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Original Article

Automated Sentiment Analysis Using Pigeon Inspired Optimization Algorithm with Attention Bidirectional Gated Recurrent on Social Media

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Abstract *- Sentiment Analysis (SA) is a model employed in Natural Language Processing (NLP), which describes the feeling or sentiment conveyed in textual content. It uses automated tools to identify psychological data like thoughts, attitudes, and mental states shown in writing and indirectly over social network platforms. SA model is regularly executed on text datasets to help understand user desires, responses, and businesses observing products. Therefore, the Deep Learning (DL) technique has been developed as a promising model that has been commonly used and reached significant results. As DL approaches mechanically eliminate features from the database, there exists a possibility that an intermediate symbol, which has been disregarded may serve as a related factor. This study introduces an automated SA using the Pigeon-Inspired Optimization Algorithm with Attention Bidirectional Gated Recurrent Unit (PIOA-ABGRU) technique for social networking. The presented PIOA-ABGRU technique mainly focused on detecting multiple classes of feelings that occur in social media. The PIOA-ABGRU approach undergoes various sub-processes to alter the input data into a beneficial layout. Also, the Word Embedding (WE) procedure is performed using the BERT approach. For sentiment detection, the PIOA-ABGRU technique applies the ABGRU model, which detects sentiments in distinct classes. Finally, the PIOA-based hyperparameter tuning procedure is executed to select ABGRU's hyperparameters. The simulation results of the PIOA-ABGRU model take place on a social media dataset. The experimental analysis specified that the PIOA-ABGRU model reaches effectual achievement over other models using distinct measures.*

Keywords *- Sentiment analysis, Word embedding, Social media, Natural Language Processing, Pigeon Inspired Optimization.*

1. Introduction

Social networks are one of the most illustrative tools of Web 2.0, permitting numerous consumers worldwide to post and share data rapidly and smoothly and allowing a constant flow of data [1]. A large quantity of social data includes blogs, tweets, and feedback from frequent areas, which creates numerous tasks and probabilities for NLP researchers to define beneficial data [2]. Furthermore, such data allows everybody to realize the features of persons on an exact theme and display data that can be leveraged to perform forecasts in the area of the stock marketplace, political elections, product sales, and so on [3]. For enchanting the decisions in an on-time method dependent upon people's reviews, SA has been measured as one of the critical tasks from a trade viewpoint, and it is very required in research fields [4]. SA contracts with defining the emotional attitude behind a sequence of words to categorize them through their opposition (neutral, positive, or negative) or feeling (sad, happy, etc.) [5]. Moreover, content on social networks like Twitter has a dissimilar nature depending upon the verbal use, which is unique, making it different from other language usages. Some significant complex features of tweets have been linked to their short distance (i.e. 280 characters), the need for more context, lower concern for grammar, data sparsity, and the usage of an informal language style (phrases, abbreviations, and slang). These features make it very complex to incorporate fully effectual SA methods into social network platforms [6].

Besides, the SA application in social networks is highly beneficial in numerous cases, like evaluating the effect of social media events, aiding to know what users think about products, businesses, and specific topics, creating enhanced decisions on advertising plans for products or services growth, or even helping in forecasting the actions of consumers [7]. Due to these purposes, applying NLP plans and SA is an effective field of useful and simple study to make social networking more functional and helpful. Furthermore, in DL models, the feature vector is collected of WE, which is abundant in word-related data; they take more data about words' resemblance and semantic features [8]. But, despite these significant profits, there are some proposals for SA in social network platforms utilizing DL, particularly on Twitter [9]. So, the structure of an innovative hybrid technique is suggested based on DL approaches that are helpful in a standard amount of labelled Twitter data sets, which enhances the accuracy of other present methods [10]. This article introduces an automated SA using the pigeon-inspired optimization algorithm with an attention bidirectional gated recurrent unit (PIOA-ABGRU) model for social networking. The presented PIOA-ABGRU technique mainly focused on detecting multiple classes of feelings that happen in social media.

The PIOA-ABGRU technique undergoes various sub-processes to alter the input data into a beneficial layout. Also, the WE procedure is performed using the BERT approach. For sentiment detection, the PIOA-ABGRU technique applies the ABGRU model, which detects sentiments in distinct classes. Finally, the PIOA-based hyperparameter tuning procedure is implemented to select ABGRU's hyperparameters. The simulation outputs of the PIOA-ABGRU method occur on a social media dataset.

2. Literature Works

In [11], pre-processing models and ML techniques for the multi-class classification of opinions have been discovered to enhance efficiency. The movie analyses database was employed to implement because of its similitude with social media text. Supervised ML methods, namely Naïve Bayes (NB), Support Vector Machine (SVM), and Decision Tree (DT), are utilized for classification. Li et al. [12] developed an emoji vectorization methodology. Subsequently, an Emoji-Text Incorporated Bidirectional Long Short-Term Memory (ET-BiLSTM) approach for SA was developed. Assessment of text-based sentence representations has been removed using the Bi-LSTM approach.

The dual techniques can be combined into the last evaluation representation vectors. In [13], the authors considered improving the effectiveness of sentiment classification by employing a modified DL model with a progressive WE approach and making an LSTM network. Additionally, the authors developed an ensemble method that integrates this baseline algorithm with a recent alternative method employing SA. In [14], Twitter data must be explored through the R computer languages. The authors have composed the Twitter information reliant on hashtag keywords, encompassing new cases, deaths, Coronavirus, and COVID-19 recovered. This is named as a hybrid heterogeneous SVM (H-SVM). Arbane et al. [15] developed an NLP technique dependent upon the Bi-LSTM method for executing sentiment classification and uncovering different problems relevant to the COVID-19 views of the public. Bi-LSTM has been an enhanced form of standard LSTM for producing the output. Khan et al. [16] aimed to calculate the effectiveness of diverse WE for Roman, English, and Urdu languages employing the CNN-LSTM technique with standard ML techniques and introduced an innovative DL method under two models such as LSTM and CNN model. To achieve the last categorization, the feature map provides numerous ML methods. Many WE systems help this theory.

Imran et al. [17] intended to evaluate the reactions of persons from numerous cultures to the new Coronavirus and individual's sentiments regarding the following activities offered by various nations. Deep LSTM methods employed to evaluate the sentiment emotions and polarity from removed tweets were trained.

Yuan and Yang [18] propose a network rumour detection model using an attention-enhanced GRU model. Continuous Bag-of-Words (CBoW) and Adam methods are employed for word vectorization and binary cross-entropy loss function. In [19], a Gated Attention Recurrent Network (GARN) technique is presented. Log Term Frequency-assisted Modified Inverse Class Frequency (LTF-MICF) and Hybrid Mutation-Assisted White Shark Optimizer (HMWSO) methods are utilized for extraction and selection. Natarajan et al. [20] introduced a BiLSTM with the Ranger AdaBelief Optimizer (Bi-LSTM RAO) model. BoW and Gazelle Optimization Algorithm (GOA) approaches are utilized for feature extraction and selection.

3. The Proposed Method

This research introduces a programmed SA using the PIOA-ABGRU technique for social networking. The presented PIOA-ABGRU technique mainly focuses on detecting multiple classes of sentiments on social media platforms. The PIOA-ABGRU technique undergoes various sub-processes like data pre-processing, WE, classification, and hyperparameter tuning to achieve this. Figure 1 illustrates the workflow of the PIOA-ABGRU model.

3.1. Data Pre-Processing

The PIOA-ABGRU technique involves various sub-processes to alter the input data into a useful layout. The sub-processes are given below.

- Text Cleaning: Eliminate irrelevant characters, special symbols, and needless whitespace to safeguard a reliable and clean text corpus.
- Tokenization: Break down the manuscript into separate words or tokens, a vital stage for subsequent analysis.
- Lowercasing: Change all words to lower-case to safeguard evenness and stop the method from handling differently-cased words as separate entities.
- Stopword Removal: Remove common words (stopwords) that do not donate significant meaning to SA.
- Stemming or Lemmatization: Decrease words to their origin form to handle variants and enhance model generalization.

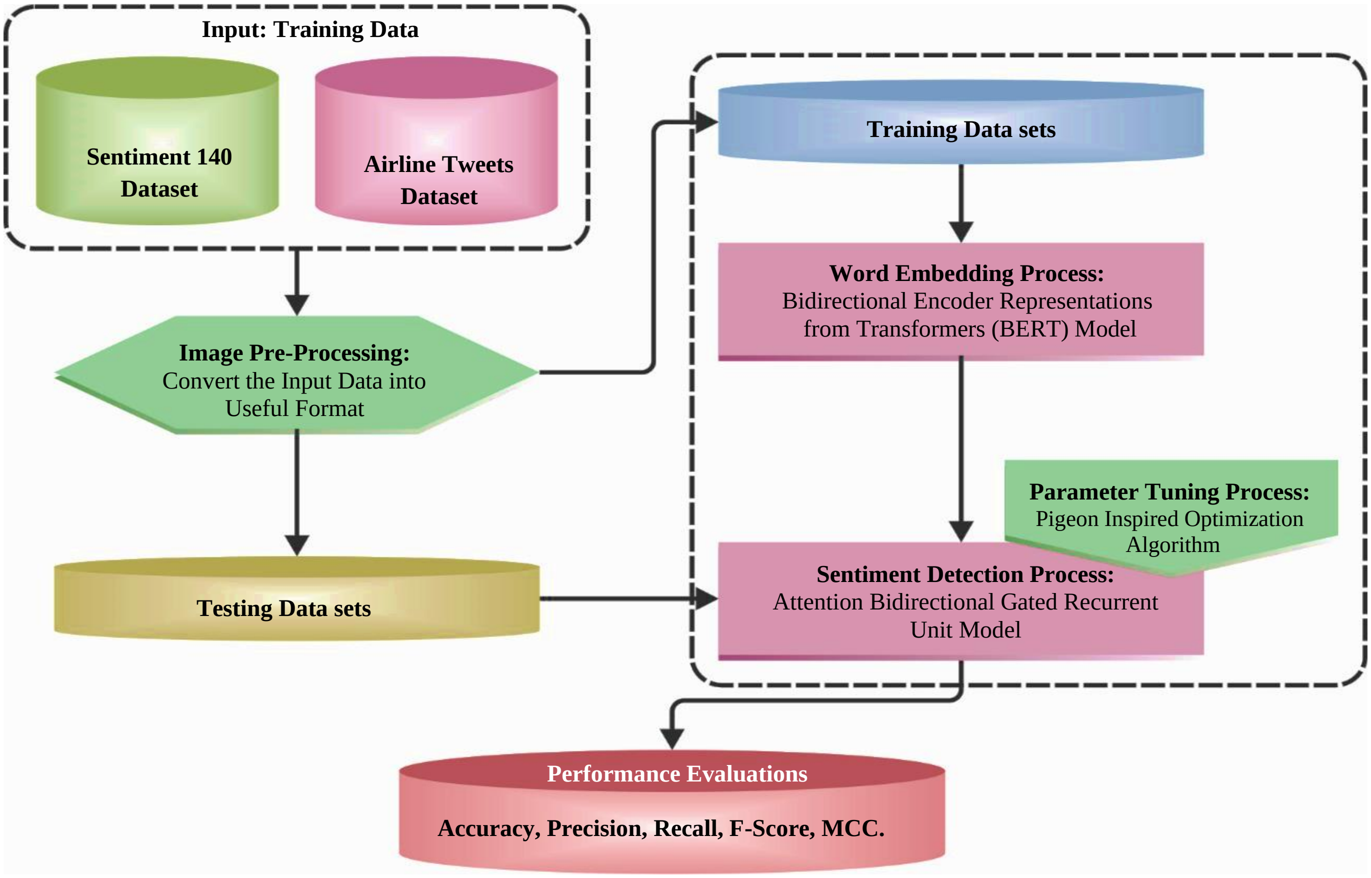

Fig. 1 Workflow of PIOA-ABGRU technique

3.2. WE Using the BERT Approach

In this work, the WE process is performed using the BERT approach. The BERT method employs bi-directional changers as encoders, combining the context data of the left and right ways of the present character [18]. The encoder has no extensive encoded sentence from right to left or vice versa to forecast characters but arbitrarily hides or substitutes some characters as per a definite amount and forecasts the new characters as per the context. Furthermore, the BERT technique also inserts sentence-level training tasks, chiefly learning the context relation among sentences. The exact practice is substituting a few sentences randomly, and the encoder employs the preceding sentence to estimate whether the subsequent sentence is novel. These dual tasks have been together skilled to take vector symbols at the sentence and character level. BERT employs the modification parameter device. The input series is fixed to $([CLS], c_1, c_2, \dots, c_n, [SEP])$, whereas $[CLS]$ signifies the start of a sample sentence series, and $[SEP]$ denotes the space symbol among sentences. They are utilized for sentence-level training tasks. The symbol of every character vector contains three fragments, such as embedding vectors of character, sentence, and position, where they are definite as $e^c = (e^c_{[CLS]}, e^c_{c_1}, e^c_{c_2}, \dots, e^c_{c_n}, e^c_{[SEP]})$, $e^s = (e^s_A, e^s_A, e^s_A, \dots, e^s_A, e^s_A)$, and $e^p = (e^p_0, e^p_1, e^p_2, \dots, e^p_n, e^p_{n+1})$, respectively. Between them, the embedding vector of character is moulded by the language delivered by BERT. Enlarge the three embedding vectors equally to acquire character features as BERT method input. The character vector is presented in Equation (1).

$$x = [x_1, x_2, \dots, x_n] \tag{1}$$

3.3. Sentiment Detection Using ABGRU

For sentiment detection, the PIOA-ABGRU technique applies the ABGRU model, which detects sentiments in distinct classes. GRU is developed to permit every recurrent unit to take dependencies of dissimilar time measures [19] conveniently. The GRU technique is very simple when compared to LSTM because it contains only the reset gate r and update gate z, so there is faster convergence time and fewer parameters throughout training, and Equations (2)-(5) upgrade the parameters.

$$r_t = \sigma(W_r x_t + U_r h_{t-1}) \tag{2}$$

$$z_t = \sigma(W_z x_t + U_z h_{t-1}) \tag{3}$$

$$\tilde{h}_t = tanh\big(W x_t + U(r_t \odot h_{t-1})\big) \tag{4}$$

$$h_t = (1 - z_t) h_{t-1} + z_t \tilde{h}_t \tag{5}$$

Whereas $\odot$ signifies the element increase process, r_t refers to the reset gate, σ denotes the logical sigmoid function,

W_*, U_* denotes the weight matrix, z_t is the update gate, which defines the upgrade degree in the GRU model by the present input state and the preceding Hidden Layer (HL), $\tilde{h}_t$ embodies the candidate HL, and h_t signifies the HL. GRU is an alternative to LSTM; it chiefly combines the gate of forgetting and input in LSTM, which decreases the convergence time, training parameters, and complexity. At present, it is one of the common RNN methods.

The unidirectional GRU is spread using a unidirectional method from front to back. The output is dependent upon the dual effects of backward and forward conditions; it resolves the issue of unidirectional GRU by generating the last output more precisely. The attention method was used for the machine translation task. This device is presented to remove the semantic data of significant words present in sentences. It is separated into dual modules, namely Decoder and Encoder. The Encoder executes a definite alteration on the data provided as input to get a semantic vector, while the Decoder attains a certain change later. It can be displayed in Equations $(6)-(8)$:

$$u_i = \tanh(W_i h_i + b_i) \tag{6}$$

$$\alpha_i = \frac{\exp(u_i^T u_w)}{\sum_i \exp(u_i^T u_w)} \tag{7}$$

$$h_i = \sum_i \alpha_i h_i \tag{8}$$

Whereas u_w is an initialized context vector at random, which is upgraded throughout training; u_i is the outcome of a complete connection process of the HL vector h_i; W_i and b_i represent the weight matrix and bias, respectively; α_i represents the attention score. Figure 2 indicates the ABGRU structure.

3.4. PIOA-Based Hyperparameter Tuning

Here, the PIOA-based tuning process is executed for selecting the hyperparameters of ABGRU. PIOA is stimulated by the flying pattern of the pigeon, together with their intelligence of pigeon swarm and behaviours for effective food search [20]. Finding the route and long-distance flight to the pigeon's home (or starting point) is the astonishing point of the pigeon. The visual eminence of geographical features, the solar position, and the terrestrial magnetic field are different indicators employed in this process. The navigation and communication are based mainly on the leader pigeon. Pigeon preserves side-by-side flocking distance by communicating between the leader and flock. Here, map and compass operators and landmark operators are the two operators used to model this homing trait.

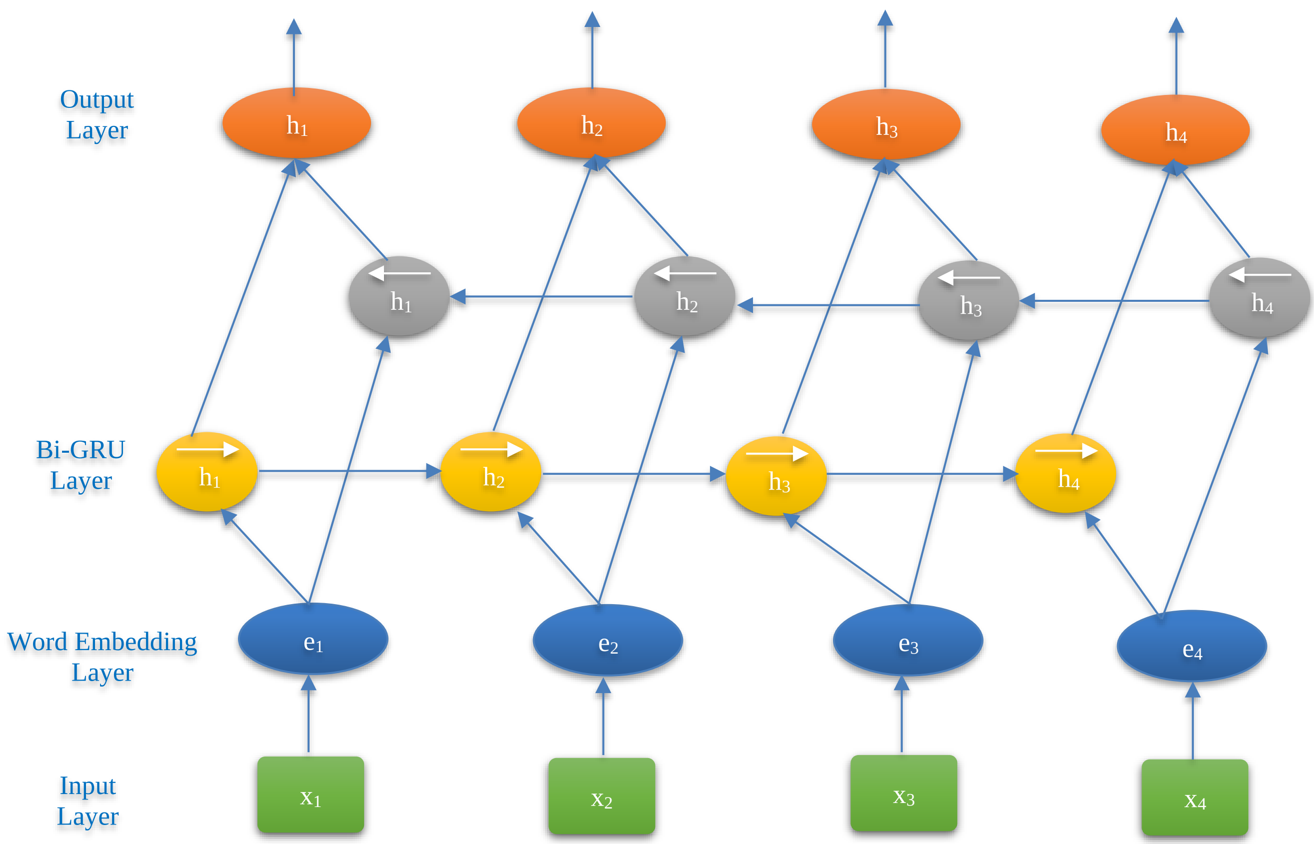

Fig. 2 Structure of ABGRU

3.5. Map and Compass Operator

Magneto reception is the primary advantage of pigeons, which helps to create a map through the magnetic field of the Earth. Next, the sun's altitude helps to alter the location towards the destination, like a compass. The initial position and current velocity are used to determine the further pigeon movement during the swarm.

$X_i = (x_{i,1}, x_{i,2}, \dots, x_{i,N})$ is the location of i^{th} individuals in the swarm within the search space with N-dimension. $V_i = (v_{i,1}, v_{i,2}, \dots, v_{i,N})$ is the location alteration of a pigeon and its velocity. $i = 1,2,\dots,M$ is the dimension of the group. $G = (g_1, g_2, \dots, g_N)$ denotes the global optimum location of the swarm.

The velocity and updated locations of i^{th} pigeon at t^{th} iteration is evaluated by the following expression:

$$v_{i,j}^t = v_{i,j}^{t-1} e^{-Rt} + \rho\left(g_j^{t-1} - x_{i,j}^{t-1}\right) \tag{9}$$

$$x_{i,j}^t = x_{i,j}^{t-1} + v_{i,j}^t \tag{10}$$

Using Equation (9), the velocity of a pigeon can be defined by considering the prior pigeon velocity and distance towards the global optimum location. R is the operator labelled to control the effect of current velocity, ρ is an even distribution random number within [0,1]. After changing its velocity, the pigeon can change its location using Equation (10).

3.6. Landmark Operator

Pigeons use already-known patterns or landmarks to find the route toward the destination, just like a person remembers the surroundings to find the path. The pigeon quickly finds the route and directly flies toward the proper destination if a singularity occurs. Or else, it saves energy by following the pigeon that already has details regarding the landmark. The lesser aligns with the greater sub-group, while the majority aligns with the central group.

$$c_j^t = \frac{\Sigma_{i=1}^N \left(x_{i,j}^{t-1} f\left((x_i^{t-1})\right)\right)}{N\Sigma_{i=1}^N \left(f(x_i^{t-1})\right)} \tag{11}$$

Equation (11) for selecting the middle pigeon. $i = 1,2,\dots,N$, where N refers to the dimension of the best part. $F(x)$ denotes the fitness values of i^{th} pigeons at t^{th} iteration. Equation (12) is used to update the pigeon position.

$$x_{i,j}^t = x_{i,j}^{t-1} + r\left(c_j^t - x_i^{t-1}\right) \tag{12}$$

The search efficacy of PIOA can be improved by balancing exploitation and using a map compass and landmark operators. The PIOA enhances a Fitness Function (FF) to achieve amended classifier achievement. It defines an optimistic number to suggest the enhanced act of the candidate solution. Also, the classification rate of error minimization is considered as FF, as assumed in Equation (13).

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{No.of\ misclassified\ samples}{Total\ no.of\ samples} \times 100 \tag{13}$$

4. Result Analysis

The investigational evaluation of the PIOA-ABGRU method is verified utilizing the Sentiment140 dataset, available on Kaggle [21]. Compiled by the creator "KazAnova," the dataset holds 1.6 million tweets, labelled with sentiments for "0" and "4" for negative and positive. Initially derived from Twitter, this dataset is pre-processed and widely used in SA studies and ML applications. Every tweet in the dataset is considered as per the sentiment conveyed by the consumer, creating a respected resource for training and assessing SA methods. The dataset's size and accessibility improved its popularity among researchers, enabling the advancement of efficient sentiment analysis methods for short text snippets. For researchers and practitioners employed on SA projects, the Sentiment140 dataset gives a different and wide range of tweets, making it a suitable choice for training and testing SA systems. Table 1 shows the dataset description.

Figure 3 portrays the classifier outputs of the PIOA-ABGRU approach under the Sentiment140 dataset. Figures 3a and 3b portrays the confusion matrices presented by the PIOA-ABGRU method at 70:30 of TRAPH/TESPH. The figure indicated that the PIOA-ABGRU method precisely detected and classified the two classes overall. Also, Figure 3c shows the PR research of the PIOA-ABGRU method. The figure specified that the PIOA-ABGRU method acquired the greatest PR achievement under overall classes. At last, Figure 3d establishes the ROC analysis of the PIOA-ABGRU method. The figure exhibited that the PIOA-ABGRU method has given output in greater outputs with the largest ROC values below separate classes.

Table 1. Descriptions on sentiment140 dataset

Class	No. of Instances
Negative	1000
Positive	1000
Total Instances	**2000**

Table 2. SA output of PIOA-ABGRU technique under Sentiment140 dataset

Classes	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	MCC
TRAPH (70%)					
Negative	88.70	98.12	88.70	93.18	87.28
Positive	98.27	89.47	98.27	93.66	87.28
Average	**93.48**	**93.80**	**93.48**	**93.42**	**87.28**
TESPH (30%)					
Negative	87.33	98.46	87.33	92.56	86.81
Positive	98.70	89.15	98.70	93.68	86.81
Average	**93.02**	**93.80**	**93.02**	**93.12**	**86.81**

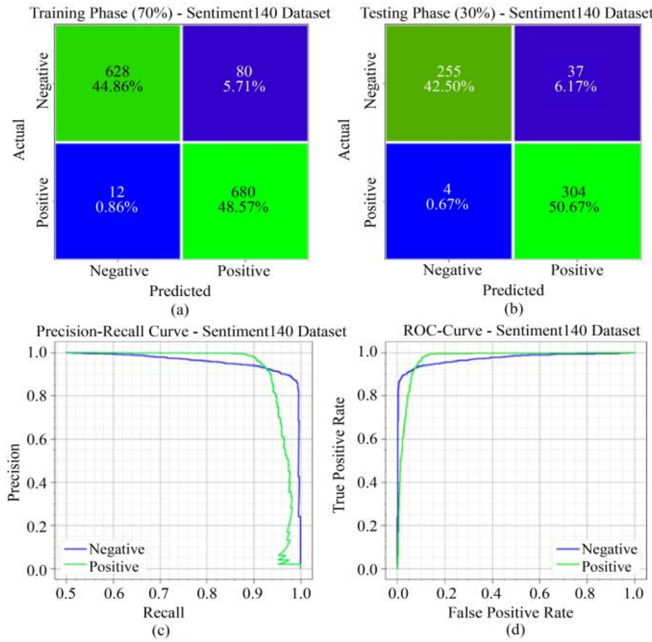

Fig. 3 (a-b) Confusion matrices and (c-d) PR and ROC curves under the Sentiment140 dataset

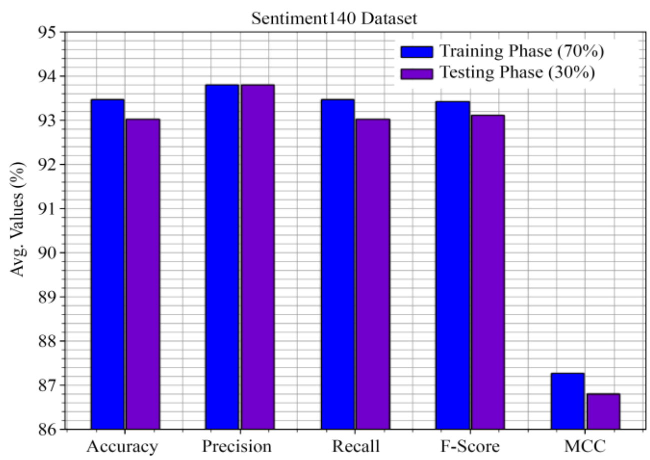

Fig. 4 Average of PIOA-ABGRU technique under Sentiment140 dataset

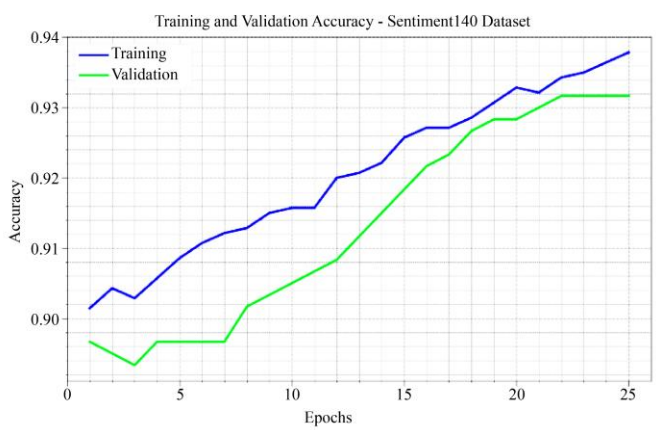

Fig. 5 $Accu_y$ the curve of the PIOA-ABGRU technique under the Sentiment140 dataset

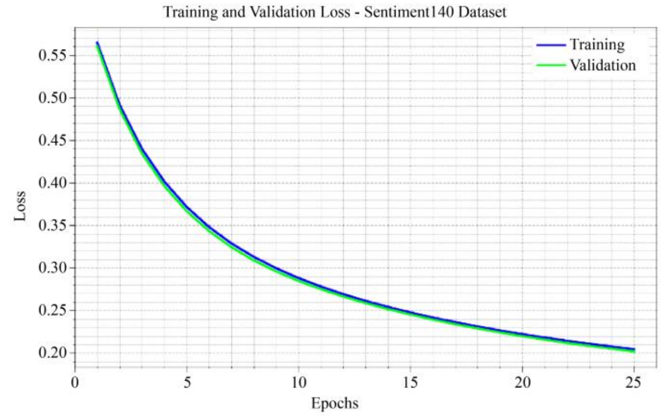

Fig. 6 Loss curve of PIOA-ABGRU technique under Sentiment140 dataset

Table 3. Comparative output of PIOA-ABGRU technique with other models under Sentiment140 dataset

Methods	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}
TFDNN	78.05	75.10	82.25	77.24
TFCNN	82.80	79.59	83.48	75.94
TFRNN	75.05	80.18	81.95	83.32
WVDNN	81.93	79.95	76.47	83.48
WVCNN	79.72	82.63	83.77	79.71
WVRNN	80.98	75.65	78.45	75.98
ASA-SMHHODL	84.25	85.83	86.37	86.13
PIOA-ABGRU	93.48	93.80	93.48	93.42

In Table 2 and Figure 4, the SA outputs of the PIOA-ABGRU technique are precisely illustrated. The results underlined that the PIOA-ABGRU technique appropriately detected the negative and positive class labels. On 70% of TRAPH, the PIOA-ABGRU method acquires an average $accu_y$ of 93.48%, $prec_n$ of 93.80%, $reca_l$ of 93.48%, F_{score} of 93.42%, and MCC of 87.28%. Additionally, on 30% of TESPH, the PIOA-ABGRU method increases average $accu_y$ of 93.02%, $prec_n$ of 93.80%, $reca_l$ of 93.02%, F_{score} of 93.12%, and MCC of 86.81%. The $accu_y$ curves for training (TRA) and validation (VL) shown in Figure 5 for the PIOA-ABGRU technique below the Sentiment140 dataset deliver valuable visions into its achievement under frequent epochs. Mainly, there is a constant development in both TRA and TES $accu_y$ to increasing epochs, demonstrating the capability of the method to recognize and learn patterns from both TRA and TES data. The rising trend in TES $accu_y$ underlines the flexibility of the method to the TRA dataset and its ability to produce precise anticipations on hidden data, underlining robust generalization skills.

Figure 6 portrays the loss values of the TRA and TES for the PIOA-ABGRU methodology below the Sentiment140 dataset under various epochs. The TRA loss reliably declines as the method improves its weights to lessen classifying errors in both datasets. The loss curves show the location of the method with the TRA data, underlining its capacity to take patterns effectually in both datasets. Notably, there is a steady modification of parameters in the PIOA-ABGRU method, projected to minimize divergences among predictions and actual TRA labels. Table 3 and Figure 7 highlight the comparative outputs of the PIOA-ABGRU approach on the Sentiment140 dataset [22]. The outputs highlighted that the PIOA-ABGRU technique attains improved accomplishment. Based on $accu_y$ and $prec_n$, the PIOA-ABGRU technique gets an increased value of 93.48% and 93.80%, while the TFDNN, TFCNN, TFRNN, WVDNN, WVCNN, WVRNN, and ASA-SMHHODL approaches obtain decreased $accu_y$ and $prec_n$ of 78.05%, 82.08%, 75.05%, 81.93%, 79.72%, 80.98%, and 84.25%; and 75.10%, 79.59%, 80.18%, 79.95%, 82.63%, 75.65%, and 85.83%, subsequently. Moreover, based on F_{score}, the PIOA-ABGRU approach attains an improved F_{score} of 93.42%, where the TFDNN, TFCNN, TFRNN, WVDNN, WVCNN, WVRNN, and ASA-SMHHODL approaches get reduced F_{score} of 77.24%, 75.94%, 83.32%, 83.48%, 79.71%, 75.98%, and 86.13%, subsequently.

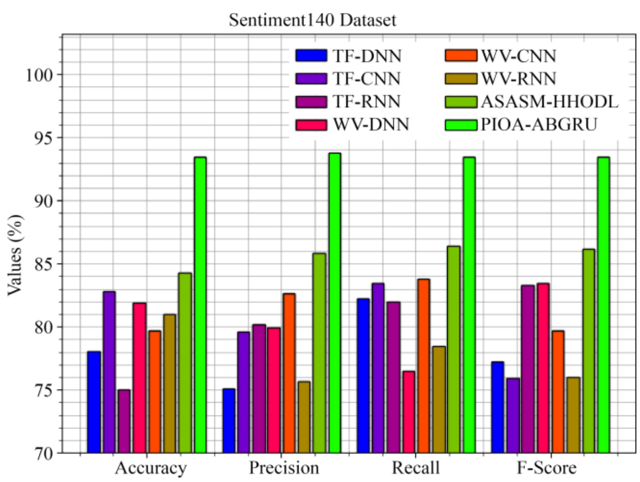

Fig. 7 Comparative outcome of PIOA-ABGRU technique under Sentiment140 dataset

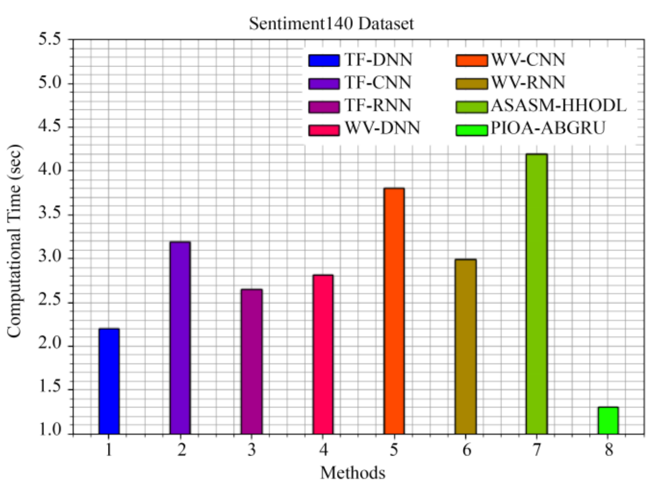

Fig. 8. CT outcome of PIOA-ABGRU technique under Sentiment140 dataset

Table 4. CT outcome of PIOA-ABGRU technique with other methods under Sentiment140 dataset

Methods	CT (sec)
TFDNN	2.20
TFCNN	3.19
TFRNN	2.65
WVDNN	2.81
WVCNN	3.81
WVRNN	2.99
ASA-SMHHODL	4.19
PIOA-ABGRU	1.30

Table 4 and Figure 8 exhibit the Computational Time (CT) outputs of the PIOA-ABGRU approach on the Sentiment140 dataset. The outputs showed superior performance of the PIOA-ABGRU approach. Created on CT, the PIOA-ABGRU techniques increase smaller CT of 1.30s while the TFDNN, TFCNN, TFRNN, WVDNN, WVCNN, WVRNN, and ASA-SMHHODL techniques get larger CT of 2.20s, 3.19s, 2.65s, 2.81s, 3.81s, 2.99s, and 4.19s, subsequently.

The "Airlines" dataset [23] is available on Kaggle, specifically from the CrowdFlower platform, which focuses on SA related to tweets about various airline companies. This dataset is particularly valuable to understand public sentiments expressed on Twitter toward different airlines. The sentiment labels include "positive", "neutral", and "negative", providing an overall view of public opinions on airline services.

The dataset includes data such as tweet content, user mentions, and the airline mentioned in each tweet. Analyzing this data can present details into the merits and weaknesses of diverse airline services, enabling companies to understand customer feedback and make data-driven improvements. Researchers and data scientists interested in SA, customer feedback, or the airline industry can use the "Airlines" dataset to develop models and gain a deeper understanding of customer sentiments expressed on social media platforms like Twitter.

This dataset serves as a valued resource for evaluating and training SA models precisely tailored to the airline industry. Table 5 represents a comprehensive description of the airline dataset. Figure 9 exhibits the confusion matrices of the PIOA-ABGRU technique in the airline dataset. Figures 9a-9b portray the classifier output at 70:30 of TRAPH/TESPH. The figure shows that the PIOA-ABGRU approach precisely detects and classifies the two classes. Similarly, Figure 9c indicates the PR research of the PIOA-ABGRU approach. The figure specified that the PIOA-ABGRU approach has acquired the largest PR achievement under overall classes. Finally, Figure 9d depicts the ROC study. The figure represented that the PIOA-ABGRU approach has exhibited capable outputs with the greatest ROC values below separate classes.

Table 5. Details on Airlines dataset

Class	No. of Samples
Negative	1000
Positive	1000
Total Samples	**2000**

In Table 6 and Figure 10, the SA outputs of the PIOA-ABGRU method are shown. The results exhibited that the PIOA-ABGRU method correctly predicted the negative and positive classes. On 70% of TRAPH, the PIOA-ABGRU model gains an average $accu_y$ of 96.78%, $prec_n$ of 96.79%, $reca_l$ of 96.78%, F_{score} of 96.79%, and MCC of 93.58%. Also, on 30% of TESPH, the PIOA-ABGRU model attains an average $accu_y$ of 96.51%, $prec_n$ of 96.50%, $reca_l$ of 96.51%, F_{score} of 96.50%, and MCC of 93.01%.

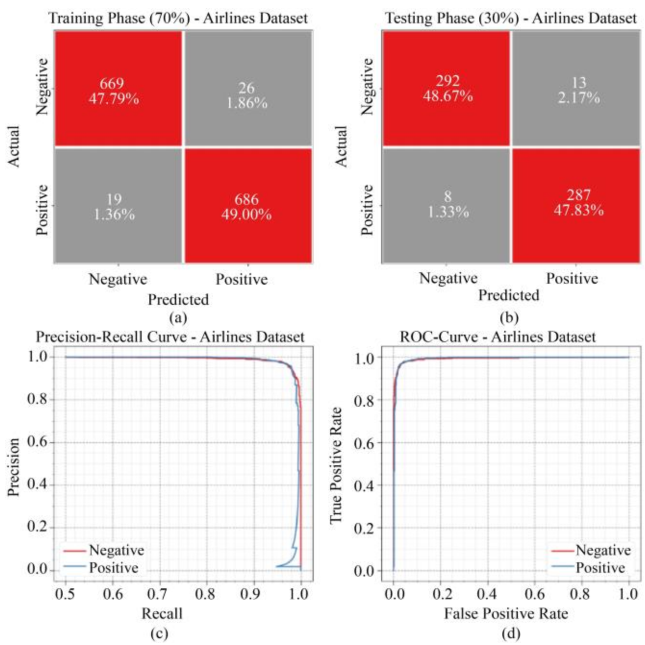

Fig. 9 (a-b) Confusion matrices and (c-d) PR and ROC curves under the airlines dataset

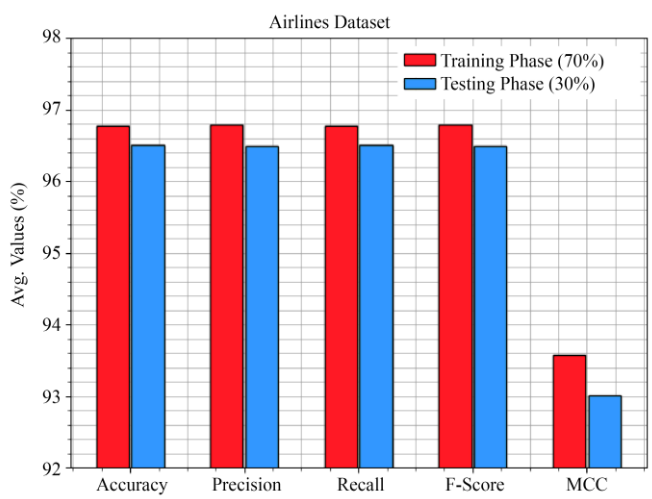

Fig. 10 Average of PIOA-ABGRU technique under airlines dataset

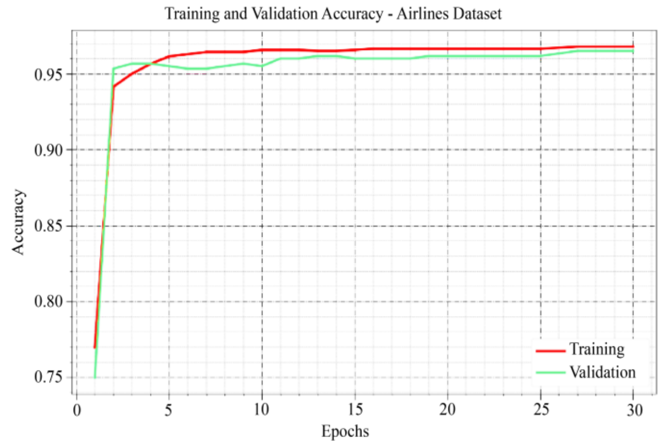

Fig. 11 $Accu_y$ the curve of the PIOA-ABGRU technique under the airline dataset

Table 6. SA outcome of PIOA-ABGRU technique under Airlines dataset

Classes	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	MCC
TRAPH (70%)					
Negative	96.26	97.24	96.26	96.75	93.58
Positive	97.30	96.35	97.30	96.82	93.58
Average	**96.78**	**96.79**	**96.78**	**96.79**	**93.58**
TESPH (30%)					
Negative	95.74	97.33	95.74	96.53	93.01
Positive	97.29	95.67	97.29	96.47	93.01
Average	**96.51**	**96.50**	**96.51**	**96.50**	**93.01**

The $accu_y$ curves for TRA and VL provided in Figure 11 for the PIOA-ABGRU method below the airline dataset deliver valued insights into its achievement under diverse epochs. Mainly, there is a consistent development in both TRA and TES $accu_y$ to rising epochs, demonstrating the capability of the model to attain and recognize patterns from both TRA and TES data. The upward trend in TES $accu_y$ underlines the flexibility of the model to the TRA dataset and its ability to produce precise estimates on unseen data, highlighting robust generalized capabilities. Figure 12 shows the loss values of the TRA and TES for the PIOA-ABGRU approach below the airline dataset under various epochs. The TRA loss reliably lessens as the technique improves its weights to lessen classifying errors on both datasets. The loss curves openly depict the location of the method by the TRA data, underlining its capacity to take patterns efficiently in both datasets. Notably, there is a non-stop modification of parameters in the PIOA-ABGRU method, projected to reduce variances among anticipations and actual TRA labels. Table 7 and Figure 13 highlight the relative outputs of the PIOA-ABGRU method on the airline dataset. The outputs determined that the PIOA-ABGRU method gains improved performance. Based on $accu_y$, the PIOA-ABGRU method acquires enhanced $accu_y$ of 96.78%, whereas the TFDNN, TFCNN, TFRNN, WVDNN, WVCNN, WVRNN, and ASA-SMHHODL techniques attain reduced $accu_y$ of 93.77%, 92.38%, 93.74%, 88%, 89.83%, 90.69%, and 95.50%, correspondingly. Meanwhile, based on $prec_n$, the PIOA-ABGRU method gains an enlarged $prec_n$ of 96.79%, where the TFDNN, TFCNN, TFRNN, WVDNN, WVCNN, WVRNN, and ASA-SMHHODL techniques get reduced $prec_n$ of 89.67%, 85.17%, 87.87%, 94.03%, 93.77%, 85.72%, and 95.19%, correspondingly.

Furthermore, based on F_{score}, the PIOA-ABGRU method gains enlarged F_{score} of 96.79%, while the TFDNN, TFCNN, TFRNN, WVDNN, WVCNN, WVRNN, and ASA-SMHHODL techniques get diminished F_{score} of 86.87%, 90%, 86.48%, 91.27%, 91.96%, 93.57%, and 94.33%, subsequently.

Table 7. Comparative outcome of PIOA-ABGRU technique with other methods under the Airlines dataset

Methods	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}
TFDNN	93.77	89.67	95.08	86.87
TFCNN	92.38	85.17	93.25	90.00
TFRNN	93.74	87.87	90.35	86.48
WVDNN	88.00	94.03	92.93	91.27
WVCNN	89.83	93.77	94.24	91.96
WVRNN	90.69	85.72	92.71	93.57
ASA-SMHHODL	95.50	95.19	95.36	94.33
PIOA-ABGRU	96.78	96.79	96.78	96.79

Table 8. CT outcome of PIOA-ABGRU technique with other methods under Airlines dataset

Methods	CT (sec)
TFDNN	6.19
TFCNN	5.39
TFRNN	3.83
WVDNN	3.67
WVCNN	6.53
WVRNN	4.39
ASA-SMHHODL	5.62
PIOA-ABGRU	2.01

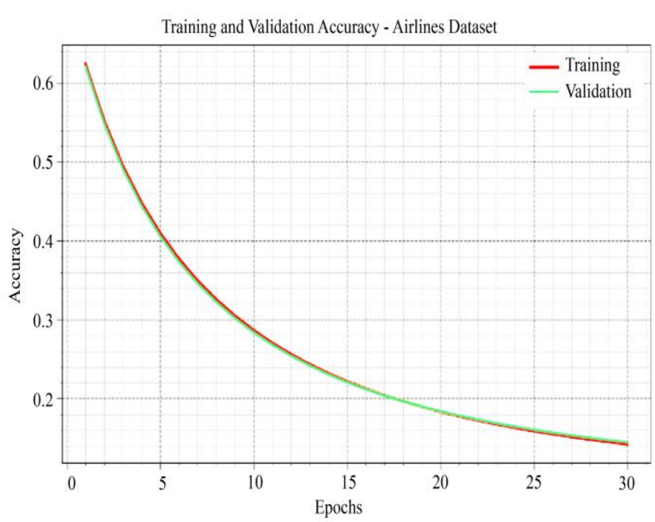

Fig. 12 Loss curve of PIOA-ABGRU technique under Airlines dataset

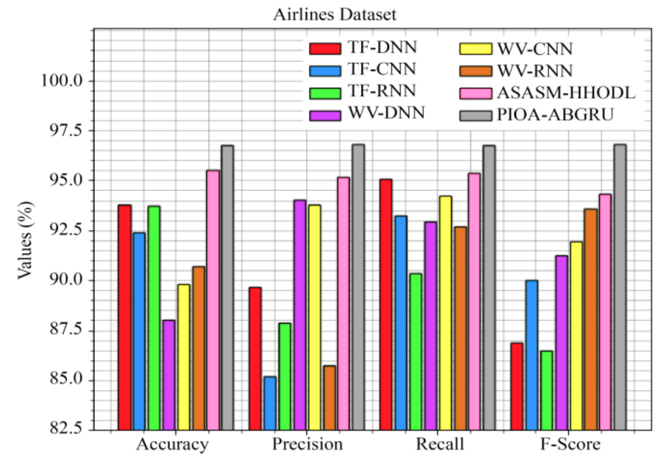

Fig. 13 Comparative outcome of PIOA-ABGRU technique under Airlines dataset

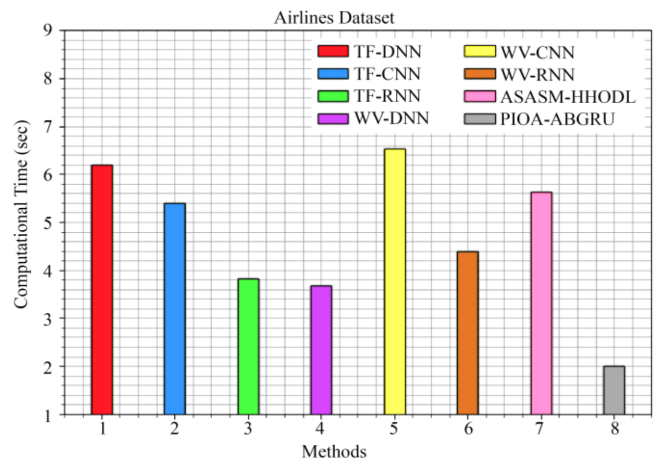

Fig. 14 CT outcome of PIOA-ABGRU model under Airlines dataset

Table 8 and Figure 14 highlight the CT outputs of the PIOA-ABGRU approach on the airline dataset. Based on CT, the PIOA-ABGRU method gains lesser CT of 2.01s, whereas the TF-DNN, TF-CNN, TF-RNN, WV-DNN, WV-CNN, WV-RNN, and ASASM-HHODL models get highest CT of 6.19s, 5.39s, 3.83s, 3.67s, 6.53s, 4.39s, and 5.62s, subsequently. The outputs showed that the PIOA-ABGRU method gains better performance. Thus, the PIOA-ABGRU method can be exploited to automate SA on social media.

5. Conclusion

In this article, an automated SA utilizing the PIOA-ABGRU technique for social networking is introduced. The presented PIOA-ABGRU technique mainly focused on the detection of multiple classes of sentiments that occur in social media. To accomplish this, the PIOA-ABGRU technique undergoes various sub-processes like data pre-processing, WE, classification, and parameter tuning. Initially, the PIOA-ABGRU technique takes place data pre-processing to adapt the input data into a beneficial layout. Besides, the WE procedure is performed using the BERT technique.

For sentiment detection, the PIOA-ABGRU technique applies the ABGRU model, which detects sentiments in distinct classes. Finally, the PIOA-based hyperparameter tuning procedure is executed to select ABGRU's hyperparameters.

The simulation outcomes of the PIOA-ABGRU model take place on a social media dataset. The experimental values specified that the PIOA-ABGRU model attains effectual achievement over other methods by means of distinct measures.

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