AN INTEGRATED DEEP LEARNING WITH NATURAL LANGUAGE PROCESSING MODELS FOR SENTIMENT ANALYSIS AND CLASSIFICATION USING ARABIC TWEETS

Ebtesam Hussain Almansour

Department of Computer Science, Applied Collage, Najran University, Najran, Saudi Arabia

ABSTRACT

The growing acceptance of social media networks as a platform to share opinions on several features emerged opinion mining or sentiment analysis (SA) as an active investigation part. In recent times, SA has attracted significant attention owing to its various applications in different features of our lives. SA is one of the Natural Language Processing (NLP) that purposes to analyze and process data that is transcribed in human languages. Even though the Arabic language is the most extensively spoken language utilized for content sharing through social media, the SA on Arabic content is restricted owing to numerous challenges with the language's morphologic structures, the dialect's variabilities, and the absence of the proper corpora. In recent times, deep learning (DL) and machine learning (ML) have demonstrated extraordinary achievements in the field of SA for Arabic tweet classification in social media platforms. In this manuscript, we design and develop an Integrated Deep Learning with Natural Language Processing Models for Sentiment Analysis and Classification (IDLNLPM-SAC) technique. The IDLNLPM-SAC model presents a sentiment analysis and classification using Arabic tweets. The presented IDLNLPM-SAC model follows different levels of data preprocessing to transform the raw Arabic tweet data into a compatible format. For the process of word embedding, the latent semantic analysis (LSA) technique can be deployed. Besides, the hybrid of parallel temporal convolutional network–gated recurrent unit (PTCN-GRU) classifier can be implemented for the classification process. Eventually, the parameter choice of the PTCN-GRU algorithm can be implemented by the design of the improved marine predator algorithm (IMPA). The simulation evaluation of the IDLNLPM-SAC technique takes place using the Arabic tweets database. The experimental results pointed out the heightened solution of the IDLNLPM-SAC technique compared to recent approaches.

KEYWORDS

Sentiment Analysis; Deep Learning; Arabic Tweet; Latent Semantic Analysis; Marine Predator Algorithm

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1. INTRODUCTION

The Arabic language is interesting and complex. It is curious owing to its previous, strategical influence on its individuals and the zone they live, and its conventional and community literature [1]. Conventional Arabic has persisted clear, unaffected, and valuable for different times at a previous level. The Arabic language, still, lacks education and resources from the social-emotional study region, and methods to remove and categorize feelings in Arabic Twitter would be helpful in an area of diversity, with increasing E-learning applications, assisting psychologists in the identification of terrorist performances, increasing product qualities, improving customer service, and so on [2]. The investigation's importance in Arabic Sentiment Analysis (SA) upsurges significantly because of greater number of Arabic language users. Nevertheless, sentiment detection from Arabic text, however, required huge attempts to improve more precise emotion-mining techniques in MSA and dialectic Arabic by a larger-scale emotion lexicon [3]. Language is multifaceted and handling it computationally is not direct. The simple component of language is words, in natural language processing (NLP) we are required to transform words into mathematical designs to constitute an appropriate representation that might assist machines to know the language [4]. SA is the most important investigation area of NLP at present. It has developed as a dynamic investigation area through the propagation of textual data by the Web mainly on social media web pages [5]. It is achieved over either supervised or unsupervised learning models. In both methods, labeled data has been essential to test and train in supervised learning and to test in unsupervised learning. In the past few years, many social network sites like Facebook, Twitter, Instagram, and so on have improved their existence on the web [6]. These sites have a huge number of users who give an enormous data amount which contains images, texts, videos, and so forth. There are numerous approaches for data analytics on data gathered from the web, and using SA is an important one. SA is the research of people's emotions, options, and attitudes, and includes a grouping of NLP and text mining [7].

SA concentrated on testing text messages that keep people's sentiments. SA is defined as NLP tasks targeting to recognize a subjected content that comprises sentiment and feeling, which are categorized as neutral, positive, or negative [8]. Additionally, textual data is separated into dual groups: opinions and facts. Emotional Analysis on Twitter contains various problems since these tweets have numerous misspellings, multimedia content, grammatical errors, slang social, and shortcuts [9]. Several investigators examine sentiments in English language tweets, but none of those involved categorize the sentiments in Arabic language tweets due to their tasks. The majority of emotional analyses of Arabic tweets are concentrated on classifying an emotion into a negative or positive sentiment [10]. The SA's objective is to classify the writer's approach regarding a product, topic, or the complete tonalities in a text.

In this manuscript, we design and develop an Integrated DL with NLP Models for Sentiment Analysis and Classification (IDLNLPM-SAC) technique. The IDLNLPM-SAC model presents a sentiment analysis and classification using Arabic tweets. The presented IDLNLPM-SAC model follows different levels of data preprocessing to convert the raw Arabic tweet data into a compatible format. For the process of word embedding, the latent semantic analysis (LSA) technique can be deployed. Besides, the hybrid of parallel temporal convolutional network–gated recurrent unit (PTCN-GRU) classifier can be implemented for the classification process. Eventually, the parameter choice of the PTCN-GRU approach can be implemented by the design of the improved marine predator algorithm (IMPA). The experimental evaluation of the IDLNLPM-SAC technique takes place using the Arabic tweets dataset.

2. RELATED WORKS

In [11], an ensemble method that incorporates convolutional neural networks (CNNs), bi-directional long short-term memory (Bi-LSTM), and attention mechanism has been presented. The convolution layer was applied for the feature extractor from the layer of high-level sentence representations, the Bi-LSTM has been incorporated to additionally take the context-related data from the created feature sets. Dual attention mechanism components can be integrated to emphasize the crucial data from the contextual feature vectors formed by the BiLSTM of HLs. Alhumoud et al. [12] intended to discover Arabic SA for Vaccine-Related COVID19 Tweets (ASAVACT) to calculate sentiment polarities shared openly. This study has been completed with advanced deep learning (DL) techniques that have shown superiorities in the domain of language analysis and processing. Furthermore, this work offers the major Arabic Twitter amount on COVID19 vaccination. Saleh et al. [13] presented a stacking ensemble approach that united the predictive control of CNN and hybrid DL methods. The stacking ensemble approach contains dual major stages. Three DL techniques have been enhanced in the initial stage with a hybrid of CNN-LSTM, a hybrid of CNN-GRU, and DCNN. During the next stage, these 3 distinct pre-trained outputs were combined with the SVM meta-learner.

In [14], a fusion majority voting approach has been utilized to develop the efficiency of the analysis of Arabic sentiment. Formerly, the outputs of these 4 techniques were forwarded to a fusion phase that performed majority voting and displayed the consistently recognized class. This model is named FusionAraSA which depends on incorporating four methods and fusion to enlarge the application of pre-trained techniques. Al Shamsi and Abdallah [15] presented and used seven dissimilar DL algorithms for SA. Formerly, an ensemble stacking approach was presented to associate the efficient DL algorithms utilized in this work. The initial technique joined the dual highest-performance DL techniques, the next joined the four highest-performance methods, and the last approach joined all seven trained DL algorithms. In [16], a novel hybrid approach, RNN-BiLSTM, which combines BiLSTM and recurrent neural networks (RNN) networks has been introduced. The method applied Arabic bi-directional Encoder Representations from Transformers (AraBERT), an advanced Arabic language pre-trained transformer-based technique, to make word-embedding vector. The RNN-BiLSTM method incorporates the capability for learning bidirectional context and sequential dependencies.

Alhazzani et al. [17] to find out the difficulty of categorizing patient experience (PX) commentaries transcribed in Arabic by utilizing DL- and BERT-based techniques. Features are removed from the dataset and then applied for training DL-based classifiers—with Bi-LSTM and Bi-GRU—for which pre-training vector word embedding and pre-trained statical word embedding are used. Additionally, the investigation uses several Arabic pre-trained BERT techniques, regarding structure PX_BERT, a modified BERT approach by the PX unlabeled database. In [18], an efficient technique that utilizes the advantages of CNN and Bi-LSTM to classify Arabic tweets with stacked ensemble learning techniques has been presented. Initially, the tweets are signified as vectors with word embedding techniques, formerly the text feature was removed by CNNs, and eventually, the context information of texts was developed by Bi-LSTM.

3. *The Proposed Methodology*

In this study, we design and develop an IDLNLPM-SAC system. The IDLNLPM-SAC model presents a sentiment analysis and classification using Arabic tweets. To accomplish that, the IDLNLPM-SAC technique encompasses various processes such as data preprocessing, word embedding, a hybrid of DL model-based classification, and IMPA-based parameter selection. Fig. 1 establishes the entire workflow of the IDLNLPM-SAC system.

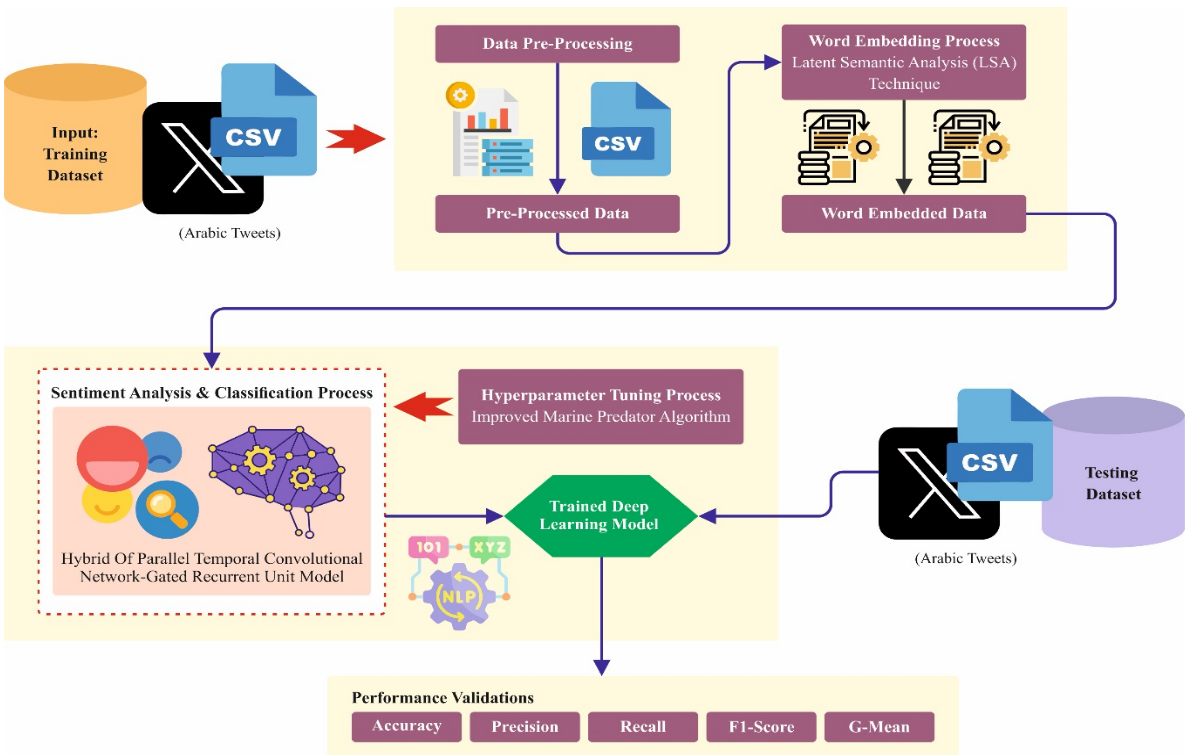

Fig. 1. Overall flow of IDLNLPM-SAC technique

3.1. DATA PREPROCESSING

Initially, the presented IDLNLPM-SAC model follows different levels of data preprocessing to transform the raw Arabic tweet data into a compatible format. During the preprocessing stage, we inspected a wide range of Arabic language models, which we carried out using Python programming language (PPL) [19]. Before working on Twitter, we primarily tokenized it into lists of numbers, symbols, and words which are named as tokens by employing NLTK tokenization. Formerly we eliminated stop words namely pronouns, prepositions, and articles, for example, في, هذا, من, أن, and so on. Subsequently, we extracted blank space and punctuation. Moreover, we extracted the diacritics from either the tweets dataset or the Arabic sentiment lexicon to decrease confusion after looking for words in the lexicon. Amongst the social media platforms, the users of Twitter posts are likely to be the poorest regarding grammar and spelling. One in 150 English words posts on Twitter is mistyped. To overwhelm these issues, we utilized an Arabic device named Ghalatawi: Arabic Auto-Correct, which is maintained in Python. To decrease the neutral outcomes, we utilized the proper noun extracted features, owing to the most proper nouns taking a neutral score in Arabic SentiWordNet (ArSenL). Nevertheless, we utilized a list of 14,000 Arabic-proper nouns with most Arabic family cities, names, and so on. Similarly, the pre-processing stage comprises the subsequent tasks:

(1) Arabic Stemmer: As everyone knows, the words in the Arabic language are obtained from sets of roots that define a fundamental idea with additional affixes, which modify the pronunciation of the word. Therefore, in our model we utilized dual major kinds of stemming procedures that utilize the Arabic language: a Root extraction stemmer, like the Information Science Research Institute (ISRI) Stemmer; the second category is a Light stemmer.

Utilizing Arabic stemmers is somewhat problematic as there are no precise Arabic stemmer devices we might depend on to utilize in our research and supporting PPL. Consequently, we performed some added phases to improve the accuracy level. Initially, the system will look for a word without utilizing the stem in ArSenL; when can it not discover the word's sentiment, then it will stem the word by ISRI stemmer; when a word might not be stemmed, then it will go to the second method, the Light stemmer, rather than leaves the word unchanged.

(2) Part of Speech (POS): Arabic contains a scientific grammatical system, whereas an Arabic word is classified into 3 main POS: Verb (Fia'al-فيال), Particle (Harf-حرف), or Nominal (Ism-اسم). We utilized POS tagging to select precise synsets due to the SentiWordNet lexicon depends on POS for classification. There is a unique Arabic POS tagging device maintained by Python; it's NLP Sanford POS tagging and it's less accurate than MADAMIRA3 which, inappropriately, is not maintained by Python. The NLP Sanford POS device reads Arabic text and allocates POS to every word with Penn Treebank Tags. Nevertheless, before working on these tools, we were required to download them on a machine that was equipped with Java.

(3) Handling Negation: Negation plays a basic part in SA by disturbing the text polarities. Additionally, handling negation would be more problematic in the implied procedure, where the sentence transfers a negative sentiment without the usage of negative words, like sarcastic sentences, for example, this represents the initial and final time, "هذه هي المرة الأولى والأخيرة". For the investigation, we gathered a list of the most often applied negation words in the Arabic language; after the classifier set up such negation words, it would provide the word in the list with a score of (negative =1). The objective of this process of handling negations is to improve the sum of the negative scores within a sentence.

The emojis play a major role as they express sentiment and emotions, necessitating suitable handling by both mapping them to particular sentiment labels and eliminating them to ensure correct text analysis.

3.*2. Word Embedding using* LSA

For the process of word embedding, the LSA technique can be deployed. The latent semantic study is a novel algebraic method of retrieval of information, which discovers the possible concepts and meaning in this document by examining records [20]. When every word signifies a unique theory. And every theory has been explained in unique words. The LSA basis generated a words matrix in which every index word uses a row and every title uses a column. In general, the LSA matrix would be sparse and large. It's for every document or title that normally contains a smaller portion of the complete vocabulary. The more complicated LSA models make use of these sparsities to increase the temporal and spatial complexities. The fundamental notion of latent semantic investigation is to map the documents within the lower-dimension latent semantic space representations to the higher-dimensional vector space model (VSM). These mappings have been understood by the SVD of the document or item matrix. The Conventional VSM assumes that the word's semantics are autonomous of one another, and every word is observed as an orthogonal essential vector in the space vector.

The SVD model is a normal space constructing approach extensively applied currently. SVD doesn't need the matrix breakdown to remain a matrix of squares. Assume matrix A is MxN, formerly we describe the SVD of matrix A as:

$$A = U\Sigma V^T \tag{1}$$

Here, U represents mxm matrix, Σ represents mxn matrix and the complete elements are all zero apart from that on diagonals. The components on the diagonal are singular values. V and $U$are single matrix, which fulfills $U^T U = I$ and $V^T V = I$. When we increase the A$'s$ transpose and transpose of A, we attain nxn square matrix of $A^T A$:

$$(A^T A)V_i = \lambda_i V_i \tag{2}$$

Accordingly, we can obtain the n eigenvalue of the matrix in addition to the equivalent n eigenvector. Formerly we might discover every singular value after that discover the particular valued matrix Σ.

3.3. HYBRID OF DL MODELS

Besides, the hybrid of the PTCN-GRU model is executed for the classification procedure. The architecture of the PTCN-GRU hybrid network technique [21]. It mainly contains five key modules: the PTCN, input, GRU, output, and fully connected (Dense) layer. This structural design is intended to fully utilize the benefits of every layer, attaining effective feature extraction and non-linear relationship modeling.

The input layer of the method incorporates multi-dimensional features with historical data, meteorologic conditions, and holiday pieces of information. Unlike the classical layered stack hybrid approach, but an output of a single layer helps as the input to next as TCN-GRU technique, the PTCN layer presents a parallel TCN architecture. This architecture uses convolution kernels of various dimensions like 3, 5, and 7. These changing kernels widely remove temporal features through numerous scales. Output and Feature fusion are attained over parallel concatenation.

In detail, the parallel architecture of the PTCN uses distinguished temporal convolution kernels depending on the particular attributes of every feature. This model efficiently prevents the general problems in the conventional TCN-GRU technique, like feature confusion and the insufficient capturing of composite inter-feature relationships after processing multi-dimensional data. Moreover, the PTCN uses a multiple-scale convolutional approach. By utilizing convolutional kernels of changing dimensions, it removes features through numerous temporal scales. Therefore, it overwhelms the restrictions of single-scaled extracting features in conventional TCN techniques. It additionally takes intricate feature communications, improving the models' capabilities to signify multi-dimensional features. This process guarantees the full application of information through various temporal measures and deals with the drawbacks of the conventional TCN-GRU approach. To enhance recognize the PTCN layer function, the succeeding mathematical formulations are utilized to signify it:

$$S_1 = C_3(x) \tag{3}$$

$$S_2 = C_5(x) \tag{4}$$

$$S_3 = C_7(x) \tag{5}$$

$$S = Concat(S_1, S_2, S_3) \tag{6}$$

Now, C_k characterizes the convolution operation through a k kernel size, whereas k captures the values 7, 3, and 5, correspondingly. The x variable signifies the input data to the method, and S symbolizes the PTCN layer's outputs. The Concat function has been employed for concatenating the convolutional outcomes through dissimilar scales.

The fused features are transferred to GRU for handling. Over its singular reset and update gate methods, the GRU might concurrently consider numerous inspiring factors and their non-linear communications. With dynamism adjusted to the memory unit condition, the GRU adaptably reproduces these composite relations. These mechanisms allow the GRU to efficiently learn and mimic composite non-linear patterns, offering a strong basis for precise calculation. Fig. 2 shows the infrastructure of GRU.

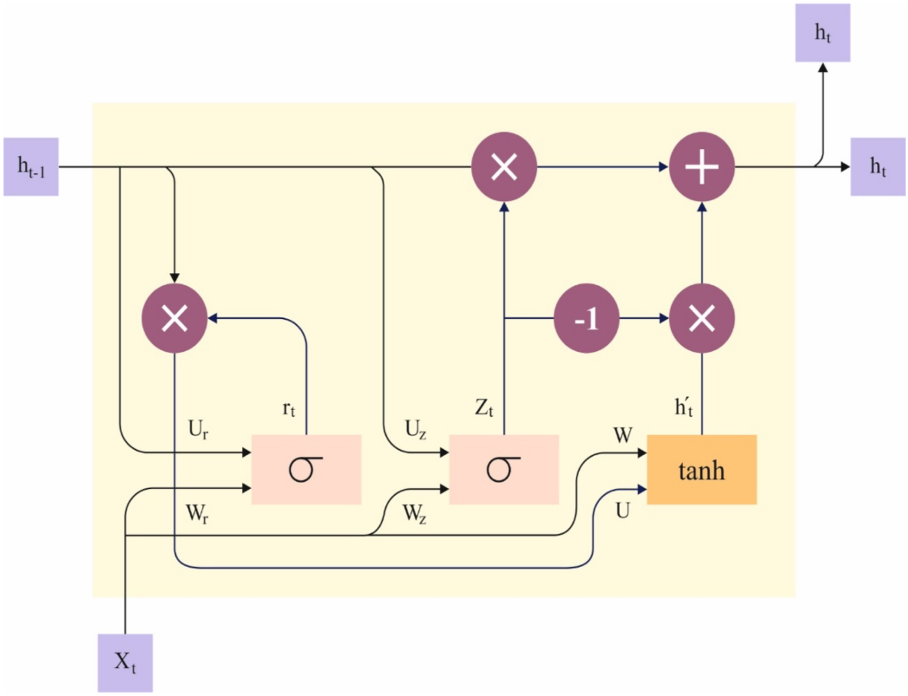

Fig. 2. Structure of GRU

The computation procedure from the GRU is as shown:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{7}$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{8}$$

$$h_t = \tanh(W \cdot [r_t \odot h_{t-1}, x]) \tag{9}$$

$$h_t = (1 - z_t)s \odot h_{t-1} + z_t \odot h_t \tag{10}$$

Here, σ characterizes the sigmoid activation function; W, W_z, and W_r refer to the weight matrices; $\odot$ designates element-to-element multiplications; z_t and r_t represent reset and update gate outputs, correspondingly; x_i denotes input at the present step, and h_{t-1} characterizes hidden layer (HL) in the prior time step. The candidate's HL $\tilde{h}_t$ has been calculated depending on the present input and familiar HL in the preceding time step, replicating the data at the present phase. The upgraded HL h_t has been developed by joining the candidate HL with updated gate z_t, thus balancing the impact of present and previous data.

The resultant from the GRU layer has been managed by a Dense layer. It uses the sigmoid activation function, reducing multi-dimensional features within 1D output to make the last value $\hat{y}_t$.

$$\hat{y}_t = \sigma(W_a \cdot A + b_a) \tag{11}$$

Now, $\sigma(\cdot)$ signifies the sigmoid; A symbolizes the output from the GRU layer; W_a represents the weighted matrix; and b_a characterizes the biased vector.

3.4. IMPA-BASED PARAMETER SELECTION

Eventually, the parameter choice of the PTCN-GRU approach can be implemented by the design of the IMPA. Some ideas about the MPA are required to be defined previously in the presented enhanced MPA model IMPA [22]. Like other optimization models, previously initializing iterating, a primary candidate solution distributed at random has been generated in the searching field. The process of generation is defined in Eq. (12):

$$Z = Z_{\min} + random[0,1] \times (Z_{\min} - Z_{\max}) \tag{12}$$

Whereas $Z_{\min}$ and $Z_{\max}$ represent the maxima and minima of variables and $random[0, 1]$ signifies a number generated at the uniform that may capture values from (0-1).

According to comparative outcomes of fitness value, those who with optimum fitness can be designated to construct the matrix of E_{lite}, the shape is $n \times d$ and it is stated in Eq. (13):

$$E_{lite} = \begin{bmatrix} Z_{1,1}^{O} & Z_{1,2}^{O} & \cdots & Z_{1,d}^{O} \\ Z_{2,1}^{O} & Z_{2,2}^{O} & \cdots & Z_{2,d}^{O} \\ & \cdots\cdot & & \\ & \cdots\cdot & & \\ & \cdots\cdot & & \\ Z_{n,1}^{O} & Z_{n,2}^{O} & \cdots & Z_{n,d}^{O} \end{bmatrix}_{n\times d} \quad P_{rey} = \begin{bmatrix} Z_{1,1} & Z_{1,2} & \cdots & Z_{1,d} \\ Z_{2,1} & Z_{2,2} & \cdots & Z_{2,d} \\ & \cdots\cdot & & \\ & \cdots\cdot & & \\ & \cdots\cdot & & \\ Z_{n,1} & Z_{n,2} & \cdots & Z_{n,d} \end{bmatrix}_{n\times d} \tag{13}$$

Here, Z^O represent prey associated with the optimum fitness and imitates n times to form matrix E_{lite}. n signifies search individual dimensions and d means the dimensional variable counts. $Z_{i,j}$ designates the ith prey location information at the jth dimension. The P_{rey} matrix are other matrices, that contribute to upgrading the information of the E_{lite} matrix.

Here, the complete process of optimization has been separated into 3 portions on average based on dissimilar values v_e. The 3 stages are defined below:

Stage 1 Ratio of high-speed: This happens in the initial phase of iteration. The mathematical representation has been demonstrated in Eq. (14):

$$\begin{cases} \overrightarrow{v_i} = \overrightarrow{R_B} \otimes \left(\overrightarrow{E_{lite}} - \overrightarrow{R_B} \otimes \vec{P}_{rey-i}\right) i = 1, 2, \dots, n \\ \vec{P}_{rey-i} = \vec{P}_{rey-i} + Q \cdot \vec{R} \otimes \overrightarrow{v_i} \end{cases} , iter < \frac{Iter}{3} \tag{14}$$

Whereas $\overrightarrow{R_B}$ represents a matrix containing a data sequence made by a function of standard distribution that mimics Brownian motion. Q equivalents 0.5. Now $\vec{R}$ specifies a randomly generated variable from (0-1). iter and Iter represent present and maximal iteration counts.

Stage 2 Ratio of unit speed: Here, the exploration approach slowly reduces whereas the exploitation approach slowly improves, and both are essential. This initial population portion has the responsibility for searching for the global optimum results.

$$\begin{cases} \begin{cases} \overrightarrow{v_i} = \overrightarrow{R_L} \otimes \left(\vec{E}_{lite} - \overrightarrow{R_L} \otimes \vec{P}_{rey-i}\right) \\ \vec{P}_{rey-i} = \vec{P}_{rey-i} + Q \cdot \vec{R} \otimes \overrightarrow{v_i} \end{cases} , i = 1, \dots, \frac{n}{2} \\ \begin{cases} \overrightarrow{v_i} = \overrightarrow{R_B} \otimes \left(\overrightarrow{R_B} - \vec{E}_{lite} - \vec{P}_{rey-i}\right) \\ \vec{P}_{rey-i} = \vec{P}_{rey-i} + Q \cdot \left(1 - \frac{iter}{Iter}\right)^{\frac{2\times iter}{Iter}} \otimes \overrightarrow{v_i} \end{cases} , i = \frac{n}{2} + 1, \dots, n \end{cases} \tag{15}$$

whereas $\overrightarrow{R_L}$ represents randomly generated variables made by Lévy distribution and utilized to multiply the P_{rey}.

Stage 3 Ratio of low-speed: During the previous optimization method, the predator ensures local exploitation moves in Lévy way. These methods have been exposed in Eq. (16):

$$\begin{cases} \overrightarrow{v_i} = \overrightarrow{R_L} \otimes \left(\overrightarrow{R_L} \otimes \vec{E}_{lite} - \vec{P}_{rey-i}\right) i = 1,2, \cdots, n, \\ \vec{P}_{rey-i} = \vec{E}_{lite} + Q \cdot CF \otimes \overrightarrow{v_i} \end{cases} , iter > \frac{2\times Iter}{3} \tag{16}$$

This algorithm represents greater optimization abilities, this model, similar to various other meta-heuristic models, even undergoes the lack of early convergence. Hence, a novel form of MPA depends on the AIE mechanism as recommended. During this formation of Eddy and effect phase of FADs, the prey executes along jumping to discover other fish distributions, which is equal to the MPA behavior avoiding the stagnation of the local solution. Through experimental explanations, they create some MPA search agents that frequently walk randomly outer the possible area afterward the effect of FADs. Hence, we present an AIE mechanism.

Since the location information of the best predator in similar sizes is outstanding, whereas the location information of some another size might be poor, in these approaches, we arbitrarily choose different sizes and stochastically position this prey's dimension information and best predator. Therefore, preys are permissible to transfer in dual methods with β probabilities, $\beta \times search\_num$ agents transfer within the optimum solution, and the remaining ones upgrade their locations where the best predator travels near themselves. The data exchange model quickens the search speediness for the finest solution and makes up for the search efficiency reduction produced by some populations flying off of the limitations.

The fitness selection is the main aspect of adjusting the value of IMPA. The parameter tuning method holds the encrypted process to evaluate the solution of candidate outcomes. During this case, the IMPA adopts that accuracy is a principal form to design the fitness function (FF).

$$Fitness = \max(P) \tag{17}$$

$$P = \frac{TP}{TP + FP} \tag{18}$$

In which, FP and TP define the false and true positive values.

4. Performance Validation

The simulation validation of the IDLNLPM-SAC method is examined under the Arabic Sentiment Twitter Corpus dataset [23]. The dataset holds 2000 tweets with positive and negative classes as signified in Table1. Table 2 portrays sample tweets.

Table 1 Details of Dataset

Classes	**No. of Tweets**
Positive	1000
Negative	1000
Total Tweets	**2000**

Table 2 Sample Tweets

S. No	**Class Labels**	**Tweets**
1	Positive	🌸 صباحك خيرات ومسرات
2	Positive	💪 جدا الصراحه بس المغرب قدها
6	Negative	😫 تتمغط ومعها سداع
7	Negative	💔 اترك لكم التعليق
8	Negative	😪 اقسم بالله غالبني اكتب و المغصة كاتلاني عديل كدا
9	Negative	🙈 عند محامي
10	Negative	😭 من قاعد فالمستشفى ناو وبيطعم وخايف

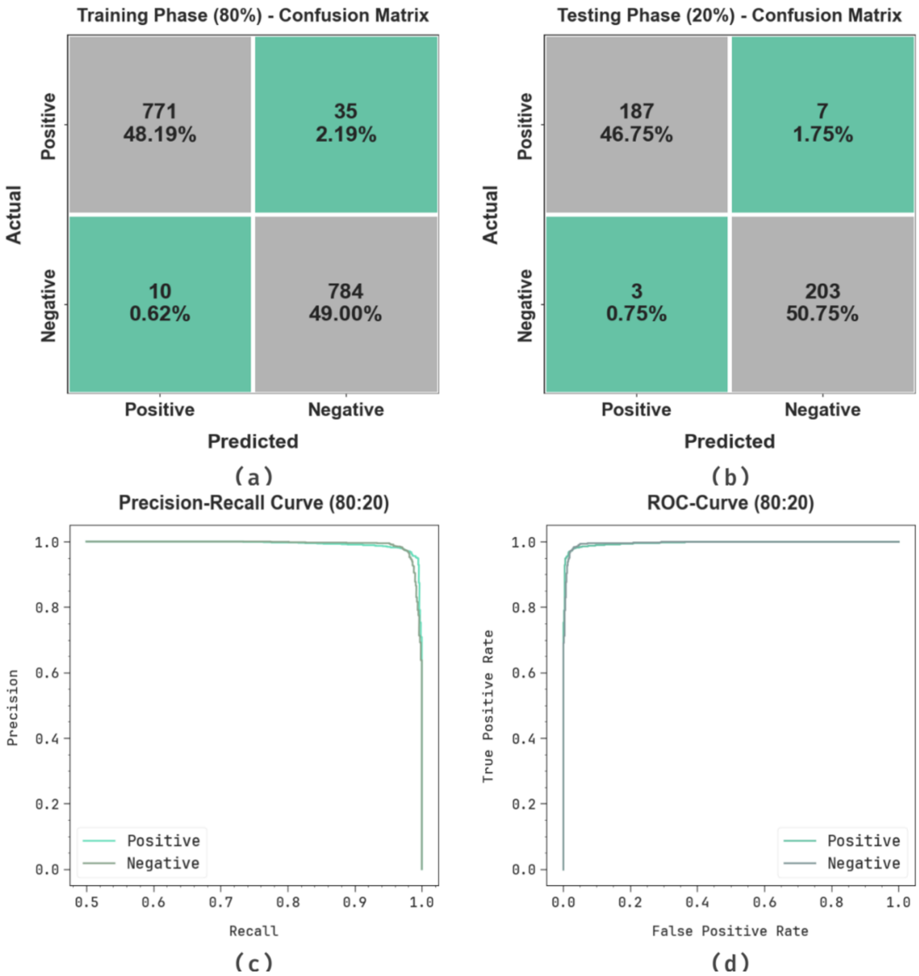

Fig. 3. 80% and 20% of (a-b) confusion matrices (c) curve of PR and (d) curve of ROC

Fig. 3 delivers the classifier outcomes of the IDLNLPM-SAC technique under 80%TRAPH and 20%TESPH. Figs. 3a-3b displays the confusion matrix with the precise classification of all class labels. Fig. 3c displays the PR analysis, demonstrating supreme performance across all class labels. Finally, Fig. 3d demonstrates the ROC analysis, indicating proficient results with high ROC values for different classes.

Table 3 and Fig. 4 denote the SA recognition of the IDLNLPM-SAC model under 80%TRAPH and 20%TESPH. The results imply that the IDLNLPM-SAC approach correctly identified the samples. With 80%TRAPH, the IDLNLPM-SAC system provides average $accu_y$, $prec_n$, $reca_l$, $F1_{score}$, and G_{Mean} of 97.19%, 97.22%, 97.20%, 97.19%, and 97.20%, correspondingly. Likewise, with 20%TESPH, the IDLNLPM-SAC system offers average $accu_y$, $prec_n$, $reca_l$, $F1_{score}$, and G_{Mean} of 97.50%, 97.54%, 97.47%, 97.50%, and 97.50%, respectively.

Table 3 SA detection of IDLNLPM-SAC model under TRAPH of 80% and TESPH of 20%

Class	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{score}$	G_{Mean}
80% TRAPH					
Positive	97.19	98.72	95.66	97.16	97.18
Negative	97.19	95.73	98.74	97.21	97.22
Average	**97.19**	**97.22**	**97.20**	**97.19**	**97.20**
20% TESPH					
Positive	97.50	98.42	96.39	97.40	97.40
Negative	97.50	96.67	98.54	97.60	97.60
Average	**97.50**	**97.54**	**97.47**	**97.50**	**97.50**

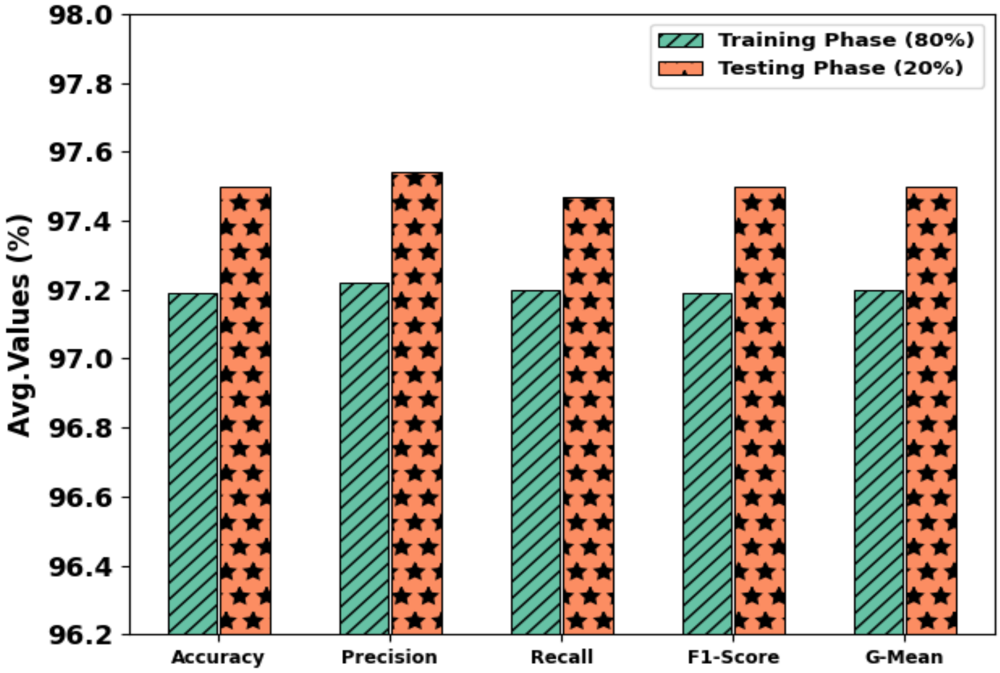

Fig. 4. Average of IDLNLPM-SAC model under TRAPH of 80% and TESPH of 20%

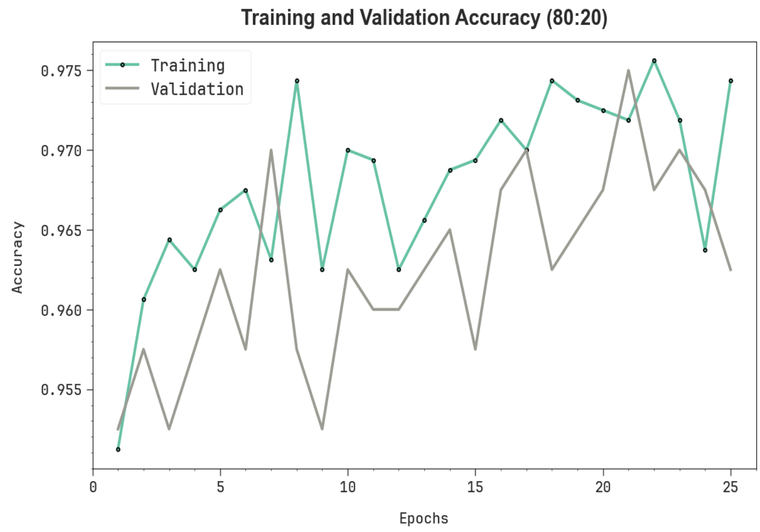

Fig. 5. $Accu_y$ curve of IDLNLPM-SAC method under TRAPH of 80% and TESPH of 20%

In Fig. 5, the training accuracy (TRAAC) and validation accuracy (VLAAC) results of the IDLNLPM-SAC approach under 80% TRAPH and 20% TESPH are recognized. The accuracy values were intended over a range of 0-25 epochs. The results emphasized that the TRAAC and VLAAC values show an increasing tendency which alerted the ability of the IDLNLPM-SAC system with heightened performance over abundant iterations. Moreover, the TRAAC and VLAAC remain closer over the epochs, which entitles the least over-fitting and reveals the superior performance of the IDLNLPM-SAC model, promising reliable prediction on hidden samples.

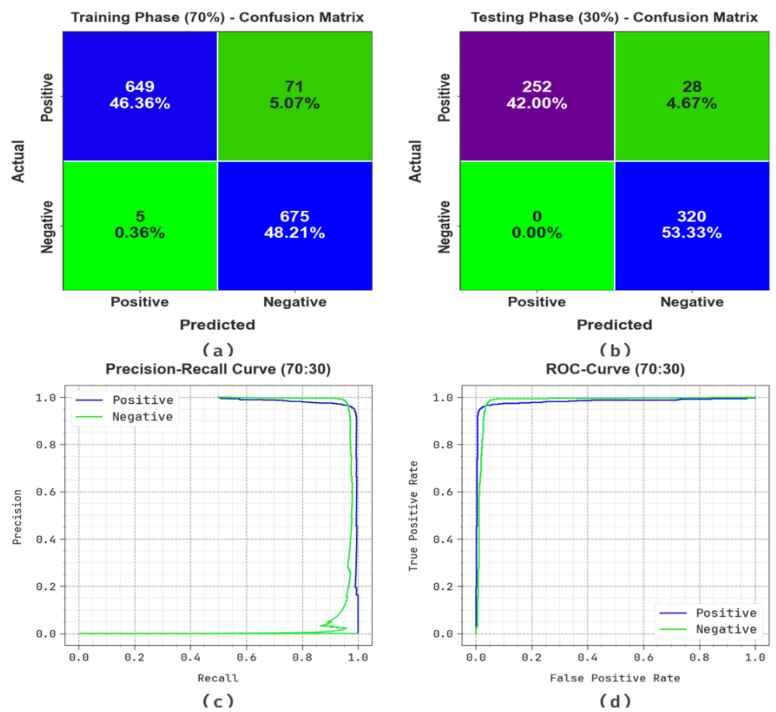

Fig. 6. 70% and 30% of (a-b) confusion matrices (c) curve of PR and (d) curve of ROC

Fig. 6 delivers a classifier outcome of the IDLNLPM-SAC approach under 70%TRAPH and 30%TESPH. Figs. 7a-7b displays the confusion matrix with a precise classification of every class label. Fig. 7c shows the PR analysis, demonstrating supreme performance across each class. Lastly, Fig. 7d exemplifies the ROC analysis, indicating proficient outcomes with great ROC values for diverse class labels.

Table 4 and Fig. 7 provide the SA detection of the IDLNLPM-SAC system under 70%TRAPH and 30%TESPH. The outcomes recommend that the IDLNLPM-SAC methodology appropriately identify the samples. With 70%TRAPH, the IDLNLPM-SAC model provides an average $accu_y$, $prec_n$, $reca_l$, $F1_{score}$, and G_{Mean} of 94.70%, 94.86%, 94.70%, 94.57%, and 94.67%, correspondingly. Similarly, with 30%TESPH, the IDLNLPM-SAC approach delivers average $accu_y$, $prec_n$, $reca_l$, $F1_{score}$, and G_{Mean} of 95.00%, 95.98%, 95.00%, 95.27%, and 95.38%, respectively.

Table 4 SA detection of IDLNLPM-SAC technique under TRAPH of 70% and TESPH of 30%

Class	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{score}$	G_{Mean}
70% TRAPH					
Positive	90.14	99.24	90.14	94.47	94.58
Negative	99.26	90.48	99.26	94.67	94.77
Average	**94.70**	**94.86**	**94.70**	**94.57**	**94.67**
30% TESPH					
Positive	90.00	100.00	90.00	94.74	94.87
Negative	100.00	91.95	100.00	95.81	95.89
Average	**95.00**	**95.98**	**95.00**	**95.27**	**95.38**

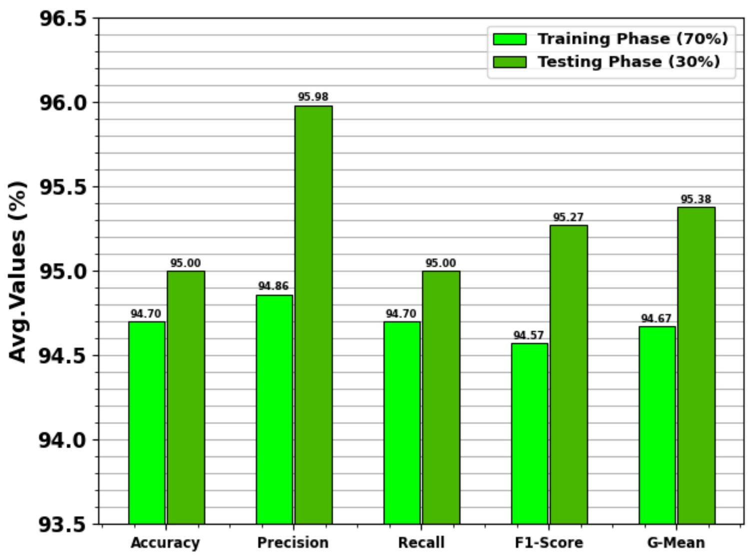

Fig. 7. Average of IDLNLPM-SAC model under TRAPH of 70% and TESPH of 30%

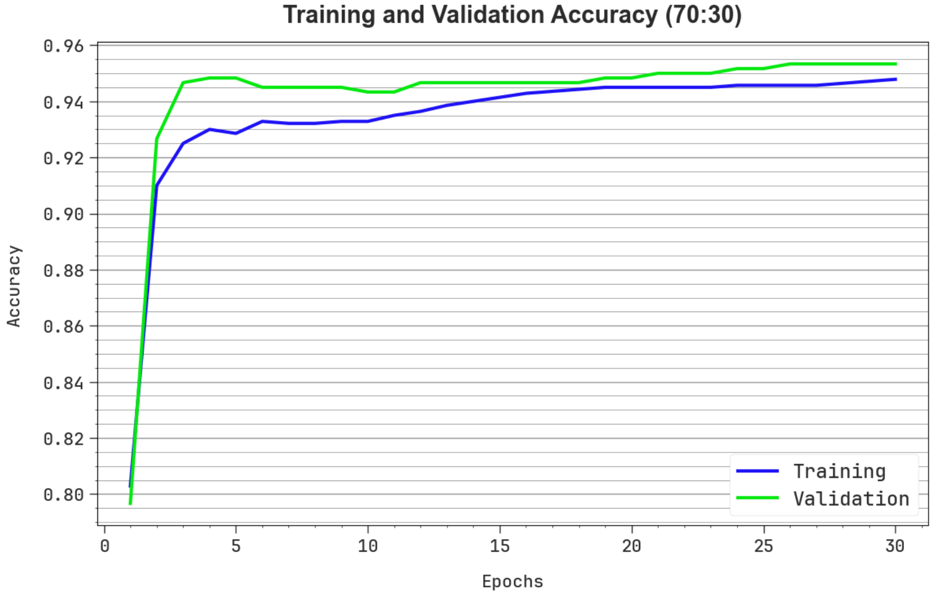

Fig. 8. $Accu_y$ curve of IDLNLPM-SAC model under TRAPH of 70% and TESPH of 30%

In Fig. 8, the TRAAC and VLAAC outcomes of the IDLNLPM-SAC technique under 70 %TRAPH and 30%TESPH are verified. The value of accuracy is figured for 0-30 epochs. The outcome emphasized that the TRAAC and VLAAC values show an increasing tendency which informed the capability of the IDLNLPM-SAC system with improved performance over frequent iterations. Moreover, the TRAAC and VLAAC stay nearer over the epochs, which directs insignificant overfitting and shows heightened performance of the IDLNLPM-SAC model, assuring consistent forecasts on hidden samples.

Table 5 and Fig. 9 survey the comparison analysis of the IDLNLPM-SAC model with the existing models [24-26]. The results emphasized that the 3sBi-LSTM, SF (Surface Feature) +ASEH, SF+GE (Generic Embeddings), and Ensemble systems have reported worse performance. In the meantime, SVM, Bi-GRU, and MSGODL-ACAT approaches have acquired closer outcomes. Additionally, the IDLNLPM-SAC approach conveyed improved performance with maximum $prec_n$, $reca_l$, $accu_y$, and $F1_{score}$ of 97.54%, 97.47%, 97.50%, and 97.50%, respectively.

Table 5 Comparative analysis of IDLNLPM-SAC model with existing techniques

Methods	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{score}$
IDLNLPM-SAC	97.50	97.54	97.47	97.50
MSGODL-ACAT	96.88	93.60	94.05	93.69
Ensemble Model	72.69	72.70	72.36	73.64
SF+GE Model	83.44	77.68	75.17	76.40
SF+ASEH	77.48	75.43	76.44	83.55
3sBi-LSTM	81.36	79.11	74.59	76.53
Bi-GRU Model	90.21	85.06	89.23	87.92
SVM Classifier	92.67	90.45	89.56	90.21

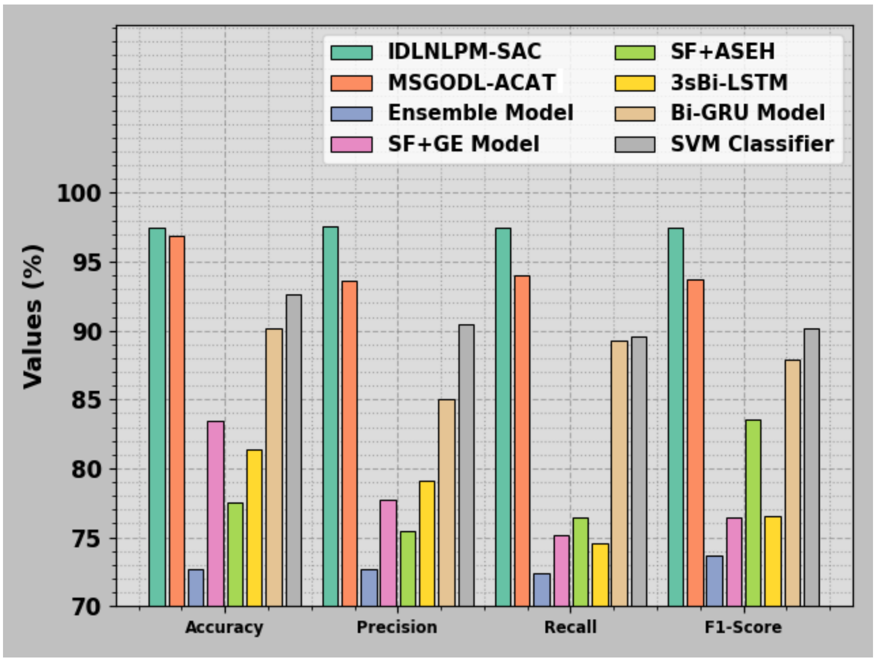

Fig. 9 Comparative analysis of IDLNLPM-SAC model with existing methods

5. CONCLUSION

In this manuscript, we design and develop an IDLNLPM-SAC technique. The IDLNLPM-SAC model presents a sentiment analysis and classification using Arabic tweets. To accomplish that, the IDLNLPM-SAC technique encompasses various processes such as data preprocessing, word embedding, a hybrid of DL model-based classification, and IMPA based parameter selection. Initially, the presented IDLNLPM-SAC model follows different levels of data preprocessing to transform the raw Arabic tweet data into a compatible format. For the process of word embedding, the LSA technique can be deployed. Besides, the hybrid of PTCN-GRU approach is implemented for the classification process. Eventually, the parameter choice of the PTCN-GRU model can be implemented by the design of the IMPA. The experimental evaluation of the IDLNLPM-SAC technique takes place using the Arabic tweets database. The experimentation results pointed out the improved solution of the IDLNLPM-SAC technique compared to recent algorithms.

***DATA AVAILABILITY STATEMENT*:** The data that support the findings of this study are openly available in Kaggle repository at https://www.kaggle.com/datasets/mksaad/arabic-sentiment-twitter-corpus, reference number [23].

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AUTHOR

Ebtesam Hussain Almansor, Received a M.Sc. in computer science from the University of Technology Sydney in 2018, and received a Ph.D. in the Computer Science from the University of Technology in Sydney. Previously, she worked as a computer technology and security assistant lecturer in the Community College, Najran University. Currently, she is assistant professor in Najran University, applied college. Her research interests focus on natural language processing, image processing and artificial intelligence.