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RESEARCH ARTICLE

Applied Linguistics With Red-Tailed Hawk Optimizer-Based Ensemble Learning Strategy in Natural Language Processing

HALA J. ALSHAHRANI[1], ABDULKHALEQ Q. A. HASSAN[2], NABIL SHARAF ALMALKI[3], MRIM M. ALNFIAI[4], AHMED S. SALAMA[5], AND MANAR AHMED HAMZA[6]

[1]Department of Applied Linguistics, College of Languages, Princess Nourah bint Abdulrahman University, Riyadh 11671, Saudi Arabia
[2]Department of English and Applied Linguistics, College of Science and Arts at Mahayil, King Khalid University, Abha 62529, Saudi Arabia
[3]Department of Special Education, College of Education, King Saud University, Riyadh 12372, Saudi Arabia
[4]Department of Information Technology, College of Computers and Information Technology, Taif University, Taif 21944, Saudi Arabia
[5]Department of Electrical Engineering, Faculty of Engineering and Technology, Future University in Egypt, New Cairo 11845, Egypt
[6]Department of Computer and Self Development, Preparatory Year Deanship, Prince Sattam bin Abdulaziz University, Al-Kharj 16278, Saudi Arabia

Corresponding authors: Manar Ahmed Hamza (ma.hamza@psau.edu.sa) and Ahmed S. Salama (a.salama@fue.edu.eg)

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ABSTRACT Natural Language Processing (NLP) is the most vital technology in currently utilized, specifically caused by the huge and growing count of online texts that requires that understood for its massive value that completely asserted. NLP is create a sense of unstructured data, which are created by social networks and other social data sources, and is supported to organize them into an additional structured model that assists several kinds of tasks and applications. Sentiment analysis (SA), a subfield of NLP contains determining the sentiment expressed or emotional tone from a piece of text. Deep learning (DL) approaches are significantly advanced the field of SA, permitting for more accurate and nuanced classification of sentiments from the text data. In this article, we present an Advanced Sentiment Analysis using a Red-Tailed Hawk Optimizer with Ensemble Learning (ASA-RTHEL) Strategy in NLP. The aim of ASA-RTHEL technique is to exploit the strategies of ensemble learning with a hyperparameter tuning process for SA. The ASA-RTHEL technique mainly follows an ensemble learning-based classification process, which combines prediction from three DL approaches convolutional neural network (CNN), gated recurrent unit (GRU), and long short-term memory (LSTM). The ensemble process results in enhanced SA performance and decreases the risk of depending only on a single model bias or error. To boost the SA performance, the hyperparameter tuning strategy is performed by the use of the RTH algorithm. An extensive set of experiments were carried out for ensuring the superior SA results of ASA-RTHEL technique. The comprehensive comparison study highlighted the enhanced results of the MPONLP-TSA method on the recognition of various kinds of sentiments.

INDEX TERMS Sentiment analysis, natural language processing, red-tailed hawk optimizer, deep learning, ensemble learning.

I. INTRODUCTION

Social media has become more prominent for people to share instant stories, emotions, feelings, and opinions. Consider a foremost social media platform; Twitter is achieved huge popularity since its establishment [1]. The most recent statistical data exhibit to be more than 500 million tweets are transferred every day, creating a large quantity of social information that is employed by various higher-level analytical applications for making more benefits [2]. In the

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meantime, several analyses are implemented on Twitter information for creating natural language processing (NLP) applications namely, topic modelling, sentiment analysis (SA), relation extraction, named entity recognition (NER), and question and answer (Q&A) [3]. SA has been frequently called sentiment mining, which is a main element of NLP and aims to help users for detecting and analyzing the sentiments comprised in subjective texts. It is widely employed to analyse social media information in digital communities (Twitter comments, reviews, blogs, and so on), and detect the sentiment polarity of textual information.

Sentiment polarity of a given item specified feelings of a user connected with a part of words, for example, if the text characterizes the user's negative, positive, or neutral opinion towards the given item [4]. Users may make correct buying decisions by recognizing the sentiment orientation of a huge count of online product analyses. In the ML-based technique, the approach attempts to detect patterns from the provided information whereas in the lexicon-based, lists of negative and positive words are provided [5]. This word is calculated for every sentence. The sentiment is determined by the occurrence of negative and positive-oriented words. Hence, in this lexicon-based method, field dependency makes them lesser appropriate for the fields with no particular lexicons [6]. But, these approaches frequently have a lower accuracy rate owing to the absence of robust linguistic resources.

Recent developments in deep learning (DL) are used methods to overcome these difficulties, which is usually in other NLP tasks [7]. Convolutional neural networks (CNNs) are extensively utilized in various computer vision (CV) tasks and are efficiently utilized in NLP systems because of their capability for feature extraction and representation [8]. Recurrent neural networks (RNNs) and their common variants GRU and LSTM cannot only be appropriate for overall sequential modelling tasks but give the ability for capturing extended dependency data among words in a sentence [9]. Additionally, GRU and LSTM can well meet the gradient explosion and vanishing problems and enable a trained method to combine. Another development design is BERT which stacks layers of Transformer encoded with a multi-headed attention mechanism for improving a model's capability to obtain contextual data [10].

In this article, we present an Advanced Sentiment Analysis using a Red-Tailed Hawk Optimizer with Ensemble Learning (ASA-RTHEL) Strategy in NLP. The aim of ASA-RTHEL method is to exploit the strategies of ensemble learning with a hyperparameter tuning process for SA. The ASA-RTHEL technique mainly follows an ensemble learning-based classification process, which combines prediction from three DL approaches convolutional neural network (CNN), gated recurrent unit (GRU), and long short-term memory (LSTM). The ensemble process results in enhanced SA performance and decreases the risk of depending only on a single model bias or error. To boost the SA performance, the hyperparameter tuning strategy is implemented by the use of the RTH algorithm. An extensive set of experiments were carried out for ensuring the enhanced SA outcomes of the ASA-RTHEL approach. The main contribution of the study is summarized below.

- Design a new ASA-RTHEL technique comprising preprocessing, ensemble classification, and RTH based hyperparameter tuning was introduced. To the best of our knowledge, the ASA-RTHEL method never existed in the literature.
- Introduces an ensemble learning-based classification approach that combines predictions from three distinct DL models: CNN, GRU, and LSTM. This ensemble strategy leads to improved SA performance while reducing the risks associated with relying solely on a single model.
- Hyperparameter Tuning with RTH algorithm ensures that the SA model operates at its peak performance. This aspect enhances the adaptability and effectiveness of the ASA-RTHEL approach.

The rest of the paper is organized as follows. Section II gives the related works and section III provides the proposed model. Next, section IV offers the result analysis and section V concludes the paper.

II. RELATED WORKS

Sait and Ishak [11] present a DL with an NLP-enabled SA method for the classification of sarcasm. The preprocessing is implemented at first in various forms viz., multiple space removal, single character elimination, stopword removal, tokenization, and URL removal. Then, the conversion of the feature vector is carried out utilizing N-gram feature vectors. Lastly, MFO with a multi-head self-attention-based GRU mechanism was exploited. Bibi et al. [12] designed an unsupervised learning architecture that depends on Concept-based and hierarchical clustering for the SA method. Two dissimilar feature representation approaches such as Boolean and TF-IDF are considered. In [13], developed a computation model based on ML technique for the product reviews classification. The information was transmuted using the BoG method before designing a model with LR, SVM, NN, and NB procedures for ML-based techniques. The word embedding method is used to transmute information before employing the GRU and LSTM strategies for DL techniques.

Başarslan and Kayaalp [14] introduced a DL-based approach for SA on reviews of IMDB movies. This technique implements sentimental classification on vectorized reviews through two approaches of Word2Vec, such as Skip Gram and Continuous BoGs, in 3 dissimilar vector sizes (100, 200, 300), using 2 Convolution layers and 6 BiGRU. Mohbey [15] applied NLP and ML-based approaches to SA. DL techniques such as CNN and RNN. Particularly, LSTM with an attentive layer, pays great concentration to the sentiment impacts. The study applied the LSTM model for the prediction of user reviews. Kaur and Sharma [16] proposed a hybrid mechanism for the SA technique. For effectively extracting the features, a hybrid module encompassing aspect-related and review-related features are used to construct the distinct hybrid feature vectors analogous to all the reviews. Using the DL classifier LSTM, sentiment classification is implemented.

Khan et al. [17] exploit twofold processes: (1) develop benchmark data for resource-deprived Urdu language and (2) assess different ML and DL procedures for SA. Two techniques are compared: count-based, where the n-gram feature vector and the next signifies the text based on fastText pretrained word embedding for Urdu. In [18], user reviews are gathered from Facebook communities. Firstly, it implements SA and categorizes all the comments as positive, or negative. Then, comments are classified automatically based on the feedback with the help of the text classification technique.

Ahmad et al. [19] introduced a terrorism-related content analysis framework in order to categorize tweets as extremist and non-extremist classes. The study introduce a tweet classification technique using DL-based SA approaches for classifying the tweets into extremist or non-extremist based on user-generated social network post on Twitter. In [20], we show that the usage of Hybrid features attained by concatenating ML features (TF, TF-IDF) with Lexicon features (Positive-Negative word count, Connotation) provides best outcomes in terms of accuracy and complexity once tested against classifiers such as NB, SVM, Maximum Entropy and KNN. Li et al. [21] devises an emoji vectorization technique to accomplish emoji vectors. Then, an emoji-text integrated bidirectional LSTM (ET-BiLSTM) model for SA is presented. In this approach, review text-based sentence representation is extracted by the BiLSTM model. Emoji-based auxiliary representation is attained by the new attention mechanism.

III. THE PROPOSED MODEL

In this article, we have presented the ASA-RTHEL technique for sentiment classification. The drive of the ASA-RTHEL technique is to exploit the strategies of ensemble learning with a hyperparameter tuning process for SA. In the ASA-RTHEL technique, a four-stage process is involved as discussed in the following. Fig. 1 describes the entire procedure of the ASA-RTHEL algorithm.

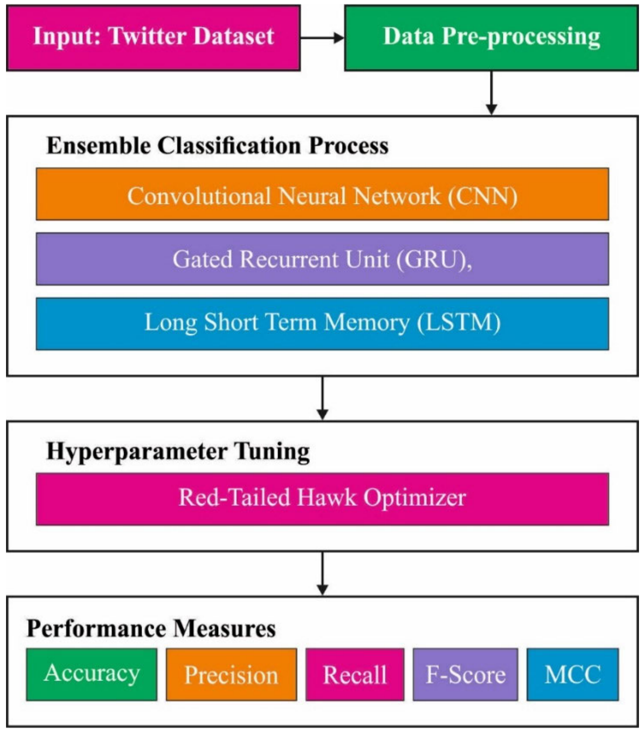

FIGURE 1. Overall procedure of ASA-RTHEL algorithm.

A. STAGE I: PRE-PROCESSING

Primarily, the proposed approach pre-processes tweets in different manners like numerals, stemming, stopwords, link punctuations, and removing usernames.

- Eliminating links and usernames on Twitter that do not affect SA.
- Elimination of punctuation marks like conversion to lowercase and hashtags
- Elimination of stopwords and numerals

Moreover, the stemming was performed to decrease the term to the root method. Besides, the process of minimizing the term supports decreasing the difficulty of text features. Afterwards, the TextBlob approach can be employed to define the sentimental scores. Next, the BERT algorithm has been carried out to generate a group of feature vectors.

B. STAGE II: BERT MODEL

The BERT approach has been deployed for valuable extraction features on the pre-processing data [22]. BERT is a ground-breaking NLP method that is transformed the domain of ML and language understanding. Established by Google AI in 2018, BERT deploys a transformer structure and employs bi-directional context to extremely understand the nuances of language. Different previous approaches that processed text in a unidirectional approach, BERT proceeds into account the neighbouring words on both sides of the target text, allowing it to capture intricate contextual connections and generate extremely accurate performances in tasks namely question answering text classification, and NER. By being pre-trained on huge corpora of text data and subsequently fine-tuned on particular tasks, BERT has set novel benchmarks in many language-related benchmarks and taken assistance as the foundation for following developments in natural language understanding and generation methods.

C. SENTIMENT CLASSIFICATION USING ENSEMBLE PROCESS

The ASA-RTHEL technique mainly follows an ensemble learning-based classification process, which combines prediction from three DL approaches namely CNN, GRU, and LSTM. The convolutional ANN is the most significant design of DL which is a multiple-layered FFNN method [23].

CNN contains 3 layers namely fully connected (FC), convolution, and pooling layers. In different standard ANN, a convolutional layer automatically carries out extraction features and a pooling layer has been employed to feature reduction. In CNN, visual representation proceeds the word as input and signifies the connection among the layers of the CNN technique for determining the text classes. During the convolutional layer, the extracted feature in the image/text with the support of distinct filters. The intermediate procedure was executed among pooling and convolution layers towards the features that are nonlinear with the support of the ReLU function. The sizes of these mapping features are diminished during the pooling layer, which decreases the calculation workforce from the next layers and reveals the features from the text/image more efficiently. The last layer of CNN is in the procedure of typical FC-ANN. During this layer, an FC infrastructure among the artificial neurons signifies the features of image or text and target classes. A novel text assists as an input to CNN. If the trained method has been accomplished, CNN provides the forecast class probability.

The GRU is an extensively utilized RNN network structure. In RNN networks, the GRU has been established for the vanishing gradient problem, related to the LSTM structure. GRU design is easier than LSTM structure. However, the LSTM design contains forget, input, and output gates, GRU structure takes to update and reset gates. While GRU computation is easier than LSTM computation, it acts faster computations along with low memory.

The RNN is a special type of NNs in which the outcomes of feedforward typical ANN are offered as new input to neurons depending on input values. The resulting value at some neurons $(t+1)$ is based on its input at t time. As there is a link between 2 input values, this approach is well-defined as a memory network model. LSTM is the famous RNN model, but the design was established to vanish the gradient problem. Now, w_t signifies the input value at time t, and i_t denotes the resultant value at time t.

Fig. 2 depicts the infrastructure of LSTM. The design of the LSTM model comprises 3 important gates such as forget gate f_t, input gate i_t, and output gate o_t. Although the input and output gates denote the data leaving and data entering the node at time t, correspondingly. The forget gate adopts the data being forgotten connected to the earlier status data (h_{t-1}) and existing input (x_t). These 3 gates select for upgrading the existing memory cell c_t and the existing latency h_t values. At the LSTM, the connections among the gates can be mathematically computed by the subsequent formulas:

$$\text{D. } i_t = \sigma\left(w_i.\left[h_{t-1}, x_t\right] + b_i\right) \tag{1}$$

$$\text{E. } f_t = \sigma\left(w_f.\left[h_{t-1}, x_t\right] + b_f\right) \tag{2}$$

$$\text{F. } o_t = \sigma\left(w_o.\left[h_{t-1}, x_t\right] + b_o\right) \tag{3}$$

$$\text{G. } c_t' = tanh\left(w_c.\left[h_{t-1}, x_t\right] + b_c\right) \tag{4}$$

$$\text{H. } c_t = f_t * c_{t-1} + i_t * c_t' \tag{5}$$

$$\text{I. } h_t = o_t * tanh\,(C) \tag{6}$$

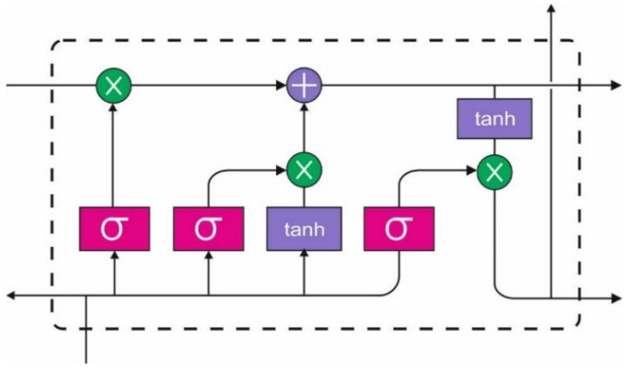

FIGURE 2. LSTM architecture.

D. DESIGN OF RTH OPTIMIZER FOR PARAMETER TUNING

Finally, the RTH optimizer selects the hyperparameter related to the DL models. The RTH technique stimulates the hunting behaviour of red-tailed hawks [24]. The activities taken during hunting are presented and modelled. This RTH algorithm consists of three phases, stooping and swooping, high soaring, and low soaring.

High soaring: the RTH will soar far into the sky, searching for a better position regarding food accessibility and it is mathematically modelled in Eq. (7):

$$X\,(t) = X_{best} + \left(X_{mean} - X\,(t-1)\right) \cdot Levy\,(\text{dim}) \cdot TF\,(t) \tag{7}$$

Let X(t) be the RTH location at t iteration , X_{best} indicates the better location attained so far, X_{mean} denotes the position mean, $TF(t)$ indicates the transition factor function evaluated by Eq. (9), and $Levy$ signifies the LF distribution function evaluated by using Eq. (8).

$$\begin{aligned} Levy(\text{dim}) &= s\frac{\mu \cdot \sigma}{|v|^{\beta-1}} \\ \sigma &= \left(\frac{\Gamma\,(1+\beta)\cdot \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(1+\frac{\beta}{2}\right)\beta \cdot 2\left(1-\frac{\beta}{2}\right)}\right) \end{aligned} \tag{8}$$

where s refers to the constant (0.01), dim indicates the dimensionality of the problem, β represents the constant (1.5), and u and v are randomly generated values within [0, 1].

$$TF\,(t) = 1 + \sin\left(2.5 + \frac{t}{T_{\max}}\right) \tag{9}$$

In Eq. (9), $T_{\max}$ implies the maximal iteration counter.

Low soaring: the hawk encircles the target by flying lower toward the ground in spiral line and the mathematical expression of low soaring is given as follows:

$$\begin{aligned} X\,(t) &= X_{best} + \left(x\,(t) + y\,(t)\right).StepSize\,(t) \\ StepSize(t) &= X(t) - X_{mean} \end{aligned} \tag{10}$$

In Eq. (10), x and y indicate direction coordinates that are evaluated according to Eq. (11), as shown at the bottom of the next page, where A means the angel gain [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], r is a control gain [1, 2], R_0

shows the primary value within [0.5−3], and *rand* denotes the randomly generated number [0, 1]. This parameter helps the hawk to fly around the target with spiral movement as follows:

Stooping and Swooping: the hawks suddenly stoop and attack the target from the better location attained at the low soaring phase:

$$X(t) = \alpha(t) \cdot X_{best} + x(t).StepSize1(t) + y(t).StepSize2(t) \quad (12)$$

$$StepSize1(t) = X(t) - TF(t) \cdot X_{mean} \quad (13)$$

$$StepSize2(t) = G(t) \cdot X(t) - TF(t) \cdot X_{best}$$

$$\alpha(t) = \sin^2\left(2.5 - \frac{t}{T_{\max}}\right)$$

$$G(t) = 2 \cdot \left(1 - \frac{t}{T_{\max}}\right) \quad (14)$$

where G denotes the gravity factors that decrease the exploitation diversity once the hawk is nearby the target, α signifies the hawk's acceleration that enhances t to improve the convergence rate.

The RTH approach grows a FF for accomplishing better classifier outcomes. It elucidates a positive integer to describe the best solution of candidate performances. In this case, the reduced classifier errors can be considered FF, as written in Eq. (15).

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{No.\ of\ misclassified\ instances}{Total\ no.\ of\ instances} * 100 \quad (15)$$

IV. PERFORMANCE VALIDATION

The sentiment classification results of the ASA-RTHEL technique can be analyzed using two datasets [25], [26]. The Twitter US Airlines dataset includes 14640 samples and the IMDB dataset includes 50000 samples.

Fig. 3 depicts the classifier outcomes of the ASA-RTHEL algorithm on the Twitter US Airlines database. Figs. 3a-3b defines the confusion matrix accomplished by the ASA-RTHEL algorithm on 70:30 of the TR set/TS set. The simulation value demonstrated that the ASA-RTHEL approach has detected and classified all 3 classes accurately. Afterwards, Fig. 3c portrays the PR investigation of the ASA-RTHEL methodology. The simulation value depicted that the ASA-RTHEL technique has achieved greater values of PR on 3 class labels. However, Fig. 3d demonstrates the ROC outcome of the ASA-RTHEL approach. The outcome outperformed the ASA-RTHEL method leading to proficient outcomes with better performances of ROC on 3 classes.

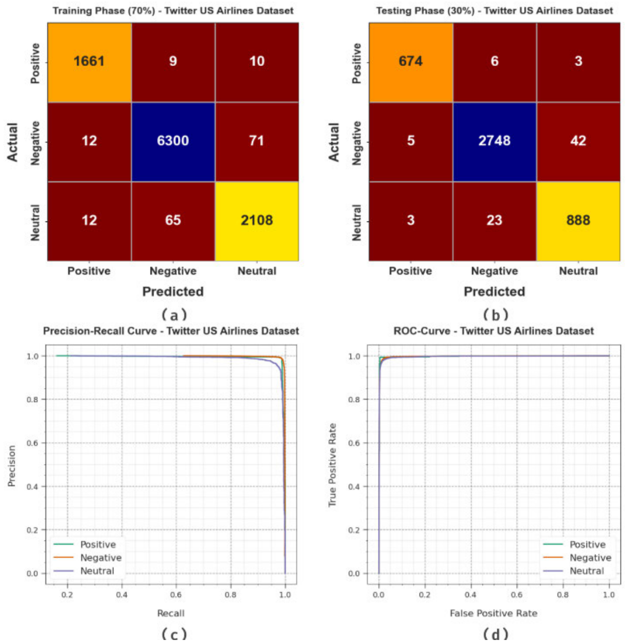

FIGURE 3. Twitter US Airlines database (a-b) Confusion matrices, (c) PR_curve, and (d) ROC.

TABLE 1. Sentiment recognition outcome of ASA-RTHEL system on Twitter US Airlines database.

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	MCC
		TR set (70%)			
Positive	99.58	98.58	98.87	98.72	98.47
Negative	98.47	98.84	98.70	98.77	96.74
Neutral	98.46	96.30	96.48	96.39	95.41
Average	98.84	97.90	98.01	97.96	96.87
		TS set (30%)			
Positive	99.61	98.83	98.68	98.75	98.53
Negative	98.27	98.96	98.32	98.64	96.27
Neutral	98.38	95.18	97.16	96.16	95.14
Average	98.76	97.65	98.05	97.85	96.65

In Table 1 and Fig. 4, the sentiment recognition results of the ASA-RTHEL technique on the Twitter US Airlines database are provided. The results ensure that the ASA-RTHEL technique recognizes three kinds of sentiments. On 70% of the TR set, the ASA-RTHEL technique accomplishes average $accu_y$, $prec_n$, $recal_l$, F_{score}, and MCC of 98.84%, 97.90%, 98.01%, 97.96%, and 96.87% correspondingly. Meanwhile, on 30% of TS set, the ASA-RTHEL approach achieves average $accu_y$, $prec_n$, $recal_l$, F_{score}, and MCC of 98.76%, 97.65%, 98.05%, 97.85%, and 96.65% correspondingly.

$$\begin{cases} x(t) = R(t) \cdot \sin(\theta(t)) \\ y(t) = R(t) \cdot \cos(\theta(t)) \end{cases} \quad \begin{cases} R(t) = R_0 \cdot \left(1 - \frac{t}{T_{\max}}\right) \cdot rand \\ \theta(t) = A \cdot \left(1 - \frac{t}{T_{\max}}\right) \cdot rand \end{cases} \quad \begin{cases} x(t) = x(t) / \max|x(t)| \\ y(t) = y(t)/\max|y(t)| \end{cases} \quad (11)$$

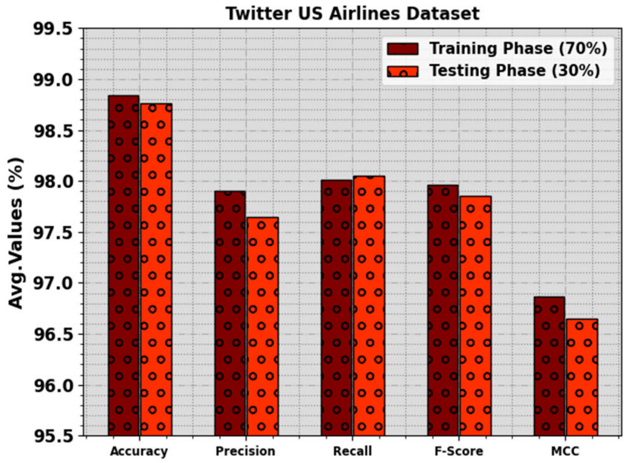

FIGURE 4. Average of ASA-RTHEL system on Twitter US Airlines database.

Fig. 5 demonstrates the TR_accu_y and VL_accu_y of the ASA-RTHEL technique on the Twitter US Airlines database. The TL_accu_y is described by the assessment of ASA-RTHEL system on the TR database whereas the VL_accu_y is calculated by assessing the performance on testing data. The outcomes shows that TR_accu_y and VL_accu_y upsurge with increased epochs. Consequently, the performance of ASA-RTHEL method gets increase on the TR and TS dataset with increasing number of epochs.

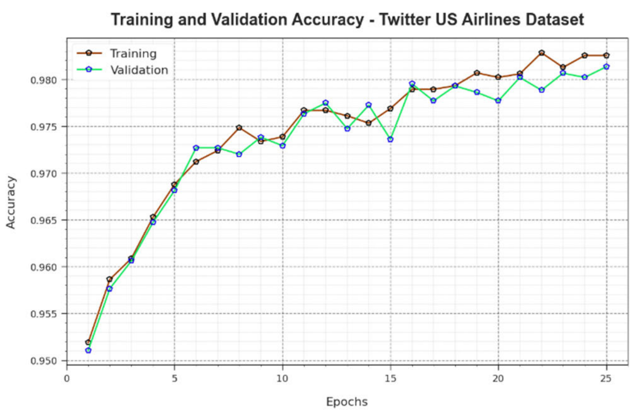

FIGURE 5. $Accu_y$ curve of ASA-RTHEL system on Twitter US Airlines database.

In Fig. 6, the TR_loss and VR_loss outcomes of the ASA-RTHEL technique on the Twitter US Airlines database are revealed. The TR_loss shows the error amongst the predictive outcome and original values on the TR dataset. The VR_loss exemplify the performance measure of the ASA-RTHEL technique on validation dataset. The outcomes designate that the TR_loss and VR_loss tend to reduce with increased epochs. It portrayed the superior outcomes of the ASA-RTHEL method and its ability to produce accurate classification. The minimized value of TR_loss and VR_loss establishes the improved outcome of the ASA-RTHEL technique on capturing patterns and relationships.

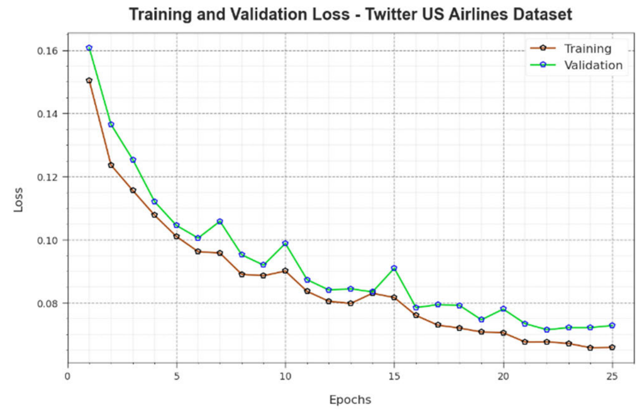

FIGURE 6. Loss curve of ASA-RTHEL system on Twitter US Airlines database.

TABLE 2. $Accu_y$ outcome of ASA-RTHEL system with other approaches on Twitter US Airlines database [7], [27], [28].

Twitter US Airlines Database	
Methods	**Accuracy (%)**
ASA-RTHEL	98.84
DMODL-TSC	98.15
ULMFit-SVM	98.06
ABCDM	92.98
CNN Model	79.80
Multinomial-NB	81.41
SVM Model	78.16
LSTM Model	77.98

In Table 2 and Fig. 7, the classifier outcomes of the ASA-RTHEL technique with other models [7], [27], [28] such as universal language model fine-tuning (ULMFiT), Dwarf Mongoose Optimization with DL Based Twitter Sentiment Classification (DMODL-TSC), ABCDM, CNN, Multinomial-NB, SVM, and LSTM models on the Twitter US Airlines database are given. The experimental results show that the ASA-RTHEL technique reaches an increasing $accu_y$ of 98.84%. On the other hand, the DMODL-TSC, ULMFit-SVM, ABCDM, CNN, Multinomial-NB, SVM, and LSTM models accomplish decreased performance with $accu_y$ values of 98.15%, 98.06%, 92.98%, 79.80%, 81.41%, 78.16%, and 77.98% respectively.

Fig. 8 defines the classifier outcomes of the ASA-RTHEL technique on the IMDB database. Figs. 8a-8b exhibits the confusion matrix gained by the ASA-RTHEL algorithm on 70:30 of the TR set/TS set. The simulation value exhibited that the ASA-RTHEL algorithm has classified and recognized all 2 classes correctly. Afterwards, Fig. 8c reveals the PR investigation of the ASA-RTHEL methodology. The outcome defined that the ASA-RTHEL technique has accomplished greater values PR on 2 classes. But, Fig. 8d portrays the ROC outcome of the ASA-RTHEL methodology. The outcome exhibited that the ASA-RTHEL system led to

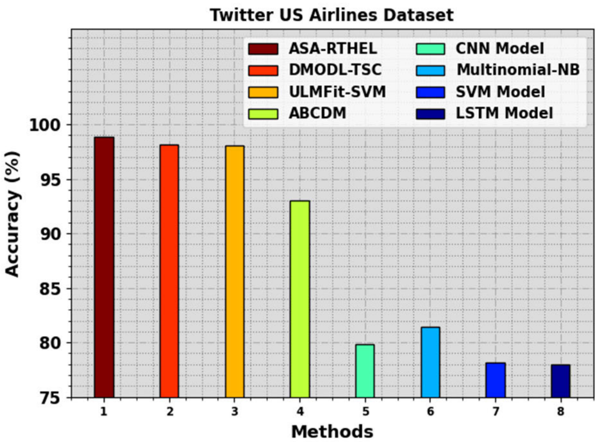

FIGURE 7. $Accu_y$ **outcome of ASA-RTHEL system on Twitter US Airlines database.**

accomplished outcomes with greater values of ROC on 2 class labels.

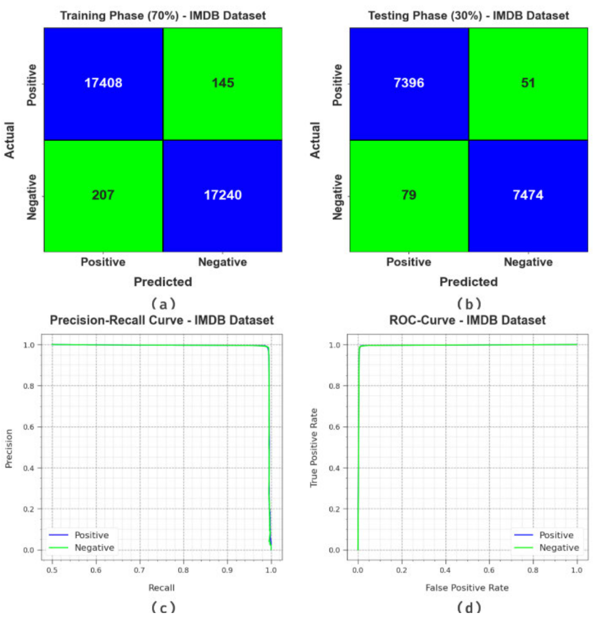

FIGURE 8. **IMDB database (a-b) Confusion matrices, (c) PR_curve, and (d) ROC.**

In Table 3 and Fig. 9, the sentiment recognition outcome of the ASA-RTHEL methodology on the IMDB database is provided. The outcomes ensure that the ASA-RTHEL system recognizes three kinds of sentiments. On 70% of the TR set, the ASA-RTHEL approach realizes average $accu_y$, $prec_n$, $reca_l$, F_{score}, and MCC of 98.99%, 99%, 98.99%, 98.99%, and 97.99% correspondingly. In the meantime, on 30% of the TS set, the ASA-RTHEL methodology achieves average $accu_y$, $prec_n$, $reca_l$, F_{score}, and MCC of 99.13%, 99.13%, 99.13%, 99.13%, and 98.27% correspondingly.

Fig. 10 exhibits the TR_accu_y and VL_accu_y of the ASA-RTHEL algorithm on the IMDB database. The TL_accu_y is described by the assessment of the ASA-RTHEL method on the TR database while the VL_accu_y is calculated by estimating the performance on separate testing dataset. The outcomes reveal that TR_accu_y and VL_accu_y increase with an upsurge in epochs. Consequently, the outcome of the ASA-RTHEL technique gets increased on the TR and TS datasets with increasing number of epochs.

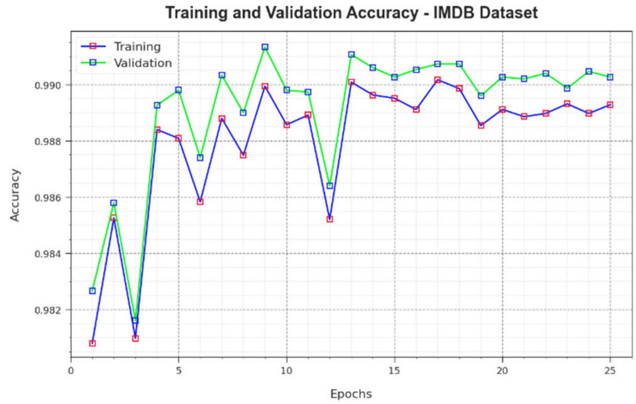

FIGURE 9. **Av** $Accu_y$ **curve of ASA-RTHEL system on IMDB database.**

TABLE 3. **Sentiment recognition outcome of ASA-RTHEL system on IMDB database.**

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	MCC
		TR set (70%)			
Positive	99.17	98.82	99.17	99.00	97.99
Negative	98.81	99.17	98.81	98.99	97.99
Average	98.99	99.00	98.99	98.99	97.99
		TS set (30%)			
Positive	99.32	98.94	99.32	99.13	98.27
Negative	98.95	99.32	98.95	99.14	98.27
Average	99.13	99.13	99.13	99.13	98.27

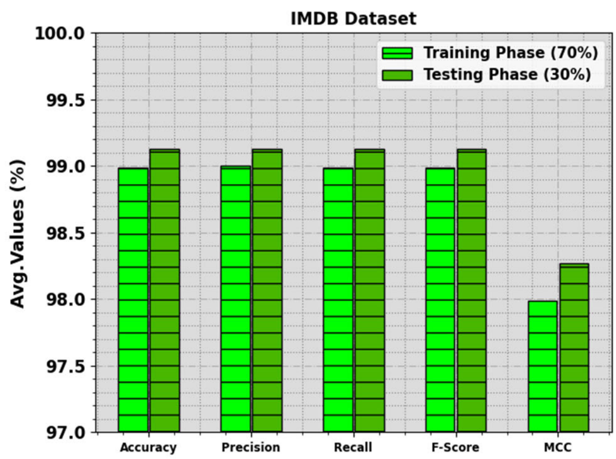

FIGURE 10. **Average of ASA-RTHEL system on IMDB database.**

In Fig. 11, the TR_loss and VR_loss curve of ASA-RTHEL methodology on the IMDB database is shown. The TR_loss defines the error amongst the predictive outcome and original values on the TR data. The VR_loss signify the performance

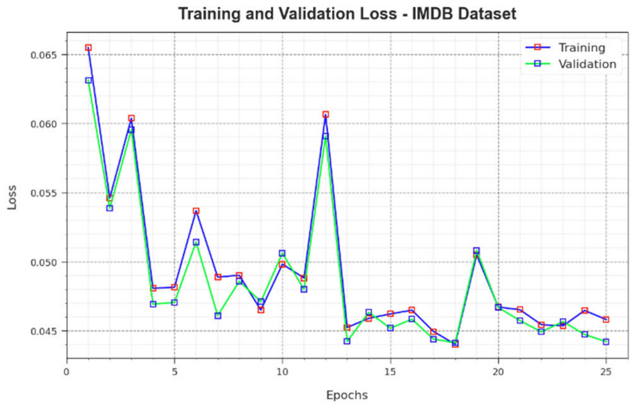

FIGURE 11. Loss curve of ASA-RTHEL system on IMDB database.

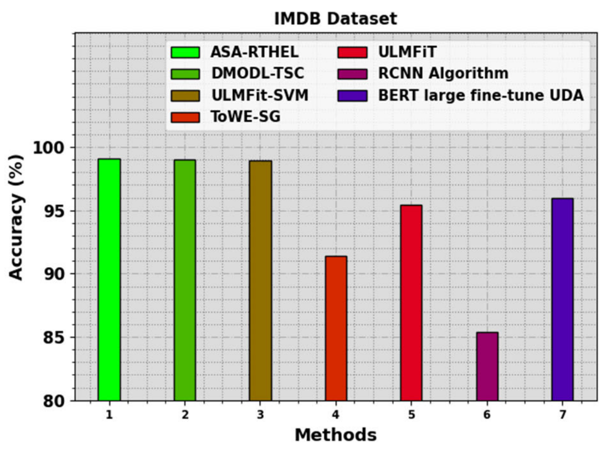

FIGURE 12. $Accu_y$ outcome of ASA-RTHEL system on IMDB database.

measure of the ASA-RTHEL technique on validation data. The outcomes point out that the *TR_loss* and *VR_loss* tend to decline with increased epochs. It portrayed the superior performance of the ASA-RTHEL method and its capability to make accurate classifications. The minimal value of *TR_loss* and *VR_loss* demonstrates the greater outcome of the ASA-RTHEL method on capturing patterns and relationships.

In Fig. 12, the classifier outcome of the ASA-RTHEL method with other approaches on the IMDB database is given. The simulation values depicted that the ASA-RTHEL method attains a higher $accu_y$ of 99.13%. On the other hand, the DMODL-TSC, ULMFit-SVM, ToWE-SG, ULMFiT, RCNN, and BERT large fine-tune UDA approaches realize decreased outcome with $accu_y$ values of 99.01%, 98.92%, 91.40%, 95.41%, 85.40%, and 95.98% correspondingly.

Lastly, the computation time (CT) results of the proposed model is compared with existing models in Table 4. The experimental values indicate that the proposed model offers reduced CT values of 1.73s and 0.82s under Twitter US Airless and IMDB datasets, respectively. These results confirmed the enhanced performance of the ASA-RTHEL method in the sentiment classification process.

TABLE 4. Comparative computation time results ASA-RTHEL model on two datasets.

Computational Time (sec)		
Methods	**Twitter US Airlines Database**	**IMDB Dataset**
ASA-RTHEL	1.73	0.82
DMODL-TSC	2.02	1.32
ULMFit-SVM	3.70	1.75
ABCDM	4.98	-
CNN Model	4.87	-
Multinomial-NB	4.30	-
SVM Model	3.77	-
LSTM Model	3.87	-
ULMFIT	-	1.72
RCNN-Algorithm	-	1.72
BERT large fine-tune UDA	-	1.53

V. CONCLUSION

In this article, we have presented the ASA-RTHEL technique for sentiment classification. The drive of the ASA-RTHEL method is to exploit the strategies of ensemble learning with a hyperparameter tuning process for SA. In the ASA-RTHEL technique, four-stage processes such as pre-processing, BERT, ensemble classification, and RTH-based parameter selection. In this work, the ensemble learning-based classification process combines prediction from three DL approaches namely CNN, GRU, and LSTM. The ensemble process results in enhanced SA performance and decreases the risk of depending only on a single model bias or error. To boost the SA performance, the hyperparameter tuning strategy is performed by the use of the RTH algorithm. An extensive set of experiments were carried out for ensuring the enhanced SA results of the ASA-RTHEL method. The comprehensive comparison study highlighted the enhanced results of the MPONLP-TSA method on the recognition of various kinds of sentiments. In the future, the ASA-RTHEL method can be extended to accommodate multilingual SA, enabling it to deal with sentiment classification in diverse languages and cultural contexts. Furthermore, exploring real-time sentiment analysis capabilities and adaptation to evolving social media trends will be valuable, ensuring the method remains relevant in the rapidly changing landscape of online communication. Furthermore, investigating the incorporation of user-specific sentiment analysis to provide personalized sentiment insights could open avenues for user experience enhancements and personalized content recommendation.

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