stock-market datasets d_S, h_S are pre-processed with the following steps,

Attribute extraction: The attributes like date, symbol, series, previous close, open, high, low, last, close, VWAP, volume, turnover, trades, deliverable volume, and % deliverable are extracted individually with their equivalent data from the d_S, h_S.

Numeralization: The strings in d_S, h_S are converted into numbers as the system can only process numerical data.

Missing value imputation:

Here, it will be imputated with the average value of previous and next time-series values of the corresponding missing data by interpolation technique if a missing value is detected in d_S, h_S. The pre-processed d_S, h_S are denoted as z_S, y_S.

3) Clustering

Next, based on the company name, the pre-processed data a_T, z_S dataset is clustered. To obtain effective sentence clusters, the mapping, shuffling as well as reducing the process of existing HDFS and Apache spark is modified.

a) Mapping.

Here, the words are stored in the distributed files, in which words are mapped based on the keywords by deploying the proposed Hamming-Correlated K-Means (H-CKMeans) algorithm. As K-means can group un-labeled data set instances into clusters based on similar attributes, it is selected. However, it does not guarantee to find the global optimum solution for optimal clustering. Thus, the Pearson Correlation Coefficient (PCC) and Hamming distance are used in the existing K-Means algorithm to solve those problems. In the H-CKMeans algorithm, the c centroids for c clusters are estimated using the PCC technique as:

$$C_n = \frac{\sum(\alpha_i - \bar{a}_T)(\beta_i - \bar{z}_T)}{\sqrt{\sum(\alpha_i - \bar{a}_T)(\beta_i - \bar{z}_T)^2}} \quad (3)$$

The n^{th} cluster centroid is depicted as C_n, $n = 1,2,...,c$, $\alpha_i, \beta_i \in \omega_i$ denotes the i^{th} data in a_T, z_S and $\bar{a}_T, \bar{z}_T$ signifies the mean data values of a_T, z_S. The distance (similarity) between C_n and data points of a_T, z_S are estimated using the Hamming distance (d) after the c centroids are estimated.

$$d_i = \sum_{i=1}^{m} |C_n - \omega_i| \quad (4)$$

The data point in a_T *or* z_S is mentioned as $\omega_i \in a_T, z_S$. The data points are mapped in the same cluster (file) for a smaller d_i. The mapped c files (k_c) are denoted as,

$$M = \{k_1, k_2, ..., k_c\} or\ k_n \quad (5)$$

the mapped file set is depicted as M.

b) Shuffling

Then, the words in k_n are shuffled, where the same word is stored in the same file. Fisher-Yates Shuffling Algorithm (FYSA) is used for shuffling.

Step 1: Generate a temporary array $(Tmp[\ ])$ and store the words of M in $Tmp[\ ]$ and give the key value of $(1,2,.....,nn)$ to each word. The same words have the same value.

Step 2: Choose the random value v from $(1,2,.....,nn)$ and store the corresponding word from $Tmp[\ ]$ in a new array $(N[\ ])$ and delete the word from the $Tmp[\ ]$.

Step 3: Until all the words in $Tmp[\ ]$ is deleted, repeat step 2. The words with the same key value are stored in the same array by doing so, and the shuffled set is depicted as (SS),

$$SS = \lfloor s_1, s_2, .., s_Q \rfloor or\ s_z, z = 1,2,.....,Q \quad (6)$$

Where, the Q^{th} shuffled file, which contains the same keyword are signified as s_Q.

c) Reducing

Significant keywords are selected in the reducer using the Tournament Selection-based Sand Cat Optimization Algorithm (TS-SCOA) from the shuffled data. As Sand Cat Optimization Algorithm (SCOA) has high convergence accuracy, and the ability to jump out of locally optimal solutions, it is chosen for the proposed model. However, the SCOA has a drawback of random wheel selection. Thus, to develop the proposed TS-SCOA algorithm, the Tournament selection approach is leveraged in the SCOA algorithm to overcome that drawback.

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Initialization: The initial position of Sand Cats (SCs), which is the shuffled keywords is initialized in the TS-SCOA and is represented within the dimension $\Re$ as,

$$P = \begin{bmatrix} \rho_{1,1} & \rho_{1,2} & \cdots & \rho_{1,\Re} \\ \rho_{2,1} & \rho_{2,2} & \cdots & \rho_{2,\Re} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{Q,1} & \rho_{Q,2} & \cdots & \rho_{Q,\Re} \end{bmatrix} or \left[\rho_{Z,Y}\right], Y = 1,2,...,\Re \quad (7)$$

Where, the position of SC Z in $\Re$ is depicted as $\rho_{Z,Y}$.

Exploration Phase (prey search): The prey equation of SC is given as,

$$\vec{\rho}_Z(I+1) = \vec{x}.\left(\vec{\rho}^*(I) - R.\vec{\rho}_z(I)\right) \quad (8)$$

Here, the position of SC Z in the iteration I is signified as $\vec{\rho}_Z(I)$, the random number within the range of $(0,1)$ is depicted as R, and the best position of SC, which is obtained by estimating the fitness of the position, is mentioned as $\vec{\rho}^*(I)$. The fitness is equated as,

$$f = \uparrow acc(cl) \quad (9)$$

Where fitness is considered as the enhanced clustering accuracy. The range of sensitivity of the of SCs is depicted as $\vec{x}$, which is equated as,

$$\vec{x} = \vec{x}_g \times R \quad (10)$$

Here, the general sensitivity range of SC, which gets linearly decreased from 2 to 0, is signified as $\vec{x}_g$. This can be equated as,

$$\vec{x}_g = \delta_q - \frac{\delta_q \times I}{I_{mxm}} \quad (11)$$

Where, I_{mxm} implies the maximum iteration, and δ_q is set to 2 as the SC can sense below 2 kHz.

Exploitation phase (attacking prey): The random distance (σ) between the prey position and the SC is estimated using the tournament selection to perform a prey attack.

$$\sigma = Q \times \left| R \times \rho^*(I) - \rho_Z(I) \right| \quad (12)$$

The sensitivity range of the SC is assumed as a circle. For selecting the random angle (ϕ), the direction of movement of the SC employs the Roulette wheel selection algorithm. Likewise, the SC moves in different circumferential direction in the search space and attack the prey using the formula,

$$\rho_Z(I+1) = \rho^*(I) - \vec{x}.\vec{\rho}_{random}.\cos(\phi) \quad (13)$$

Here, the random position generated between $\rho^*(I)$ and $\rho_Z(I)$ is depicted as $\vec{\rho}_{random}$.

Balancing exploration and exploitation: In the TS-SCOA, for balancing the exploration and exploitation phase, an adaptive factor (γ) is utilized. The (γ) is represented as,

$$\gamma = \vec{x}_g.(2 \times R - 1) \quad (14)$$

The SC updates the position using equation (8) if $|\gamma| \le 1$, else the position is updated using equation (13). By doing this, optimal position of sc (ρ^*) (that is, optimal reduced keywords) can be obtained. The selected keywords (company names) are depicted as,

$$K = \{k_1, k_2, ..., k_\aleph\} or\ k_l, l = 1,2,...,\aleph \quad (15)$$

Here, the reduced file set is depicted as K , and the $\aleph^{th}$ reduced file is mentioned as $k_\aleph$.

The pseudocode for the proposed TS-SCOA

Input: $\lfloor s_1, s_2, .., s_Q \rfloor or\ s_Z$

Output: Selected keywords

Begin

Initialize SC population, $\Re, \gamma, \vec{x}, \vec{x}_g$ and maximum iteration I_{mxm}

Set $I = 1$

Calculate Fitness

While $(I \le I_{mxm})$

For each SC **do**

Estimate distance using TS

Obtain angle ϕ $(0^o \le \phi \le 360^o)$

If $(|\gamma| \le 1)${

Update position using $\rho^*(I) - \vec{x}.\vec{\rho}_{random}.\cos(\phi)$

} **Else if** $(|\gamma| > 1)$ {

Perform $\vec{\rho}_Z(I+1) = \vec{x}.\left(\vec{\rho}^*(I) - R.\vec{\rho}_z(I)\right)$

}

End If

End For

Update (ρ^*)

End While

Return Best solution.

$I = I + 1$

End

(iv) Final Output: The final cluster of Twitter data and stock market data under the same company name is obtained from the reducers, which is equated as,

$$E = \{e_1, e_2, ..., e_\chi\} or\ e_r, r = 1,2,..., \chi \quad (16)$$

Here, the reduced file set is depicted as E , and the cluster of the χ^{th} company is signified as e_χ . Here, the unstructured data is converted to structured data.

4) Feature Extraction

The features such as ngram (relevant sequence of n-words), bigram (relevant sequence of 2-words), emoticons (i.e symbols represent the emotions), Parts of Speech (PoS), and so on are extracted from the clustered data. The extracted feature set (A) is equated as,

$$A=\{\varepsilon_1,\varepsilon_2,....,\varepsilon_t\} or\ \varepsilon_\wp, \wp=1,2,...,t \quad (17)$$

Where, the extracted t^{th} feature is depicted as ε_t.

5) Feature Selection

Significant features are optimally selected from the extracted feature set (A) to reduce the training time of the classifier. LS-DMOA is proposed for FS. Owing to the optimal FS in the high dimensional datasets, the Dwarf Mongoose Optimization Algorithm (DMOA) is considered reliable. But, DMOA has the setback of random position initialization. Thus, Linear Scaling (LS) is introduced in the DMOA and named the technique as LS-DMOA.

Initialization: The position of the Dwarf Monkey (DM) population is considered as the $\{\varepsilon_1,\varepsilon_2,....,\varepsilon_t\}$ and $\{\varepsilon_1,\varepsilon_2,....,\varepsilon_t\}$ within the problem dimension $(\Im)$ in the LS-DMOA and is equated as,

$$A=\begin{bmatrix} \varepsilon_{1,1}\ \varepsilon_{1,2}\cdots\varepsilon_{1,\Im-1}\ \varepsilon_{1,\Im} \\ \varepsilon_{2,1}\ \varepsilon_{2,2}\cdots\varepsilon_{2,\Im-1}\ \varepsilon_{2,\Im} \\ \vdots\ \vdots\ \ddots\ \vdots\ \vdots \\ \varepsilon_{t,1}\ \varepsilon_{t,2}\cdots\varepsilon_{t,\Im-1}\ \varepsilon_{t,\Im} \end{bmatrix} or\left[\varepsilon_{\wp,\eta}\right], \eta=1,2,..,\Im \quad (18)$$

Here, the DM population is depicted as A, the size of the population is signified as t, and the position of DM (t) in dimension $\Im$ is mentioned as $\varepsilon_{t,\Im}$. The distribution of $\left[\varepsilon_{\wp,\eta}\right]$ is given using the LS technique as,

$$\varepsilon_{\wp,\eta}=\lambda\left(\frac{\Im-\Im_{lb}}{\Im_{ub}-\Im_{lb}}\right) \quad (19)$$

Here, a random number, which is randomly distributed is depicted as λ.

Alpha group: The alpha female (μ) is the controller of the family unit in the DM population, which can be determined using the fitness function $F(\ )$,

$$\mu=\frac{F(\wp)}{\sum_{\wp=1}^{t}F(\wp)} \quad (20)$$

The $F(\ )$ in the proposed LS-DMOA is equated as,

$$F=\max(acc) \quad (21)$$

Fitness is the maximum accuracy. In the μ group, the number of scouting mongooses is obtained as $(t-\hbar)$, and $\hbar$ depicts the number of babysitters.

Exploitation stage: To give a signal to the path family unit in track, μ creates a peep sound (ℓ). The sleeping mount, which can be denoted using a randomly distributed number (ζ), is determined based on the candidate food solution $(\varepsilon_{\wp+1})$.

$$\varepsilon_{\wp+1}=\varepsilon_\wp+\zeta\times\ell \quad (22)$$

The fitness of $\varepsilon_{\wp+1}$ is evaluated and $\varepsilon_{\wp+1}$ with the best fitness is selected as the sleeping mount. The sleeping Mount $(M_\wp)$ is evaluated after each iteration as,

$$M_\wp=\frac{F(\wp+1)-F(\wp)}{\max(|F(\wp+1),F(\wp)|)} \quad (23)$$

The average value of $M_\wp$ (ξ) is obtained after the sleeping mount is identified.

$$\xi_\wp=\frac{\sum_{\wp=1}^{t}M_\wp}{t} \quad (24)$$

Exploration (or) scouting: The baby exchange criteria $(ct\geq pr)$ are achieved after ξ is estimated and scouting is performed using the DM scouter group. The time counter and babysitter exchange parameters are depicted as ct, pr. The movement vector $(\vec{V})$ of DM to the sleeping mount is given as,

$$\vec{V}=\sum_{\wp=1}^{t}\frac{\varepsilon_\wp.M_\wp}{\varepsilon_\wp} \quad (25)$$

Next, the scouter mongoose's next position is given with (V) as,

$$\varepsilon_{\wp+1}=\begin{cases}\varepsilon_\wp-vm*\vartheta*\left[\varepsilon_\wp-\vec{V}\right] & if\ \xi_{\wp+1}>\xi_\wp\ (Exploration)\\ \varepsilon_\wp+vm*\vartheta*\left[\varepsilon_\wp-\vec{V}\right] & else\qquad\quad (Exploitation)\end{cases} \quad (26)$$

Where, a random number is depicted as ϑ, and the collective-volatile movement of the mongoose group that linearly decreases during iterations is signified as vm.

$$vm=\left[1-\frac{It}{It_{\max}}\right]^{\left(\frac{2.It}{It_{\max}}\right)} \quad (27)$$

Here, the current and maximum iteration is delineated as $It, It_{\max}$. The feature $\varepsilon_{\wp+1}$ is selected if $F(\varepsilon_{\wp+1})>F(\varepsilon_\wp)$.

The Pseudocode of LS-DMOA:

Input: Extracted features
Output: Selected features

Begin
Initialize the population $\Im, \lambda, It_{\max}, \ell, pr$, and number of babysitters $(\hbar)$
Determine the distribution of DM using the LS
Set $It = 1$, population size $t = t - \hbar$
While $(It \le It_{\max})$ **do**
Calculate F
Set ct
Determine alpha (μ)
Generate candidate food position $\varepsilon_{\wp+1}$
Evaluate $F(\varepsilon_{\wp+1})$
Perform evaluation of $M_{\wp}$ and determine $\xi_{\wp}$
If $(\xi_{\wp+1} > \xi_{\wp})${
Update scouter position using $\varepsilon_{\wp} - vm * \vartheta * [\varepsilon_{\wp} - \vec{V}]$
} **Else** {
Update $(\varepsilon_{\wp+1})$ using $\varepsilon_{\wp} + vm * \vartheta * [\varepsilon_{\wp} - \vec{V}]$
}
End If
Update best $\varepsilon_{\wp+1}$
End While
Return selected features.
End

6) Word Embedding

The words within the feature $(\varepsilon_{\wp+1})$ are converted to numbers utilizing the SentiWordNet dictionary after the features are selected. To extract the synset of a word (i.e meaning, definition, etc.,), $word.synset(\ )$ is used. Then, synset scoring (Sc) of the word (υ) is performed using,

$$Sc = Ps - Ns \tag{28}$$

Where, Ps, Ns implies positive and negative scores. Next, as per the usage ranks, the synsets are weighted with the final score of each word in $(\varepsilon_{\wp+1})$ and is given as,

$$\Omega = \sum_{\upsilon=1}^{mm} Sc(\upsilon)/\upsilon \tag{29}$$

Here, the score predicted for a word is depicted as Ω, and the synset rank is signified as υ. The polarity will be considered as positive/negative scores if $\Omega > Th$. The desired threshold score value is depicted as Th. Hence, the SentiWordNet dictionary (Dy) with negative and positive scores corresponding to the text is obtained.

7) Sentiment Classification

(Dy) is given to the proposed PTh-IndRNN, which classifies the polarity of texts after the scores of texts are predicted; moreover, it is mainly used to evaluate the conversion process of Un-Structured data into structured data. Since Independently Recurrent Neural Network (IndRNN) prevents gradient explosion problems, it is selected. However, the back-propagation time is maximized by the IndRNN. Hence, Probability Tanh (PTh) activation is embedded in the IndRNN to solve this problem. In Figure 2, the PTh-IndRNN architecture is depicted.

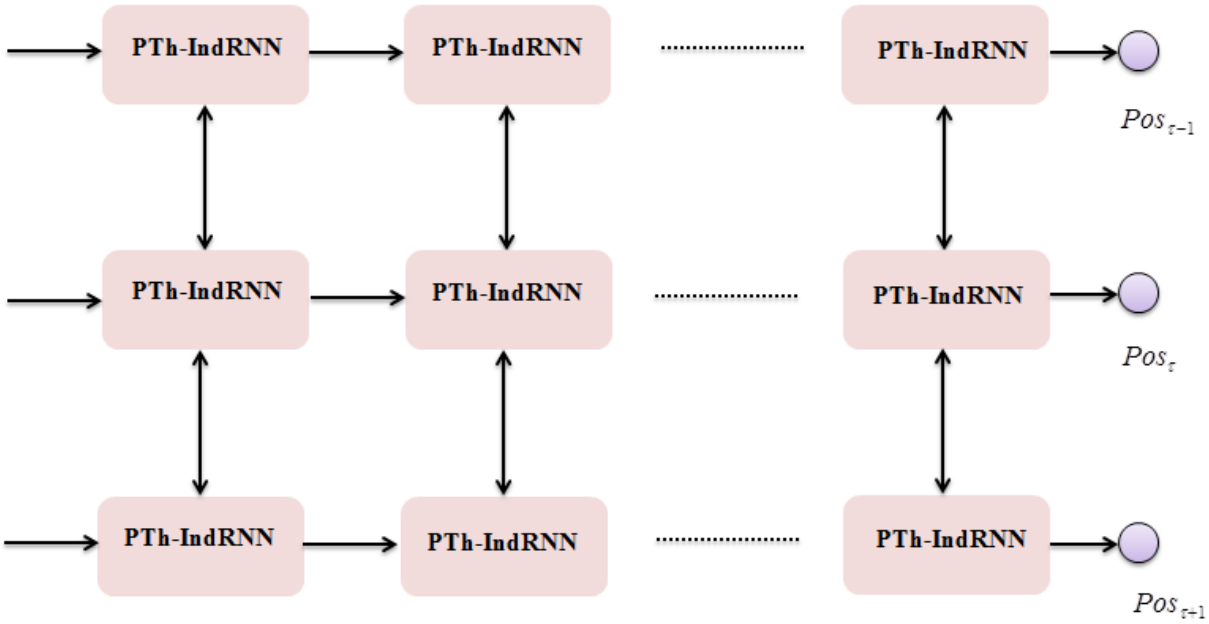


Figure 2: Proposed PTh-IndRNN architecture

Hidden states: The PTh-Ind RNN processes recurrent input weight (Γ) with the Hadamard product $(\circ)$ is equated as,

$$\varsigma_{\tau} = \kappa\left(o.Dy_{\tau} + \Gamma \circ \varsigma_{\tau-1} + B\right) \quad (29)$$

Where, the hidden state at the time step (τ) is depicted as ς_{τ}, the activation function is signified as κ, the weight matrix of Dy_{τ} is mentioned as o, and the bias value is delineated as B.

The hidden state of the neuron u (h_u, τ) is independent of the other hidden neurons In PTh-IndRNN and can be described as,

$$\varsigma_{u,\tau} = \kappa\left(o_u Dy_{\tau} + \Gamma_u \varsigma_{u.\tau-1} + B_u\right) \quad (30)$$

Here, the input weight, recurrent weight, and bias value for the neuron u are depicted as o_u, Γ_u, b_n.

Output: The output predicted polarity (Pol_{τ}) can be obtained using the PTh activation function from the hidden states as,

$$Pol_{\tau} = \left[\left(\left(\frac{\exp\left(\varsigma_{u,\tau}\right) - \exp\left(-\varsigma_{u,\tau}\right)}{\exp\left(\varsigma_{u,\tau}\right) + \exp\left(-\varsigma_{u,\tau}\right)}\right) + 1\right) \Big/ 2\right]^{\nu} \quad (31)$$

Where, constant value 3.0 is depicted as ν. This is the result obtained for the a_T, z_S dataset. Likewise, processes such as proposed HDFS, feature extraction, FS, and word embedding are performed with the b_T, y_s datasets and given to the PTh-IndRNN for training and testing. Hence, in the result section, the obtained results from the pre-processed real-time datasets and historical datasets b_T, y_s are evaluated. The stock market investor can decide whether to invest in the share market of the corresponding company or not based on the polarity predicted. Thus, the real-time BD analysis is performed.

IV. RESULTS AND DISCUSSIONS

The proposed system's performance is evaluated with the prevailing works. The experimentation was conducted on the working platform of JAVA.

A. Data Set Description

Big-data datasets are created with real-time Twitter data and stock market data in the proposed model. Moreover, for proving the proposed technique's performance, historical publicly available datasets are taken.

Financial Tweets: It includes 28k+ publicly traded companies (Company names and tickers) that are tagged with, the company they are tweeted about, the company symbols, and other attributes.

NIFTY-50 Stock Market Data (2000 - 2021): It encompasses '50' stocks' stock price data in the NIFTY-50 index from the National Stock Exchange (NSE) India. The datasets are at day-level with pricing and trading values.

B. Performance Analysis.

Proposed HDFS, FS, and sentiment classification are the '3' phases in which the proposed framework's performance is evaluated.

1) Performance analysis of proposed HDFS

Here, regarding fitness, the proposed reducer TS-SCOA's performance is weighed against the prevailing SCOA, Artificial Algae Algorithm (AAA), BAT, and Crow Search Optimization Algorithm (CSOA). Next, regarding clustering time, the proposed H-CKMeans clustering is analogized to the prevailing K-Means, Clustering Large Applications (CLARA), Partition Around Medoids (PAM), and Fuzzy C-Means (FCM).

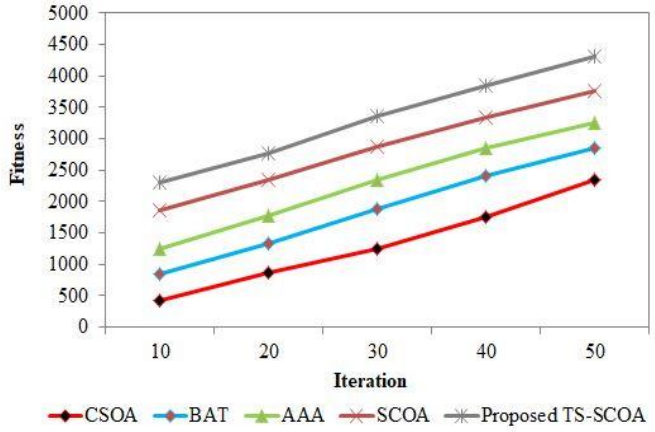


Figure 3: Fitness vs iteration

The graphical analysis of fitness values of proposed and existing algorithms for 10 to 50 iterations is depicted in Figure 3. The fitness is evaluated at 40th iteration in which the existing CSOA, BAT, and proposed algorithm selected the optimal keywords with the fitness value of 1757, 2415, and 3847. Thus, when analogized to the prevailing methodologies, the TS-SCOA achieved the best fitness, which improves the accuracy of the proposed HDFS clustering results.

Table 1: Clustering time analysis

Algorithms	Clustering time (ms)
FCM	77164
PAM	72659
CLARA	68482
K-Means	63548
H-CKMeans	58475

The proposed H-C-K Means does the clustering in less time of 5073ms, and 18689ms when analogized to the prevailing K-Means and FCM algorithms. Owing to the embedding of hamming distance and PCC function in the K-Means algorithm, superior outcomes are acquired.

2) Performance analysis of feature selection

Here, centered on the fitness value, the proposed FS is contrasted with the prevailing DMOA, Grasshopper Optimization Algorithm (GOA), Harmony Search Optimization Algorithm (HSOA), and Grey Wolf Optimization Algorithm (GWOA).

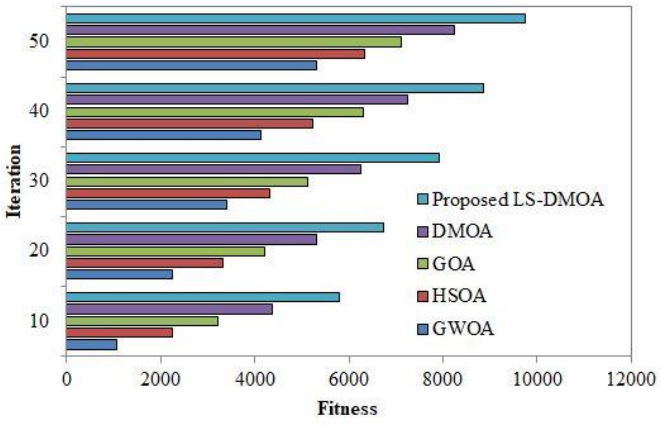
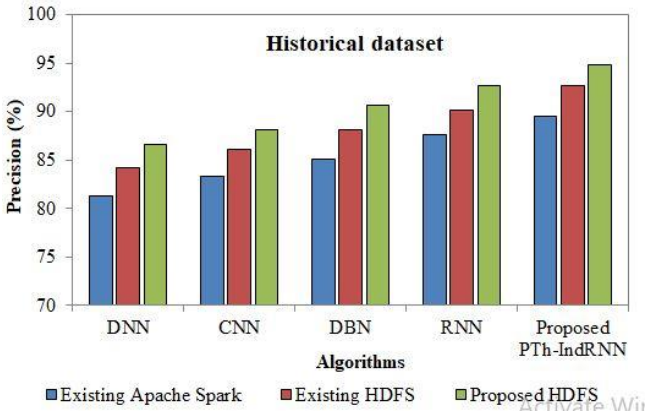


Figure 4: Fitness value analysis

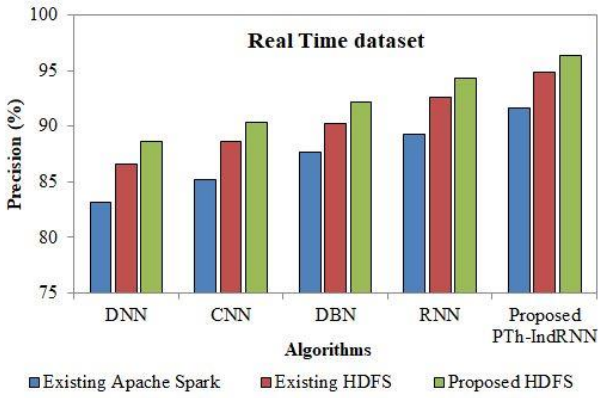
In Figure 4, the fitness obtained by the LS-DMOA and the existing algorithms for 10 to 50 iterations is pictorially depicted. At the 50th iteration, the proposed LS-DMOA selects the optimal feature with fitness level of 9756, which is better than the existing DMOA, GOA, HSOA, and GWOA. This enhancement is associated with the utilizing LS technique in the DMOA approach.

3) Performance analysis of sentiment classification.

Grounded on the accuracy, training time, precision, recall, F-Measure, sensitivity, and specificity, the proposed sentiment classification PTh-IndRNN on real-time and historical datasets are evaluated with the prevailing HDFS, Apache spark, and Proposed HDFS techniques. The PTh-IndRNN is also compared with the existing RNN, Deep Belief Network (DBN), CNN, and Deep Neural Network (DNN) to prove its efficacy.



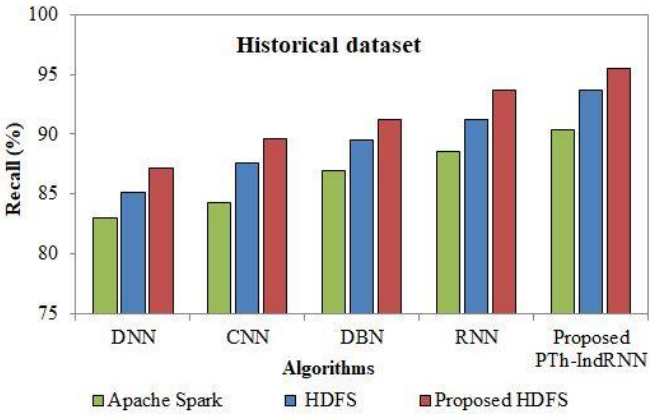
(a)



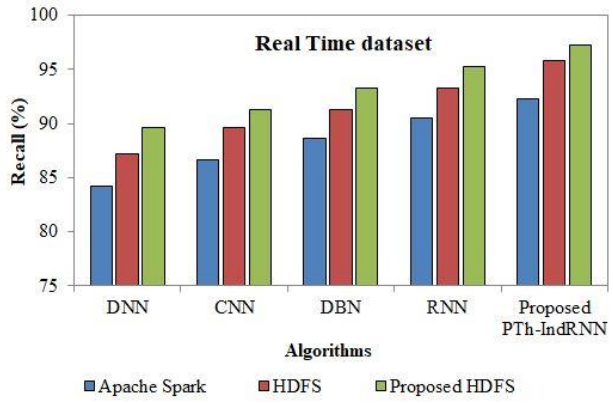
(b)

Figure 5: Precision evaluation on (a) historical dataset (b) real-time dataset

The PTh-IndRNN attained the precision level of 94.84% on the historical dataset with the proposed HDFS, which is 2.36%, 4.62%, and 9.49% higher than the prevailing RNN, DBN, and DNN respectively. The PTh-IndRNN attained a better precision level with the proposed HDFS than using the existing HDFS and Apache spark systems, which is evident in Figures 5(a) and 5(b). The precision of PTh-IndRNN with the proposed HDFS is 92.32% on the real-time dataset, which is higher than the existing RNN, DBN, CNN, and DNN approach. Thus, when analogized to other classifiers, only fewer predictions are made incorrectly with PTh-IndRNN in the proposed model.



(a)



(b)

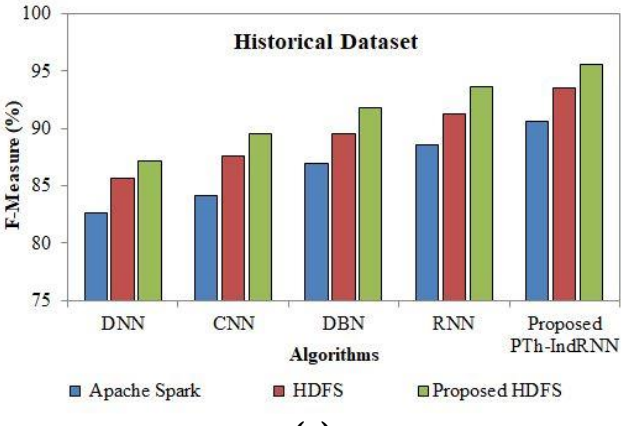
Figure 6: Recall results of classifiers

The recall levels obtained by the proposed PTh-IndRNN using traditional HDFS, and apache-spark are depicted in Figures 6(a) and 6(b). The proposed HDFS is higher than that of the existing classifier algorithms. Nevertheless, when classification is performed with the proposed HDFS system, the classifiers achieved better recall where the PTh-IndRNN perceived a higher level (95.48%, 97.23%) than the RNN (93.65%, 95.21%), DBN (91.18%, 93.21%) and CNN (87.12%, 91.32%) on both datasets. Thus, the proposed classification is made suitable for sentiment classification for the prediction of stock value.

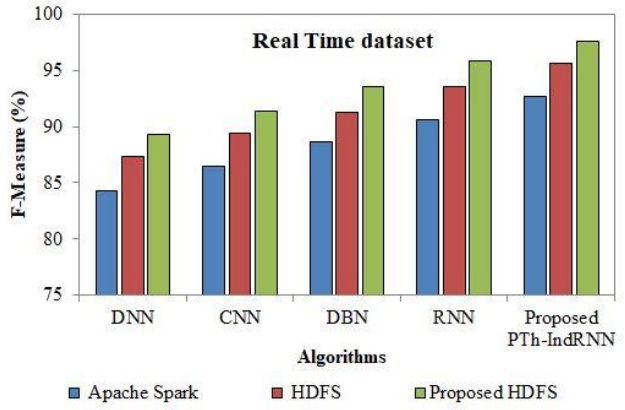
Table 2: Accuracy level (%) on the historical and real-time datasets

Algorithms	Historical dataset			Real-time dataset		
	HDFS	Apache Spark	Proposed HDFS	HDFS	Apache Spark	Proposed HDFS
DNN	85.6545	82.6298	87.2145	87.3247	84.2478	89.3584
CNN	87.6248	84.1254	89.5448	89.4578	865178	91.3658
DBN	89.5412	86.9575	91.8475	91.3256	88.6545	93.5471
RNN	91.2365	88.5148	93.6517	93.5148	90.6545	95.8475
Proposed PTh-IndRNN	93.5478	90.6548	95.6287	95.6589	92.6589	97.5478

The level of PTh-IndRNN is higher than the existing algorithms, which is shown in table 2. When analogized to HDFS and Apache spark, the accuracy of 2.32% and 6.06% is increased with the proposed HDFS on the real-time dataset. Thus, the sentiment of the texts is classified more accurately with the PTh-IndRNN than traditional classifiers.



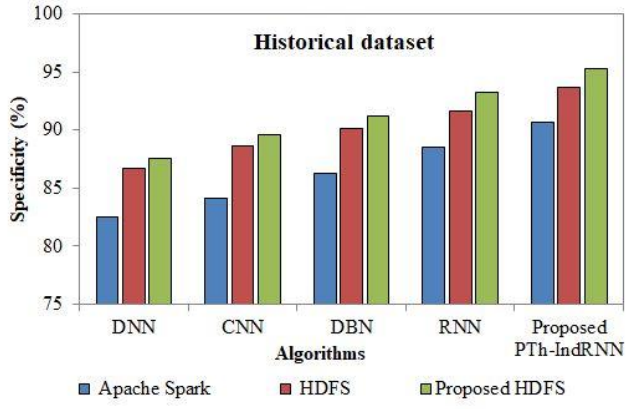
(a)



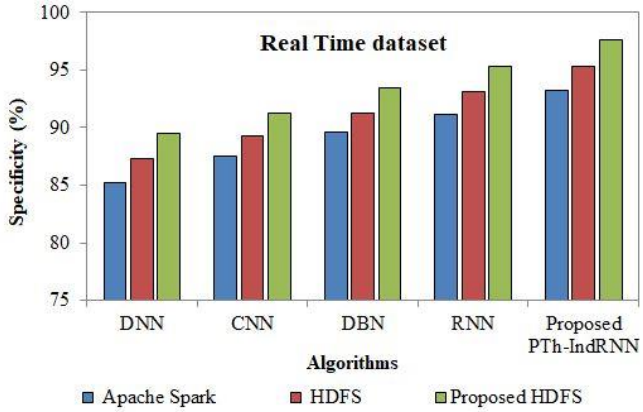
(b)

Figure 7: F-Measure values on (a) Historical dataset (b) real-time dataset

Regarding precision and recall values, the f-measure is calculated. When weighed against other classifiers, the F-Measure of PTh-IndRNN is better, which is unveiled in Figures 7(b) and 7(a). Even with the proposed HDFS, the DNN attained unreliable results (87.21%, 89.35%) on both datasets. However, the proposed model achieved a higher F-measure level, which shows the efficacy of the PTh-IndRNN in both datasets for the text sentiment classification.



(a)



(b)

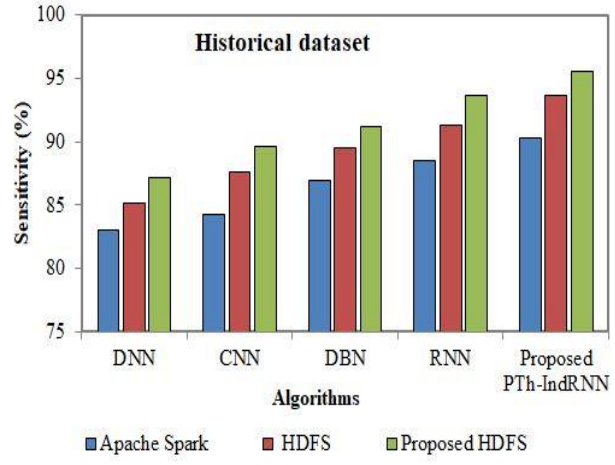
Figure 8: Specificity levels on (a) historical dataset (b) Real-time dataset

In Figures 8(a), and 8(b), the specificity level of the proposed and the traditional classifiers with the HDFS, Apache spark, and proposed HDFS on the historical and real-time data is pictorially represented. More specificity levels (91.18%, 93.15%, and 95.32%) could be achieved by the RNN with the involvement of the proposed HDFS on the real-time datasets. Nevertheless, the PTh-IndRNN acquired a higher specificity level of 93.26%, 95.32%, and 97.65%, which is the outcome of including PTh activation in the IndRNN.

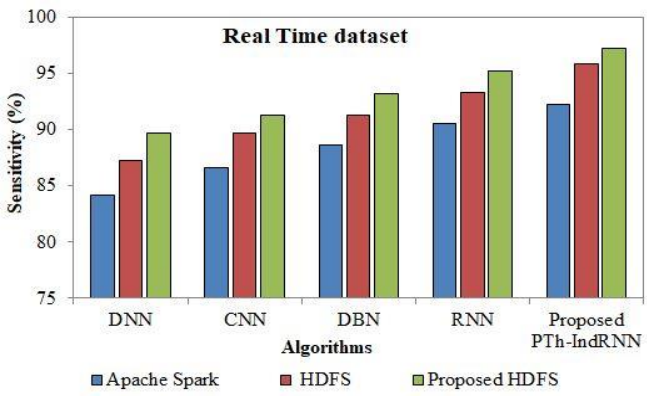
Table 3: Training time

Algorithms	Training time (ms)	
	Historical dataset	Real-Time dataset
DNN	119542	116521
CNN	114478	111457
DBN	109635	106356
RNN	104547	101478
Proposed PTh-IndRNN	99457	95658

The training time of DNN is higher (119542ms and 116521ms) on both datasets followed by CNN and DBN, which is evident in table 3. However, when analogized to the prevailing systems, the RNN takes less time. But the PTh-IndRNN depicts a higher training time of RNN by 5090ms and 5820ms, which depicts the PTh-IndRNN 's time efficiency.



(a)



(b)

Figure 9: Sensitivity analysis on (a) historical dataset (b) real-time dataset

More sensitivity level is attained by the proposed and existing classifiers with the proposed HDFS on the historical datasets (95.48%, 91.18%, and 87.12%) and on the real-time datasets (97.23%, 93.21%, and 89.65%), which is depicted in Figure 9(a) and 9(b). The PTh-IndRNN performs better with the existing HDFS and Apache spark system. Thus, on both datasets, more polarities could be identified perfectly with the PTh-IndRNN.

C. Comparative Analysis

The proposed PTh-IndRNN 's text sentiment classification accuracy is analogized to the surveyed works BERT-LSTM (Xiaofeng et al., 2021, [11]), HL-NBC(Rodrigues & Chiplunkar, 2022, [14]), and AG-LSTM.

Table 4: Comparative analysis of the existing works

Algorithms	Accuracy (%)
BERT-LSTM (Xiaofeng et al., 2021)	84.55
HL-NBC (Rodrigues & Chiplunkar, 2022)	82
AG-LSTM (Deepika & Nirupama Bhat, 2021)	90.42
Proposed PTh-IndRNN (Historical dataset)	95.6287
Proposed PTh-IndRNN (Real-Time dataset)	97.5478

The comparative analysis of the proposed text sentiment classification accuracy on real-time and historical datasets with the existing BERT-LSTM, HL-NBC, and AG-LSTM models is depicted in table 4. For accuracy, the existing BERT-LSTM and AG-LSTM achieved 84.55% and 90.42%. HL-NBC was unable to beat the proposed approach even though it used a combination of the Map Reduce programming model along with Hadoop. Thus, the stock market polarity can be predicted effectively using the PTh-IndRNN combined with the proposed HDFS system.

V. CONCLUSION

This paper proposes a novel HDFS system-based PTh-IndRNN real-time big-data analysis. The mapping, shuffling, and reducing are performed with the H-CKMeans, FYSA, and TS-SCOA in the proposed HDFS system.

The proposed techniques' performance is evaluated on the real-time and historical big-data datasets. The TS-SCOA and H-C KMeans exhibited enhanced outcomes, which enriched the proposed HDFS system. The proposed LS-DMOA attained higher fitness of 5784, 6748, 7912, 8852, and 9756, which verified the better convergence. Next, the proposed technique acquired higher accuracy, recall, sensitivity, specificity, precision, and F-measure. The PTh-IndRNN took less trained time of 119542ms and 116521ms on both datasets, which revealed the time efficiency of the proposed framework. In the end, the superiority of the proposed Twitter financial text sentiment classification is shown by the comparative analysis. Score values are included in the SentiWordNet dictionary for general words only. Thus, the financially trained dictionary can be used to improve classification accuracy in the future.

DECLARATION

Funding/ Grants/ Financial Support	No, I did not receive.
Conflicts of Interest/ Competing Interests	No conflicts of interest to the best of our knowledge.
Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material/ Data Access Statement	Data extracted from Twitter AP and AlphaVantage – Data provider
Authors Contributions	Sowmya R Main Author, Dr. Suneetha K R. Reviewer.

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