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Original Article

Aquila Optimization Algorithm with Advanced Learning Model-Based Sentiment Analysis on Social Media Environment

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Abstract *- Sentiment Analysis (SA) on social media is a text mining method that includes employing Natural Language Processing (NLP), and Machine Learning (ML) approaches to categorize and assess the opinions, attitudes, and emotional tone expressed in user-generated content on platforms including Instagram, Twitter, and Facebook. This analysis provides meaningful information for researchers, marketers, and businesses to track trends, gauge public sentiment, and make data-driven decisions by automatically classifying text as positive, negative, or neutral, which helps them understand brand perception, customer satisfaction, and emerging problems in the dynamic world of online communication. Deep Learning (DL) based SA on social networking media is a robust NLP tool that leverages neural networks, including Recurrent Neural Network (RNN) or transformer models such as GPT and BERT, to automatically define the sentiment expressed in user-generated content on platforms like Facebook, Twitter, and Instagram. This manuscript offers an Aquila Optimization Algorithm with Deep Learning based Sentiment Analysis and Classification (AOADL-SAC) technique on social networking. The AOADL-SAC technique aims to recognize and classify the sentiments on social media. In the presented AOADL-SAC technique, pre-processing was implemented to convert the data provided as input into a compatible format. In addition, the AOADL-SAC technique implements a Long Short-Term Memory (LSTM) approach for recognizing and classifying sentiments. At last, the AOA-based tuning procedure was performed to adjust the hyperparameters of the LSTM approach. The investigational output of the AOADL-SAC technique is examined on a standard dataset. The comprehensive outputs highlighted the AOADL-SAC method and stated the AOADL-SAC technique accomplishes better outcomes than recent techniques concerning distinct aspects.*

Keywords *- Social media, Sentiment Analysis, Deep Learning, Aquila Optimization Algorithm, Natural Language Processing.*

1. Introduction

Social networking assessment recognises and gathers relations and data flow among groups, people, computers, organizations and other related data entities [1]. Generally, network nodes are groups and people, whereas links display relations between particular nodes. It implements analysis, such as the visual and mathematical study of human relations [2]. Most of the researchers process the movement of the network for nodes, which involves the theory of degrees, the total number of associates a node has straight [3].

A vast range of social information covers blogs, tweets, and reviews from numerous fields, which fake many tests and chances for NLP researchers to determine adequate details [4]. However, such data permits everyone to understand the aspects of a particular topic and shows information that can be abused to execute forecasts in the stock market sector, product sales, political elections, and much more [5]. SA is measured as a vital job from a business viewpoint to make decisions on time based on a review of people. Moreover, it is a great exclusive research domain.

SA is the research of people's sentiments about products, services, commands, organizations, and much more [6]. Numerous domains like retail, business sectors, gaming, marketing industries, and healthcare societies have initiated implementing SA systems to monitor their social image [7]. Therefore, it is highly predicted that SA and emotion recognition will reach $3.8 Billion by 2025. Recently, SA's concentration moved to examining emotions expressed in social media estimates. SA usage has extended through various scopes, such as politics, harassment, sports, entertainment, and medicine [8]. SA contains enhanced NLP techniques like data mining for predictive study and an appropriate understanding of texts that present research problems. ML methodologies: Support Vector Machine, logistic regression, and Naive Bayes have been utilized for solving numerous NLP tasks for several years.

In multiple NLP-based applications, Neural Network (NN) approaches produced on compressed vector symbols have established advanced performances. DL NN primarily revealed notable performance in computer vision and pattern detection assignments. Numerous DL techniques have been utilized to handle difficult NLP issues like SA as an outcome of this development.

This manuscript offers an Aquila Optimization Algorithm with DL-based Sentiment Analysis and Classification (AOADL-SAC) technique on social networking. The AOADL-SAC technique aims to recognize and classify the sentiments on social media. In the presented AOADL-SAC technique, pre-processing was implemented to convert the data provided as input into a compatible format. In addition, the AOADL-SAC technique implements a Long Short-Term Memory (LSTM) approach for recognition and classification. At last, the AOA-based tuning procedure was performed to adjust the hyperparameters of the LSTM approach. The investigational output of the AOADL-SAC technique is examined on a standard dataset.

2. Literature Review

Ali et al. [9] developed new DL and graph-based methods for recognizing hate content, accompanied by techniques to identify societies and examine social network media to recognise hate content. Twitter has been employed as an experiment, and linguistic specialists remove and note tweets to develop a database for validation and experimentation. This introduced modified LSTM-GRU algorithm has been exploited for classification. The Girvan–Newman technique was implemented for Twitter community identification.

In [10], a method has been developed employing openly accessible Reddit databases and word-embedding systems, like hybrid DL and ML approaches for classification and Word2Vec and TF-IDF for textual depiction. A CNN and Bidirectional-LSTM (CNN–BiLSTM) algorithm and the ML XGBoost technique could be employed for classifying through textual and LIWC-22-based features by performing two experiments. The authors [11] projected a Spider Monkey Crow optimizer Algorithm (SMCA) technique to train the Deep RNN (DRNN). In this approach, the telecom evaluation was utilized.

Additionally, the feature extraction has been executed utilizing SentiWordNet. These removed SentiWordNet features and other features could be applied for the DeepRNN to classify sentiments. The fuzzy KNN was implemented to retrieve the assessment depending on a distance measurement.

Li et al. [12] projected an emoji vectorisation algorithm. Subsequently, an Emoji-Text combined Bidirectional LSTM (ET-BiLSTM) architecture was developed. An innovative attention process obtained auxiliary representations based on emoji. The two representations can be further incorporated into the final review representation vectors. Lastly, outcomes exhibit that this developed method enhances the effectiveness of the classification of sentiments determined by macro-R, F1, and P scores in social network media.

Swathi, Kasiviswanath and Rao [13] introduce a novel Teaching and Learning-Based Optimizer (TLBO) with LSTM architecture. The LSTM method was implemented for classification. The Adam optimization could be employed to evaluate the learning rate. Moreover, the TLBO algorithm was implemented to tune the LSTM technique’s output module optimally.

Priyadarshini and Cotton [14] designed a new LSTM–CNNs–grid search-assisted Deep Neural Network (DNN) architecture for SA. This analysis deliberates baseline methods such as K-NN, CNNs, CNN–LSTM, LSTM–CNN, NN, and LSTM that were estimated employing precision, accuracy, sensitivity, specificity, and F1-score with numerous databases. In [15], an innovative DL-based Multimodal SA (MSA) algorithm was introduced. This architecture utilizes the Variant and Channel Augmented Maximally Stable Extremal Region (VCA-MSER) approach. A DCNN architecture with Parallel-Dilated Convolution and Self-Attention Module (PDC-SAM) was designed. Lastly, the decision module utilizes a Boolean method.

Elaziz et al. [16] introduced an FS methodology for modifying the Dwarf Mongoose Optimization (DMO) model achievement by employing Quantum-Based Optimization (QBO). The ultimate objective is to exploit QBO as local searching of the conventional DMO to avoid the searching restrictions. In [17], the authors suggest a multi-tagging sentiment and related action analyzer integrated with a deep human counting tracking system, a systematic method for various object tracking, and count in obstructed conditions with mitigated identification switch numbers in disaster-associated images and videos.

3. The Proposed Method

In this manuscript, an AOADL-SAC technique on social media is presented. The AOADL-SAC method intends to recognize and classify the sentiments on social media. The proposed AOADL-SAC technique involves data pre-processing, LSTM, and AOA-based classification and tuning processes. Figure 1 exemplifies the complete flow of the AOADL-SAC model.

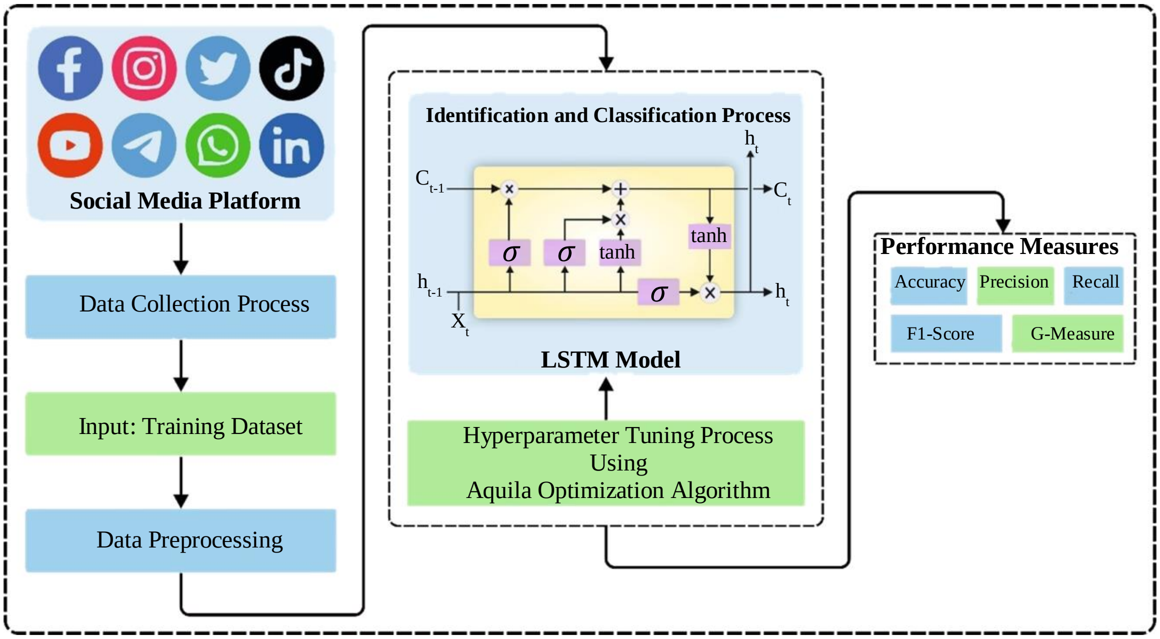

Fig. 1 Overall architecture of AOADL-SAC method

3.1. Data Pre-Processing

Initially, data pre-processing is implemented to convert the input information into a compatible format. The pre-processing step for SA in social network media is indispensable for structuring and cleaning the unstructured and noisy textual data from platforms such as Instagram, Twitter, and Facebook. The critical steps of pre-processing are given below:

3.1.1. Text Cleaning

This initial step includes distracting or removing irrelevant components, like hashtags, special characters, punctuation, and mentions. Furthermore, emojis, URLs, and emoticons must be removed or replaced by the text representation, as they don't directly contribute to SA. Handling character encoding-related issues and correcting spelling errors ensures accurate and consistent text data.

3.1.2. Tokenization and Lowercasing

After cleaning, the texts are tokenized into tokens or individual words and can be easily analyzed. Usually, all text is transformed into lowercase to improve the accuracy and ensure case consistency of sentiment classification. Also, lowercase aids in grouping words with similar meanings.

3.1.3. Stop Word Removal and Normalization

Common stop words, including "and," "the," and "in," are usually removed to diminish noise and dimensionality. Stemming or lemmatization is used for reducing words to their root form, which groups relevant words. This aids in capturing the core of sentimental expressions while decreasing vocabulary size.

3.1.4. Negation Handling

Particular emphasis should be placed on negations like "not" to understand sentiment nuance. They may change the meaning of an entire sentence, so marking negation or appropriately handling them can be significant for correct SA.

3.1.5. Text Length Limiting

You may limit the text length based on specific analyses, mainly if you are working with a model with input size constraints.

By executing the pre-processing step, you can create standardized, clean text data for SA, enhancing the efficiency of the sentiment classification model and improving the quality of insights derived from social network media.

3.2. LSTM-Based Classification

At this phase, the AOADL-SAC technique employs the LSTM for detecting and classifying the sentiments. The LSTM approach is highly relevant for these tasks because it can effectively analyse and capture long-term dependence within the data sequence [18]. These features are vital to define patterns and trends precisely within the signal analyzed.

This enables removing or adding data to the cell state and is efficiently governed by a particular module called gates. This gate acts as a discretionary conduit for the data passage. They mainly involve sigmoid NN layer and point-wise multiplication operation, if worked together to control the information flow.

The hidden layer is $h = \{h_1, h_2, \ldots\ldots h_t\}$, the input sequence is $x = x_0, h_1, h_2 \ldots. h_t$, and the output sequence is $y = y_0, y_1, y_2 \ldots. y_t$. Initially, a key decision is made based on the discriminatory removal of information from the cell state. This determination employs a sigmoid layer called the "forget gate layer". By observing the present input X and the prior hidden layer h_{t-1}, this layer generates output values ranging from 0 to 1 for all the components within the C_{t-1} cell state.

LSTM model shows an upgraded architecture for recognising extended information as an input gate compared to input processing and aggregation models exploited by the RNN. Combining a forget gate permits us to compare the internal memory and new incoming data. The LSTM involves a forgetting gate, memory cell, input gate, and output gate to handle the recognized, retained, and forgotten information successfully.

These gate mechanisms, including activation function and entry-wise multiplication, are selected to manage the information flow. The resultant output values in $[0,1]$ regulate the data flow and facilitate succeeding multiplication. The initialization gate allocates a value closer to or equivalent to 1, thus mitigating any negative impact on the training phase.

3.3. AOA-Based Hyperparameter Tuning

At last, the AOA-based parameter tuning was performed to adjust the hyperparameters of the LSTM network. AOA is a novel metaheuristic algorithm that resolves optimization problems [19]. The main objective is to search for the optimum results to an optimization problem by simulating the hunting behaviours of Aquila birds. Figure 2 depicts the steps involved in AOA.

3.3.1. Expanded Exploration

Aquila finds the prey area and chooses the finest foraging area via sky hovering. Then, it implements a vertical diving strategy from the air to define the region of the search range, but the target is positioned. This can be mathematically modelled using the following equations:

$$X_1(t+1) = X_{best}(t) \times \left(1 - \frac{t}{T}\right) + (X_M(t) - X_{best}(t) * rand) \qquad (1)$$

$$X_M(t) = \frac{1}{N}\sum_{i=1}^{N} X_i\,(t), \forall j = 1,2 \cdots, Dim \qquad (2)$$

Now, the solution produced by the following iteration is $X_1(t+1)$; the optimum solution, which reflects the prey location, is $X_{best}(t)$; the existing and maximal iterations are t and T, correspondingly; the mean location of the current value at t^{th} iteration is denoted as $X_M(t)$; the random number between $(0,1)$ is $rand$; N is population size; Dim is the dimension.

3.3.2. Small-Range Exploration

After finding it at a higher altitude, Aquila continuously flies over the prey, which prepares for landing and launching the attack, named the short glide attack. This can be scientifically stated as follows:

$$\begin{cases} X_2(t + Levy(D) + X_R(t) + (y - x) * rand \\ Levy(D)\sigma = S \times \frac{u \times \sigma}{|v|^{\frac{1}{\beta}}} \\ \left(\frac{\Gamma(1+\beta) \times \sin e\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}}\right) \\ y = r \times \cos(\theta) \\ x = r \times sin(\theta) \\ r = r_1 + U \times D_1 + \theta_1 \\ \theta = -\omega \times D_1 + \theta_1 \\ \theta_1 = \frac{3 \times \pi}{2} \end{cases} \qquad (3)$$

Now, the value produced by the following iteration of the smaller range is $X_2(t+1)$; $Levy(D)$ is levy fight distribution; the random integer within $[1,N]$ at i^{th} iteration is $X(t)$; s and β are fixed values of 1.5 and 0.01, u and v are random integers in the (0,1) interval; y and x are the spiral shapes from the search; $r1$ takes the value between 1 and 20; U and ω are a constant with the value 0.00565 and 0.005; D_1 is integers from 1 to the length of the search range.

3.3.3. Expanded Development

During this stage, Aquila defines prey region and organizes for landing and attacking. This method is known as a low-altitude fight with slow origin. The arithmetical explanation of these conducts is expressed in Equation (4).

Fig. 2 Steps involved in AOA

$$X_3(t+1) = \left(X_{best}(t) - X_M(t)\right) \times \alpha\text{-}rand + ((UB - LB) \times rand + LB) \times \delta \qquad (4)$$

Whereas $X_3(t+1)$ is the outcome formed by the following iteration of the enlargement segment; $X_{best}(t)$ signifies the location of the optimum solution till i^{th} iteration; $X_M(t)$ denotes the present solution mean value at t iteration; $rand$ is an arbitrary value among 0 and 1; α and δ are dual improvement tuning limitations stable to 0.1. LB and UB denote low as well as up bound, respectively.

3.3.4. Small-Range Development

Aquila will attack the target on land based on their arbitrary actions in this stage. Aquila will be shooting the prey in the final location.

$$\begin{cases} -4(t+1) = QF \times X_{best}(t) - (G_1 \times X(t) \times rand) \\ \quad -G_2 \times Levy(D) + rand \times G_1 \\ QF(t) = t^{(1-T)^2} \\ G_1 = 2 \times rand - 1 \\ G_2 = 2 \times \left(1 - \frac{t}{T}\right) \end{cases} \qquad (5)$$

Whereas $X_4(t+1)$ is the outcome for the subsequent iteration of the smaller range improvement stage t; QF denotes a quality function to balance the strategy of hunting; G_1 denotes several actions of chasing its prey; G_2 is a value dropped from two to zero, specifying the speed where the Aquila monitors its prey; $X(t)$ is a present solution at t^{th} iteration.

The fitness choice is the substantial factor influencing the efficiency of the AOA. The hyperparameter choice approach includes the solution encoding process for evaluating the candidate solution's effectiveness. In this, the AOA model considers the performance as the primary condition to strategy the FF given below.

$$Fitness = \max(P) \qquad (6)$$

$$P = \frac{TP}{TP+FP} \qquad (7)$$

Where FP and TP are values of false and true positives.

4. Result Analysis and Discussion

In this study, the SA outputs of the AOADL-SAC technique are tested using the Kaggle of sentiment140 dataset [20], comprising 800 instances, as demonstrated in Table 1.

Table 1. Dataset description

Class	Instance Numbers
Negative	400
Positive	400
Total Instances	800

Figure 3 portrays the confusion matrices produced by the AOADL-SAC methodology under the TR/TS phase of 80:20 and 70:30. The simulated output indicates the effectual identification of the positive and negative instances within two classes.

In Table 2 and Figure 4 portrays the SA output of the AOADL-SAC approach. According to the TR phase of 80%, the AOADL-SAC approach attains average accuracy, precision, recall, F1-score, and G-Measure of 93.27%, 93.76%, 93.27%, 93.26%, and 93.39% individually. Also, based on the TS phase of 20%, the AOADL-SAC approach gets average accuracy, precision, recall, F1-score, and G-Measure of 93.19%, 93.62%, 93.19%, 93.11%, and 93.26% respectively.

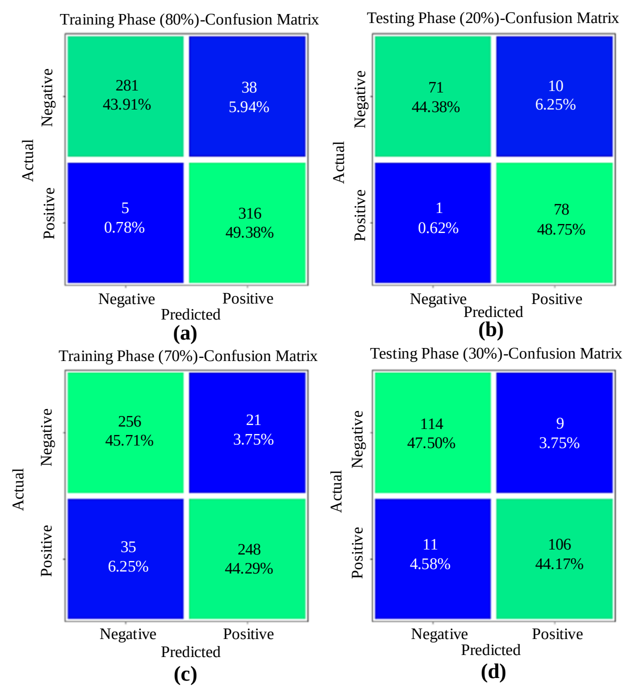

Fig. 3 Confusion matrices of TR/TS phase (a-b) 80:20 (c-d) 70:30

Table 2. SA output of AOADL-SAC approach with TR/TS phase of 80:20

Classes	Accuracy	Precision	Recall	F1-Score	G-Measure
TR Phase (80%)					
Negative	88.09	98.25	88.09	92.89	93.03
Positive	98.44	89.27	98.44	93.63	93.74
Average	**93.27**	**93.76**	**93.27**	**93.26**	**93.39**
TS Phase (20%)					
Negative	87.65	98.61	87.65	92.81	92.97
Positive	98.73	88.64	98.73	93.41	93.55
Average	**93.19**	**93.62**	**93.19**	**93.11**	**93.26**

In Table 3 and Figure 5 portrays the SA outputs of the AOADL-SAC methodology. Additionally, based on the TR phase of 70%, the AOADL-SAC methodology gets average accuracy, precision, recall, F1-score, and G-Measure of 90.03%, 90.08%, 90.03%, 90.00%, and 90.03% individually. Similarly, with 30% of the TS phase, the AOADL-SAC methodology obtains an average accuracy, precision, recall, F1-score, and G-Measure of 91.64%, 91.69%, 91.64%, 91.66%, and 91.66% respectively.

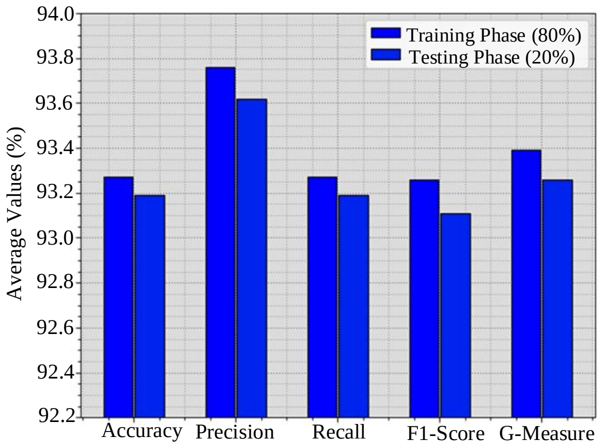

Fig. 4 Average of AOADL-SAC methodology with 80:20 of TR/TS

Table 3. SA assessment of the AOADL-SAC methodology with 70:30 of TR/TS

Classes	Accuracy	Precision	Recall	F1-Score	G-Measure
TR Phase (70%)					
Negative	92.42	87.97	92.42	90.14	90.17
Positive	87.63	92.19	87.63	89.86	89.88
Average	**90.03**	**90.08**	**90.03**	**90.00**	**90.03**
TS Phase (30%)					
Negative	92.68	91.20	92.68	91.94	91.94
Positive	90.60	92.17	90.60	91.38	91.38
Average	**91.64**	**91.69**	**91.64**	**91.66**	**91.66**

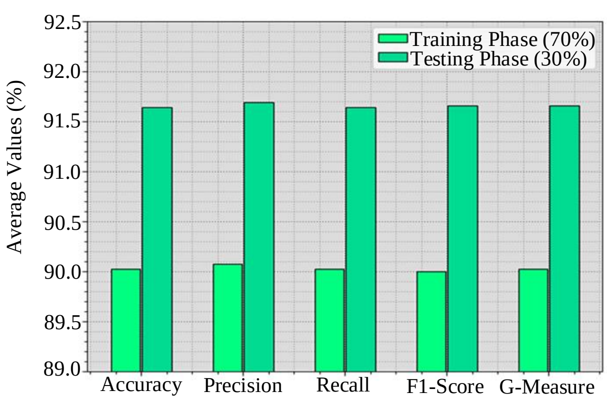

Fig. 5 Average of AOADL-SAC methodology with 70:30 of TR/TS

In Figure 6, the precision-recall curve of the AOADL-SAC system plots precision against the recall, displaying that the AOADL-SAC system attains higher precision-recall values through each class. This graph shows the model's capability for recognizing diverse classes, significantly surpassing the ability to identify positive samples appropriately but reducing false positives.

Figure 7 similarly contains ROC curves of the AOADL-SAC approach that showcase the model's capacity to discriminate among class labels. These curves offer valued understandings of the trade-off between true and false positive rates, TPR and FPR, at numerous thresholding and epoch classifications. It indicates the precisely anticipated model achievement in two classes, highlighting its classification proficiencies.

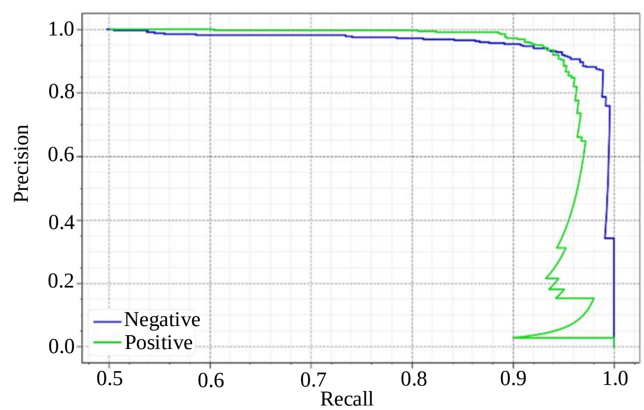

Fig. 6 Curve of PR of AOADL-SAC model at 80:20 of TR/TS

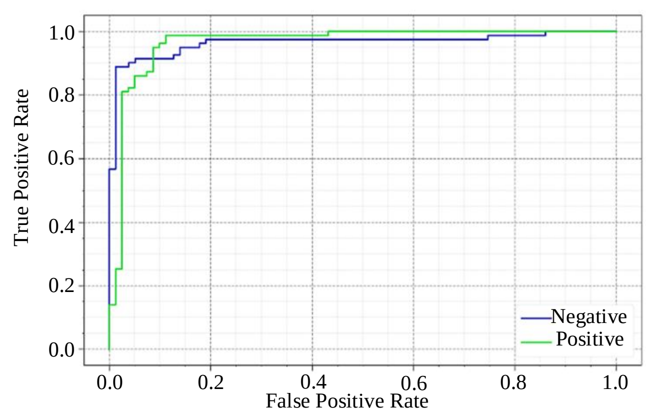

Fig. 7 Curve of ROC of AOADL-SAC model at 80:20 of TR/TS

Table 4 and Figure 8 show a wide-ranging relational output of the AOADL-SAC model with other methodologies [21]. The achieved outputs portray that the AOADL-SAC model attains improved achievement.

According to accuracy, the AOADL-SAC method offers an increasing accuracy of 93.27% while the Term Frequency-DNN, Term Frequency-CNN, Term Frequency-RNN, Word Vector-DNN, Word Vector-CNN, Word Vector-

RNN, ASASM-HHODL methods get minimizing accuracy values of 78.21%, 82.94%, 75.17%, 82.06%, 79.85%, 81.10%, and 84.40%, correspondingly.

Similarly, based on precision, the AOADL-SAC system offers an increasing precision of 93.76% but the Term Frequency-DNN, Term Frequency-CNN, Term Frequency-RNN, Word Vector-DNN, Word Vector-CNN, Word Vector-RNN, ASASM-HHODL systems get reducing precision values of 75.25%, 79.70%, 80.32%, 80.11%, 82.77%, 75.77%, and 85.96%, individually. Then, with F1-score, the AOADL-SAC model provides an improving F1-score of 93.26% while the Term Frequency-DNN, Term Frequency-CNN, Term Frequency-RNN, Word Vector-DNN, Word Vector-CNN, Word Vector-RNN, ASASM-HHODL methodologies acquires decreasing F1-score values of 77.38%, 76.09%, 83.43%, 83.60%, 79.85%, 76.12%, and 86.27%, appropriately.

Table 4. Comparison evaluation of the AOADL-SAC model with other techniques

Models	Accuracy	Precision	Recall	F1-Score
Term Frequency-DNN	78.21	75.25	82.37	77.38
Term Frequency-CNN	82.94	79.70	83.61	76.09
Term Frequency-RNN	75.17	80.32	82.08	83.43
Word Vector-DNN	82.06	80.11	76.63	83.60
Word Vector-CNN	79.85	82.77	83.91	79.85
Word Vector-RNN	81.10	75.77	78.57	76.12
ASASM-HHODL	84.40	85.96	86.53	86.27
AOADL-SAC	93.27	93.76	93.27	93.26

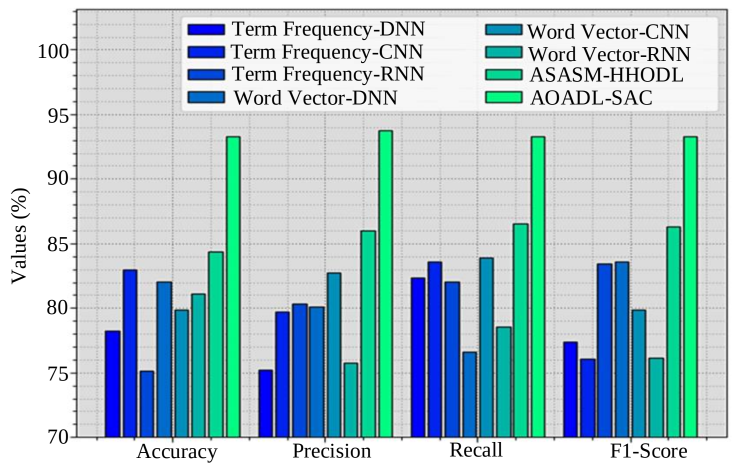

Fig. 8 Comparison analysis of AOADL-SAC model with other existing techniques

5. Conclusion

In this manuscript, an AOADL-SAC technique on social network media is presented. The AOADL-SAC technique intends to recognize and classify the sentiments on social media. The proposed AOADL-SAC technique involves data pre-processing, LSTM-based classification, and an AOA-based tuning process. However, the AOADL-SAC method employs the LSTM method to detect and classify the sentiments. At last, the AOA-based tuning procedure was performed to adjust the hyperparameters of the LSTM network. The investigational output of the AOADL-SAC technique is examined on a standard dataset.

The comprehensive outcomes highlighted the AOADL-SAC technique and stated it accomplishes better solutions than other recent systems concerning different aspects.

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