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RESEARCH ARTICLE

Modified Seagull Optimization With Deep Learning for Affect Classification in Arabic Tweets

BADRIYYA B. AL-ONAZI[1], HASSAN ALSHAMRANI[2], FATIMAH OKLEH ALDAAJEH[1], AMIRA SAYED A. AZIZ[3], AND MOHAMMED RIZWANULLAH[4]

[1]Department of Language Preparation, Arabic Language Teaching Institute, Princess Nourah bint Abdulrahman University, Riyadh 11671, Saudi Arabia
[2]Department of Teachers Training, Arabic Linguistics Institute, King Saud University, Riyadh ZIP 4545, Saudi Arabia
[3]Department of Digital Media, Faculty of Computers and Information Technology, Future University in Egypt, New Cairo 11835, Egypt
[4]Department of Computer and Self Development, Preparatory Year Deanship, Prince Sattam bin Abdulaziz University, Al-Kharj 11942, Saudi Arabia

Corresponding author: Mohammed Rizwanullah (r.mohammed@psau.edu.sa)

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ABSTRACT Arabic is one of the world's most widely spoken languages, and there is a huge amount of digital content available in Arabic. By the categorization of Arabic documents, it becomes easier to search and access specific content of interest. With the increasing quantity of user-generated content on social media platforms and online forums, text classification becomes important for content filtering and moderation. Text classification on an Arabic corpus has broad applications, ranging from information retrieval and content moderation to sentiment analysis and machine translation. It enables efficient organization, analysis, and utilization of Arabic text data, contributing to various industries and domains. Therefore, this study develops a Modified Seagull Optimization with Deep Learning based Affect Classification on Arabic Tweets (MSGODL-ACAT) technique. The goal of the MSGODL-ACAT approach lies in the recognition and categorization of effects or emotions that exist in Arabic tweets. At the preliminary level, the MSGODL-ACAT technique preprocesses the input data to make the Arabic tweets into a meaningful format. Next, the Glove technique is used for the word embedding process. Moreover, the MSGODL-ACAT technique makes use of the deep belief network (DBN) method for affect categorization. At last, the MSGO algorithm is used for the optimal hyperparameter tuning of the DBN method which in turn enhances the classification results. The experimental evaluation of the MSGODL-ACAT approach is evaluated using Arabic tweets databases. The experimental outcomes signify the effectual performance of the MSGODL-ACAT algorithm over other current approaches.

INDEX TERMS Affect analysis, Arabic tweets, text classification, natural language processing, emotion classification.

I. INTRODUCTION

Micro-blogging record has a distinct nature which denotes that humans communicate a special message through emotions and hashtags in tweets or short messages [1]. It seems to be difficult in analyzing Tweets as social media source. It is in the form of a slang language that has linguistic mistakes which cannot be easily understood by machines. Sentiment Analysis (SA), Natural Language Processing (NLP), Emotion Detection from text (ED) and Named Entity Recognition (NER) are utilized for analyzing and processing tweets [2]. Among them, Sentiment Analysis (SA) is dissimilar to ED and intends at finding the polarity (neutral, positive, or negative) for a specific Tweet [3]. In contrast, ED classifies a specific tweet into a specific emotion label like joy, annoyance, and fear. Emotion can be a stronger emotion about an individual's condition or relationship with others [4]. It had a main role in customer decisions in several fields which includes movies, e-commerce, satisfaction and restaurants with products or services [5]. Recently, Facebook included a few reactions like surprise, anger, love, and happiness to allow users for expressing their emotions about an event, a comment, or a picture. SA identifies negative, positive, or neutral opinions from the text.

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Emotion analysis was one common SA task to recognize various via text expressions [6]. Emotions can be expressed through language; but, a few emotions, like sadness, joy, and fear, were more basic than others and expressed differently [7]. The term effect represents many emotions as valence, joy, and fear, arousal. Emotion detection is important in many domains like public policy, public health, disaster management, political issues, and marketing. The research interest in Arabic SA rises extremely because of the internet's enormous amount of Arabic language users [8]. But, detecting emotion from Arabic text requires massive efforts for developing precise emotion-mining methods in dialectal Arabic and SA utilizing a large-scale emotion lexicon [9]. Multilabel emotion categorization becomes an important topic in emotion analysis tasks as it signifies real-time circumstances where humans express mixed emotions in their text concurrently. For instance, the text might express pessimism, gladness, optimism, love, and desolation [10]. Therefore, framing methods with more than single output emotions for all input texts are highly beneficial.

This study develops a Modified Seagull Optimization with Deep Learning based Affect Classification on Arabic Tweets (MSGODL-ACAT) technique. At the preliminary level, the MSGODL-ACAT technique preprocesses the input data to make the Arabic tweets into a meaningful format. Next, the Glove technique is used for the word embedding process. Moreover, the MSGODL-ACAT technique makes use of the deep belief network (DBN) method for affect classification. At last, the MSGO method is used for the optimal hyperparameter tuning of the DBN approach which in turn enhances the classification results. The experimental investigation of the MSGODL-ACAT approach is examined using Arabic tweets databases. In short, the key contributions of the paper is summarized as follows.

- Develop a new MSGODL-ACAT technique for Arabic tweets affect classification, comprising preprocessing, Glove approach, DBN classification, and MSGO based hyperparameter tuning. To the best of our knowledge, the MSGODL-ACAT technique never existed in the literature.
- Employ DBN model for affect classification which can effectively capture complex patterns and dependencies in the data, making it suitable for the challenging task of emotion classification in Arabic tweets.
- Design ESGO algorithm for hyperparameter tuning process by the integration of Levy flight (LF) with SGO algorithm. LF introduces occasional long-distance jumps, allowing the algorithm to explore new regions of the search space. This helps to strike a balance between exploration and exploitation, improving the algorithm's ability to find optimal solutions.

II. RELATED WORKS

Alwehaibi et al. [11] modelled an optimal emotion categorization for dialectal Arabic short messages at documenting level by utilizing deep learning (DL). The novelty of this work lies in 3 zones. Initially, the author derived semantic aspects for Arabic short messages at the character level and word level. Secondly, the author utilized 3 DL topologies for classification methods such as long short term memory (LSTM)-recurrent neural network (RNN), an ensemble model and convolutional neural network (CNN) integrating both method's benefits for enriching the predictive outcome. Thirdly, the author utilized a hyperparameter tuning predictive technique for optimizing the performance of NN. In [12], the issue of EDs in Arabic text can be inspected by offering a group DL method for examining user-generated texts from Twitter. The presented method depends on 3 existing DL methods. Two methods are special kinds of RNNs, and the third method can be a Pre-trained Language Method (PLMs) related to Bidirectional Encoder Representatives from Transformers (BERTs), which is known as MARBERT transformer.

In [13], the author performed an experimental analysis on the development of language methods, from the conventional TF–IDF to sophisticated word embedding word2vec, and lastly current pretrained language method, BERT. Abdullah et al. [14] introduced a Multi-Label Classification (MLC) technique for determining every emotion stated in an Arabic tweet and a Multi-Target Regression (MTR) technique for determining the intensity of emotions. MLC includes the estimation of zero or more classes per sample. The authors [15] constructed a mechanism that categorizes the emotions of Arabic tweets (especially Saudi-related tweets) into suitable feeling classifications utilizing a supervised machine learning (ML) technique. The multinomial Naive Bayes (MNB), support vector machine (SVM) and logistic regression (LR) techniques are utilized as the classification techniques.

In [16], the author aims to classify expressions based on emotions like sadness, happiness, anger, and fear. Various techniques were performed in the zone of automated textual emotion detection in the case of other languages, but only a few are relevant to DL. Therefore, the author presented this technique utilized for classifying emotions in Arabic tweets. This method applies a deep CNN trained on top of trained word vectors, particularly on this data set for sentence classifier errands. Elsayed et al. [17] focused on the serious necessity for detecting what effective role could ML techniques have in the initial identification process of psychological effect on the readers by news headlines. In this study, data sets of news headlines are collected from common online Arabic news websites and are annotated to 7 emotional classes they are surprise, anger, fear, happiness, neutral, disgust, and sadness. A CNN-related 2-level technique has been modelled for sentiment classification.

III. THE PROPOSED MODEL

In this study, we have developed a novel MSGODL-ACAT approach for automated affect classification on Arabic Tweets. The main focus of the MSGODL-ACAT technique existed is the identification and classification of effects or emotions that exist in Arabic tweets. It encompasses data preprocessing, Glove based word embedding, DBN-based affect classification, and MSGO-based parameter optimization. Fig. 1 depicts the comprehensive approach of the MSGODL-ACAT method.

Firstly, the MSGODL-ACAT technique preprocesses the input data to make the Arabic tweets into a meaningful format. The pre-processing step on a text will be regarded as one significant process [18]. In such cases, the SemEval database denotes unmodified tweets gathered in slang form, it includes unwanted noise like Arabizi, special characters, URLs, user mentions, hashtags and punctuation marks. Hence, preprocessing is needed to enrich the analysis process implemented to the raw tweet. Numerous preprocessing stages have been performed. All tweets are tokenized and later normalized. The normalizing process was essential as Arabic tweets are in dialect format. The elongation was eliminated. Lastly, non-Arabic characters and numbers are eliminated. The preprocessing steps are given in the following.

A. DATA PREPROCESSING

Normalization: In this stage, words can be standardized to the official written structure. Diacritics are eliminated like (Kasra, Fatha, Tanwin Damm, Tanwin Fath, Tatwil and Damma). English characters and emojis and words are substituted with wordings that express their sense. It is believed that hashtag comprises various words including feelings of emotion, therefore multi-words are extended for enriching the emotional quality of a tweet.

Irrelevant Noise: Tweets are generally impure and have unrelated data. (∗,/ #- (/). This unrelated data should be cleaned before further processing.

(@user آه طبعا، ما بصير هيك – normalized to اه طبعا ما بصير هيك

Note that in-text classifier issues, and stop words had a vital part in varying the situation from (sadness to happiness). In such cases, the stop words except for the negation are eliminated. The regular expressions and the Natural Language Toolkit (NLTK) utilizing python are the two tools utilized for preprocessing the tweets.

B. GLOVE-BASED WORD EMBEDDING

At this stage, the Glove technique is used for the word embedding process. Word embedding intends for transforming textual data into a vector of real value. Language or Semantic vector space model of language characterizes every word with the real-value vector [19]. Word vectorization can be separated into global matrix factorizations and local context windows such as the Skip-Gram prototype., both methods have shortcomings. Global matrix factorization efficiently applied the statistical data; however, they fail in capturing word similarity. At the same time, the Window founded method effectively capture word similarity however, it feebly applies global data. TF-IDF used the concept of a bag of words. TF-IDF depend on the arithmetical data of words from numerous documentations. The term refers to the word or an ensemble of words; TF represents the term occurrence. TF is the word frequency in the documentation; for normalizing the value, the frequency is separated by the word numbers in one document. Inverse documentation frequency can be represented as IDF whose value is a logarithmic value of the number of documentations separated by the TF. GloVe examines the global illustration of the total corpus and integrates the meaning of the words in this. *Co*-occurrence and word repetition are the two major metrics where the real-value vector of specific words is computed. The gloVe is an unsupervised technique under no human existence to present ground truth meaning into the group of wordings (corpus). The basis of computation is the exploitation of the repetition of specific wordings and the nearby wordings present around all the words. At first, gather the most common word as the context. Next, scan the word in the corpus to construct a *co*-occurrence matrix X. Assume i is an index of repeating words and j is the remaining word in the corpus. P_{ij} shows the possibility of the word j taking place with the contextual word i.

$$P_{ij} = P\left(j \mid i\right) = \frac{X_{ij}}{X_i} \tag{1}$$

Assume i, j, and k as context words; we could evaluate a ratio of *co*-occurrence probability:

$$F\left(w_{j,} w_j \tilde{W}_k\right) = \frac{P_{ij}}{P_{jk}} \tag{2}$$

Lastly, the loss function J is evaluated by:-

$$J = \sum_{i,j=1}^{V} f(X_{ij})(W_i^T \tilde{W}_j + b_i + b_j - logX_{ij})^2, \tag{3}$$

In Eq. (3), f denotes the weighting function. The training model targets to minimalize the minimum square faults. After GloVe training, all the words are allocated to specific real-valued vectors.

C. AFFECT CLASSIFICATION USING DBN MODEL

Here, the MSGODL-ACAT technique makes use of the DBN model for affect classification. The RBM is a stochastic generative ANN that is capable of fitting in a probability dispersion of the input dataset [20]. It consists of 2 dissimilar layers such as the input layer (Visible Layer (VL)) encompassing numerous neurons Hidden Layers (HLs) and input datasets including different neurons resulting from VLs. The VL neuron and HL were interconnected to all the edges, however, the neuron from the like layer was inadequate. Meanwhile, the 2 layers are symmetrically linked and bidirectional. v indicates the VLs and h signifies the HLs. The probability distribution examined by the RBMs amongst VLs and HLs is attained by an energy function and it can be stated as:

$$\begin{aligned} E\left(v, h\right) &= -h^T Wv - a^T v - b^T h \\ &= -\sum_i a_i v_i - \sum_j b_j h_j - \sum_{ij} v_i h_j \end{aligned} \tag{4}$$

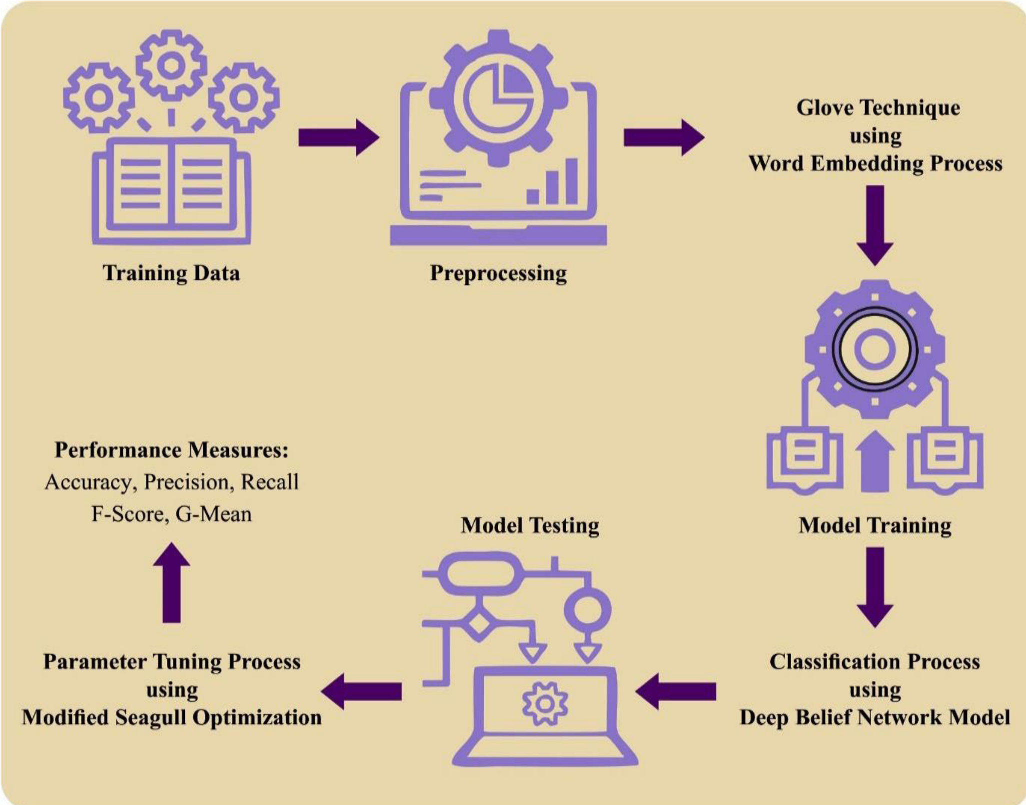

FIGURE 1. The overall process of the MSGODL-ACAT approach.

In Eq. (4), v_i represents the i^{th} VL unit and h_j shows the j^{th} HL unit; W_{ij} indicates the weighted connection amongst v_i and h_j; a_i and b_j correspondingly indicate unit threshold value to VL unit v_i and HL unit h_j.

$$p(v, h) = \exp(-E(v, h))/\{\sum_{v,h} \exp(-E(v, h)) \quad (5)$$

$$P(h_j = 1 \mid v) = sigmoid\left(b_j + \sum_j W_{ij}h_j\right) \quad (6)$$

For every HL, it is given by:

$$P(h \mid v) = \prod_j (h_j|v) \quad (7)$$

To node from the VL, its activation probability was provided by:

$$P(v_i = 1 \mid h) = sigmoid\left(a_j + \sum_i W_{ij}v_i\right) \quad (8)$$

For the VL, it is:

$$P(v \mid h) = \prod_i (v_i|h \quad (9)$$

The probability $P(v)$ could be the probability of v input vector on the concealed unit that is evaluated by:

$$P(v) = \sum_h \{\exp(-E(v, h))/\sum_{v,h} \exp(-E(v, h)) \quad (10)$$

Hence, the objective function is formulated as follows:

$$L(\theta, v) = \sum_{v \in S} \log P(v, \theta) \quad (11)$$

where $\theta \in \{a, b, W\}$;S signifies the data for training the model. By using the Bayesian statistic algorithm, the above-described optimisation problems resolve the parameter adjusting technique by maximizing log probability. Fig. 2 depicts the framework of DBN.

By implementing the gradient ascent method to the objective function, it obtains the succeeding procedures:

$$(\partial \log P(v))/(\partial W_{ij}) = E_P[h_j v_i] - E_{\hat{p}}\left[h_j v_i\right] \quad (12)$$

$$(\partial \log P(v))/(\partial a_i) = E_P[v_i] - E_{\hat{p}}[v_i] \quad (13)$$

$$(\partial \log P(v))/(\partial b_j) = E_P[h_j] - E_{\hat{p}}\left[h_j\right] \quad (14)$$

whereas $E_P[.]$ and $E_P[.]$ denotes the expectation of probability on v in model dispersion $\hat{p}$ and empirical dispersion P. In this work, the primary term of this technique is Eqs. (12) to (14) are computed directly through (6) & (8). However, the next term couldn't be accomplished straightly

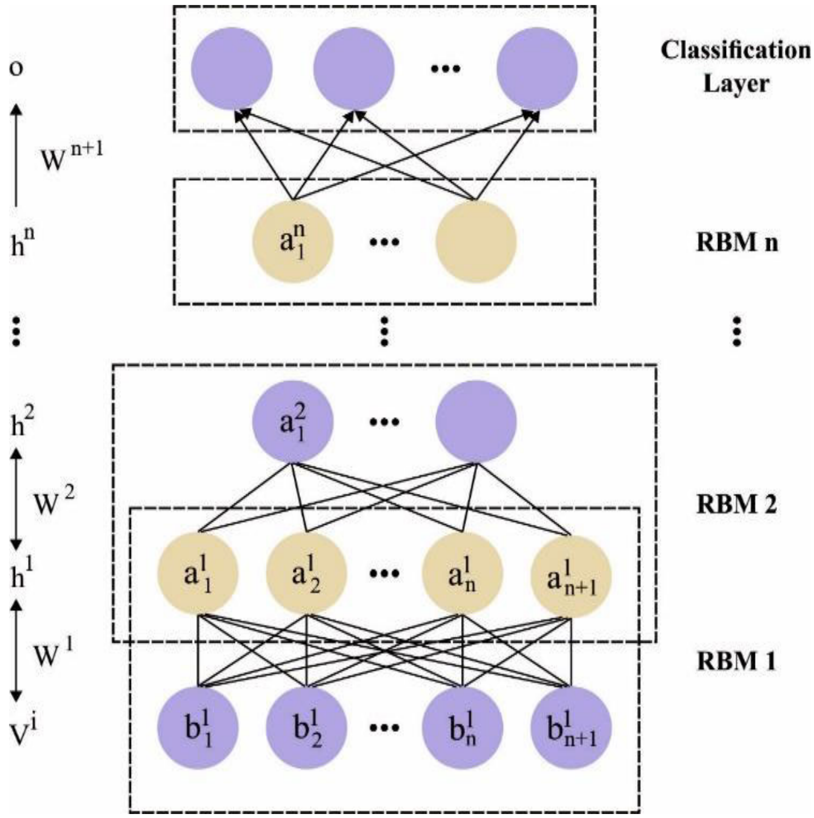

FIGURE 2. Architecture of DBN.

TABLE 1. Details of dataset.

Class	No. of Instances
Anger	500
Joy	500
Fear	500
Sadness	500
Total Number of Instances	2000

since it could be expected from the $\hat{p}$ distribution. It is initiated that alternative Gibbs trialling can be performed to compute these expectations. To obtain an optimal solution, a fast-learning algorithm, Hinton Contrast Divergence (CD) is introduced. The sampling process was sped up by succeeding 2 tricks. At first, a trained sample is used to finish initialized Markov chain and obtain k-steps of Gibbs sampling.

In such cases, CD-1 was implemented, and upgraded the rule to parameter, b, and WV from RBM are employed in Eqs. (15), (16), and (17) that are given by:

$$W^{t+1} = W^t + \varepsilon(P(h|v^{(0)})[v^{(0)}]^T - P\left(h \mid v^{(1)}\right)\left[v^{(1)}]^T\right) \tag{15}$$

$$a^{t+1} = a^t + \varepsilon\left(v^{(0)} - v^{(1)}\right) \tag{16}$$

$$b^{t+1} = b^t + \varepsilon\left(P\left(h \mid v^{(0)}\right) - P\left(h \mid v^{(1)}\right)\right) \tag{17}$$

Now t shows the time step and ε indicate the learning rate. DBN is a kind of NN encompassing l layers. The initial layer is VL with vector χ as input. The last layer could be the resulting layer h^1. The layer amongst them is called as HLs illustrated by $h^1, \ldots, h^{l-1}$.

D. HYPERPARAMETER OPTIMIZATION

Lastly, the MSGO algorithm is employed for the optimal hyperparameter tuning of the DBN prototype. The basic steps of the SGO are discussed in this section, The SGO simulate the natural seagulls' search for food [21]. Generally, the SGO simulate these behaviours through a set of stages defined in the following. Migration behaviour mimics a swarming of seagulls flying from one place to another. A seagull should satisfy the subsequent three conditions: collision avoidance, the movement towards the better neighbouring direction, and remaining closer to the better searching agent. Parameter A improves the observed seagull's value for preventing collision with neighbouring seagulls, as follows.

$$P_{\vec{N}} = A \times \vec{P}_c(i) \tag{18}$$

Now, $\vec{P}_N$ denotes the value of non-colliding agents, A shows the motion behaviour of the agent and $\vec{P}_c$ shows the existing solution at the $i-th$ iteration:

$$A = f_c - \left(i \times \left(\frac{f_c}{\text{Max}(i)}\right)\right) \tag{19}$$

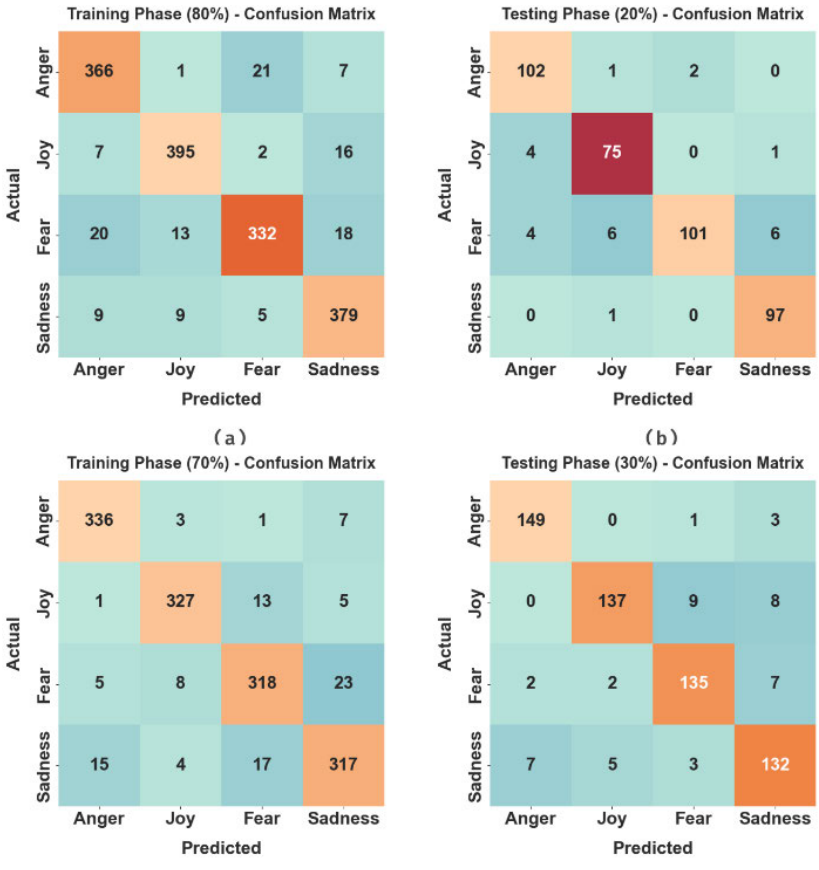

FIGURE 3. Confusion matrices of MSGODL-ACAT algorithm (a-b) TRS/TSS of 80:20 and (c-d) TRS/TSS of 70:30.

TABLE 2. Classifier outcome of MSGODL-ACAT system under 80:20 of TRS/TSS.

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	G_{mean}
Training Phase (80%)					
Anger	95.94	91.04	92.66	91.84	94.81
Joy	97.00	94.50	94.05	94.27	96.03
Fear	95.06	92.22	86.68	89.37	92.03
Sadness	96.00	90.24	94.28	92.21	95.42
Average	96.00	92.00	91.92	91.92	94.57
Testing Phase (20%)					
Anger	97.25	92.73	97.14	94.88	97.22
Joy	96.75	90.36	93.75	92.02	95.61
Fear	95.50	98.06	86.32	91.82	92.58
Sadness	98.00	93.27	98.98	96.04	98.33
Average	96.88	93.60	94.05	93.69	95.93

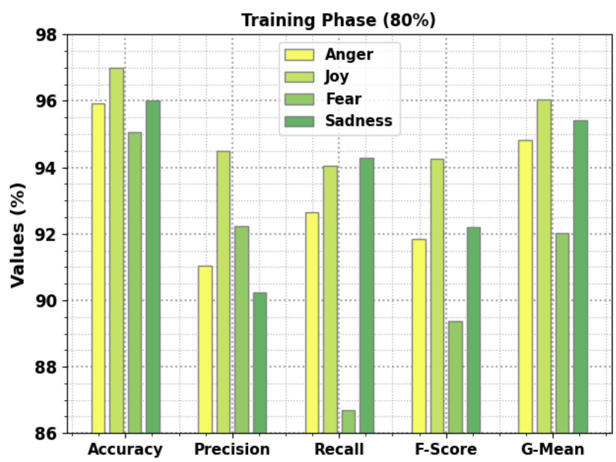

FIGURE 4. Classifier outcome of MSGODL-ACAT system on 80% of TRS.

In Eq. (19), f_c signifies the frequency control of A from $[0,f_c]$. Afterwards the effective avoidance of collision with adjacent seagulls, the searcher goes towards the direction of a better solution. This procedure can be determined by:

$$\vec{d}_e = B \times \left(\vec{P}_b(i) - \vec{P}_c(i)\right) \tag{20}$$

In Eq. (20), d_e denotes the location of $P(i)$ towards $P_b(i)$. The coefficient B represents a random number which controls exploitation and exploration. The values of B are evaluated by:

$$B = A^2 \times R \times 2 \tag{21}$$

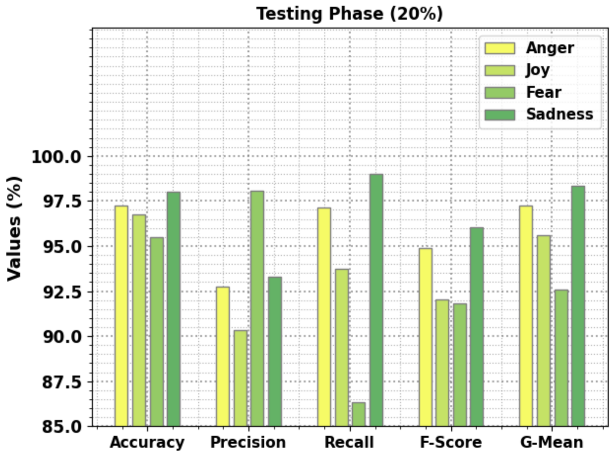

FIGURE 5. Classifier outcome of MSGODL-ACAT system on 20% of TSS.

TABLE 3. Classifier outcome of MSGODL-ACAT system under 70:30 of TRS/TSS.

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	G_{mean}
Training Phase (70%)					
Anger	97.71	94.12	96.83	95.45	97.42
Joy	97.57	95.61	94.51	95.06	96.52
Fear	95.21	91.12	89.83	90.47	93.36
Sadness	94.93	90.06	89.80	89.93	93.17
Average	96.36	92.73	92.74	92.73	95.12
Testing Phase (30%)					
Anger	97.83	94.30	97.39	95.82	97.69
Joy	96.00	95.14	88.96	91.95	93.58
Fear	96.00	91.22	92.47	91.84	94.77
Sadness	94.50	88.00	89.80	88.89	92.86
Average	96.08	92.16	92.15	92.12	94.72

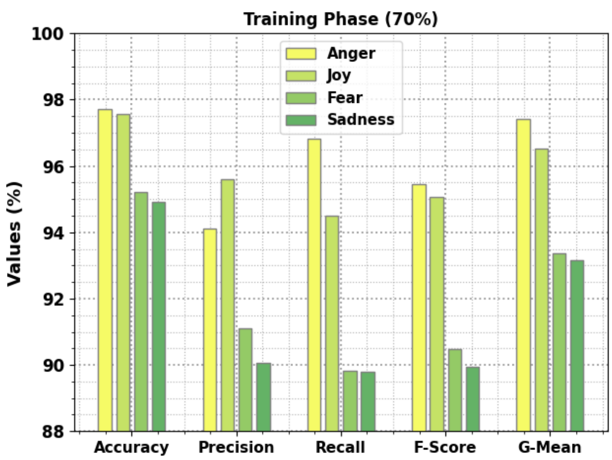

FIGURE 6. Classifier outcome of MSGODL-ACAT system on 70% of TRS.

In Eq. (21), R is produced within [0, 1]. The last stage includes updating the agent location using the better agent with the subsequent equation:

$$D_e = \rightarrow \left|\vec{P}_N + \vec{d}_e\right| \tag{22}$$

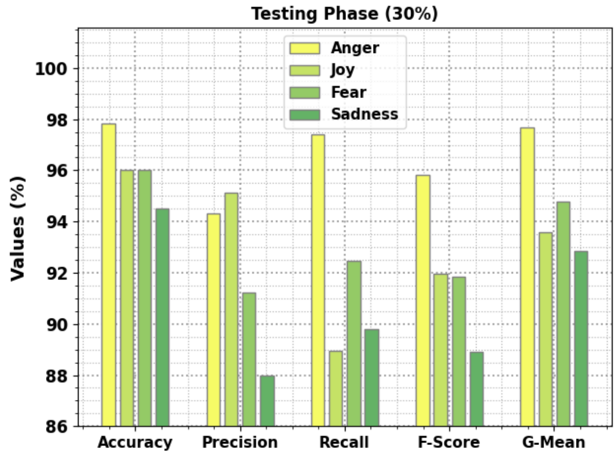

FIGURE 7. Classifier outcome of MSGODL-ACAT system on 30% of TSS.

Now, D_e shows the distance from the agent to the better agent. During the migration phase, The attack angle and speed might change continuously while seagulls strike. They preserve the altitude by utilizing the wings and weight. The attack causes the air to behave in a spiralling mode. The behaviour of the movement in the $(x, y,\ and\ z)$ planes is mathematically expressed by:

$$\hat{x} = s \times cos\,(g) \tag{23}$$

$$\hat{y} = s \times sin\,(g) \tag{24}$$

$$\hat{Z} = s \times g, s = \alpha \times e^{\beta t} \tag{25}$$

Now s indicates the radius of spiral turns and g shows the random number $[0, 2\pi]$.α and β denote the shape of a spiral. Furthermore, e represents the base of the natural logarithm. Furthermore, the seagull location is upgraded as follows:

$$\vec{P_c}\,(i) = \left(\vec{D}_e \rightarrow +\hat{x} + \hat{y} + \hat{z}\right) + \vec{P_b}\,(i) \tag{26}$$

Occasional premature convergence and Low convergence performance, i.e. local convergence, which causes low optimized performance were the main disadvantages of the SGO technique [22]. In this study, a modification was modelled for resolving such shortcomings utilizing certain systems. A powerful tool called Lévy flight (LF) was utilized for mitigating the premature convergence issue of this technique. To precisely control local search, an arbitrary movement was combined which is as follows:

$$LF\,(a) \approx a^{-1-v} \tag{27}$$

$$a = \frac{A_1}{\sqrt[v]{|A_2|}} \tag{28}$$

$$A_1, A_2 \sim N\left(0, \sigma^2\right) \tag{29}$$

$$\sigma^2 = \left\{\frac{\Gamma\,(1+v)}{v\Gamma\left(\frac{1+v}{2}\right)} \times \frac{\sin\left(\frac{\pi v}{2}\right)}{2^{\frac{1+v}{2}}}\right\}^{\frac{2}{v}} \tag{30}$$

Lévy index, displayed by v, is in the range of $[0-2]$ which is selected as 1.5 here. Eq. (29) specifies that A_1 and A_2

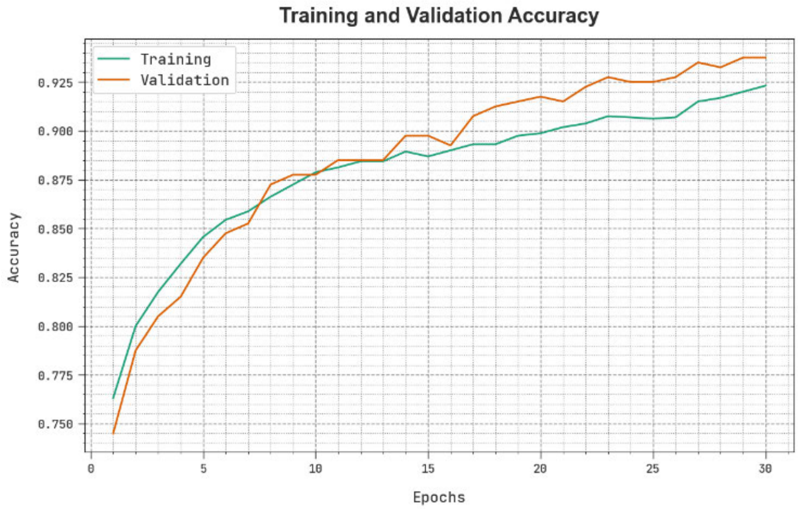

FIGURE 8. TACC and VACC analysis of MSGODL-ACAT approach.

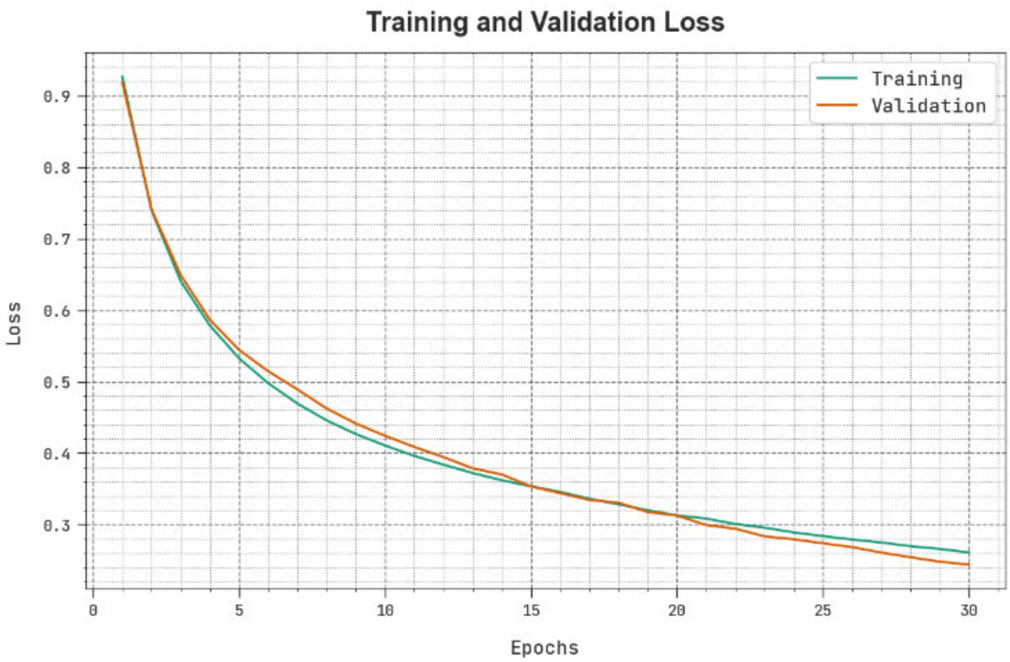

FIGURE 9. TLS and VLS analysis of MSGODL-ACAT approach.

belonged to a Gaussian distribution with an average of 0 and variance of σ^2. The novel equation to update the location of candidates is given below:

$$\vec{L}_{\text{i-fittest}_{new}} = \vec{L}_{\text{i-fittest}} + \left| PN_i - \vec{V}_{\text{i-fittest}} \right| \times LF\,(a) \quad (31)$$

Additionally, the Singer function was presented for the optimization of increasing the convergence rate. The random variables Ra, M, s, offered correspondingly, were provided novel values for incorporating the chaos function:

$$Ra_{i+1} = 1.07\left(7.9Ra_i - 23.3Ra_i^2 + 28.7Ra_i^3 - 13.3Ra_i^4\right)$$
$$M_{i+1} = 1.07\left(7.9M_i - 23.3M_i^2 + 28.7M_i^3 - 13.3M_i^4\right)$$
$$s_{i+1} = 1.07\left(7.9s_i - 23.3s_i^2 + 28.7s_i^3 - 13.3s_i^4\right) \quad (32)$$

The following value assignment can be done to achieve the fastest movement towards the fittest candidate:

$$\vec{L}_{\text{i-fittest}_{\text{new}}} = \begin{cases} \vec{L}_{i-fittest}, & F(\vec{D}_{el}|) \leq F(\vec{D}_e) \\ \vec{L}_{i-fittest_{new}}, & otherwise \end{cases} \quad (33)$$

The MSGO method derived a Fitness Function (FF) to have an enhanced classifier output. It sets positive values for signifying superior results of the candidate resolutions. In the study, the lessening of the classification error rate will be regarded as the FF, as given in Eq. (34).

$$fitness\,(x_i) = ClassifierErrorRate\,(x_i) = \frac{number\ of\ misclassified\ samples}{Total\ number\ of\ samples} * 100 \quad (34)$$

TABLE 4. Comparative evaluation of MSGODL-ACAT approach with other algorithms.

Methods	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
MSGODL-ACAT	96.88	93.60	94.05	93.69
BiGRU-CNN [19]	67.92	69.18	70.04	69.89
CNN Model [19]	71.25	71.31	70.99	70.91
XG Boost [19]	70.36	70.91	71.56	72.16
Ensemble [19]	72.69	72.70	72.36	73.64
SVM-Unigrams [24]	58.57	59.47	59.65	60.90

IV. RESULTS AND DISCUSSION

The proposed model is experimented on PC i5-8600k, GeForce 1050Ti 4GB, 16GB RAM, 250GB SSD, and 1TB HDD. The parameter settings are given as follows: learning rate: 0.01, dropout: 0.5, batch size: 5, epoch count: 50, and activation: ReLU.In this section, the affect classification outputs of the MSGODL-ACAT approach are investigated under the open access dataset [23], encompassing 2000 trials into four categories, as demonstrated in Table 1. The provided files include a header row which indicates what the columns represented such that ID, Tweets, Affect DimensionEmotion, and intensity Score which has a value between 0–1. The dataset comprising four classes namely anger, joy, fear, and sadness. The data is provided participants with annotated datasets for training and evaluation purposes. These datasets contained a large number of tweets, manually labeled with emotion categories and sentiment polarity. The availability of these datasets facilitated the development and evaluation of affect analysis systems. For experimental validation, we have used 80:20 and 70:30 of training/testing dataset.

In Figure 3, the confusion matrix of the MSGODL-ACAT approach on affect classification is shown with a distinct Training Set (TRS) and Testing Set (TSS). With 80% of TRS, the MSGODL-ACAT technique has categorized 366 instances into anger, 395 instances into joy, 332 instances into fear, and 379 instances into sadness. Eventually, with 20% of TSS, the MSGODL-ACAT approach has categorized 102 instances into anger, 75 instances into joy, 101 instances into fear, and 97 instances into sadness. Meanwhile, with 70% of TRS, the MSGODL-ACAT method has categorized 336 instances into anger, 327 instances into joy, 318 instances into fear, and 317 instances into sadness.

In Table 2, the effect of categorization outputs of the MSGODL-ACAT approach with 80:20 of TRS/TSS is provided. Fig. 4 demonstrates the classifier results of the MSGODL-ACAT technique with 80% of TRS. The outcomes inferred that the MSGODL-ACAT approach has recognized four types of effects proficiently. Additionally, it is noticed that the MSGODL-ACAT approach has obtained an average $accu_y$ of 96%, $prec_n$ of 92%, $reca_l$ of 91.92%, F_{score} of 91.92%, and G_{mean} of 94.57%.

Fig. 5 illustrates the categorizer outcomes of the MSGODL-ACAT method with 20% of TSS. The outcomes inferred that the MSGODL-ACAT algorithm has recognized four types of effects proficiently. Additionally, it is noted that the MSGODL-ACAT methodology has attained an average $accu_y$ of 96.88%, $prec_n$ of 93.60%, $reca_l$ of 94.05%, F_{score} of 93.69%, and G_{mean} of 95.93%.

In Table 3, the effect of categorization results of the MSGODL-ACAT approach with 70:30 of TRS/TSS is given. Fig. 6 exhibits the categorizer outputs of the MSGODL-ACAT procedure with 70% of TRS. The outcomes exhibit the MSGODL-ACAT method has recognized four types of effects proficiently. Additionally, it is noted that the MSGODL-ACAT method has attained an average $accu_y$ of 96.36%, $prec_n$ of 92.73%, $reca_l$ of 92.74%, F_{score} of 92.73%, and G_{mean} of 95.12%. Figure 7 shows the categorizer outcomes of the MSGODL-ACAT procedure with 30% of TSS. The results concluded that the MSGODL-ACAT approach has recognized four types of effects proficiently. Furthermore, it is noted that the MSGODL-ACAT method has attained an average $accu_y$ of 96.08%, $prec_n$ of 92.16%, $reca_l$ of 92.15%, F_{score} of 92.12%, and G_{mean} of 94.72%.

The training accuracy (TACC) and validation accuracy (VACC) of the MSGODL-ACAT technique are examined to affect categorizer accomplishment in Figure 8. The picture implied that the MSGODL-ACAT method has depicted an enhanced achievement with increased values of TACC and VACC. Notably, the MSGODL-ACAT procedure has attained maximum TACC results.

The training loss (TLS) and validation loss (VLS) of the MSGODL-ACAT algorithm are examined to affect classifier accomplishment in Figure 9. The picture exhibited the MSGODL-ACAT procedure has stated better achievement with lesser values of TLS and VLS. Seemingly the MSGODL-ACAT procedure has mitigated VLS results.

A clear precision-recall study of the MSGODL-ACAT approach under the trial dataset is given in Figure 10. The picture shows the MSGODL-ACAT procedure has enhanced values of precision-recall values under all categories.

The detailed receiver operating characteristic (ROC) curve study of the MSGODL-ACAT approach under the trial dataset is depicted in Figure 11. The outcomes exhibited by the MSGODL-ACAT method have shown its capability in classifying discrete classes under a test database.

In Table 4, an overall affect classification accomplishment of the MSGODL-ACAT procedure with other prototypes was taken place [19], [24]. The attained results specified that the SVM-unigrams prototype reaches worse results than other models. Next, the BiGRU-CNN model has managed to gain slightly improvised results over the SVM-unigrams model. Along with that, the CNN, XGBoost, and ensemble models have accomplished considerably nearer classification performance. But the MSGODL-ACAT technique shows promising results with $accu_y$ of 96.88%, $prec_n$ of 93.60%, $reca_l$ of 94.05%, and F_{score} of 93.69%. These results demonstrate the superior accomplishment of the MSGODL-ACAT method over other methods.

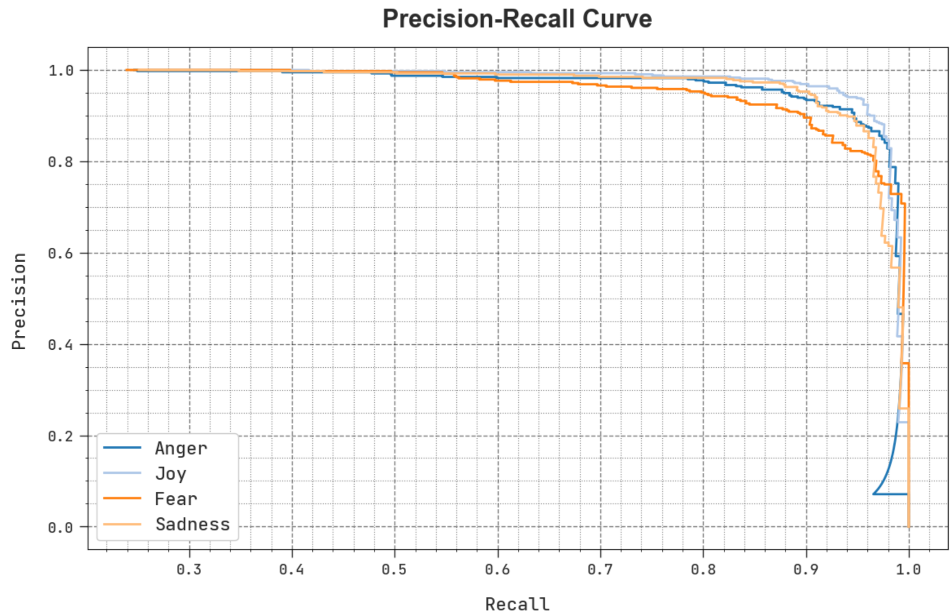

FIGURE 10. Precision-recall evaluation of MSGODL-ACAT procedure.

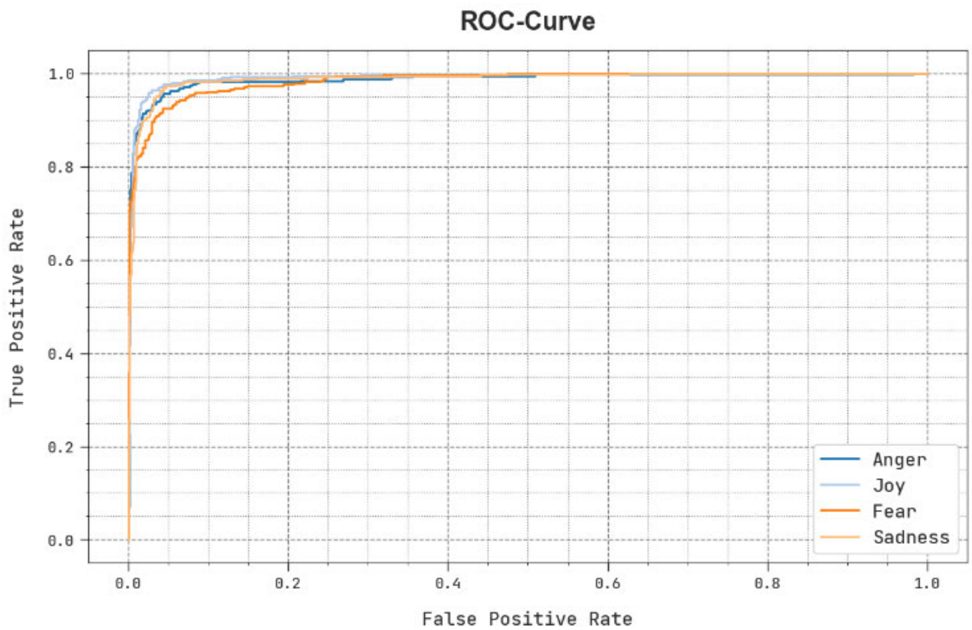

FIGURE 11. ROC evaluation of MSGODL-ACAT procedure.

V. CONCLUSION

In this study, we have established a novel MSGODL-ACAT approach for automated affect classification on Arabic Tweets. The main focus of the MSGODL-ACAT technique existed is the identification and classification of effects or emotions that exist in Arabic tweets. At the preliminary level, the MSGODL-ACAT technique preprocesses the input data to make the Arabic tweets into a meaningful format. Next, the Glove technique is used for the word embedding method. Furthermore, the MSGODL-ACAT procedure utilizes the DBN prototype for affect categorization. At last, the MSGO algorithm is employed for the optimal hyperparameter tuning of the DBN prototype which in turn enhances the classification results. The investigational examination of the MSGODL-ACAT approach is examined using Arabic tweets databases. The experimental outcome signifies the effectual performance of the MSGODL-ACAT technique over other recent approaches. Currently, affect classification typically focuses on coarse-grained emotion categories. Future work can delve into fine-grained emotion detection, distinguishing subtle variations within emotion categories, such as distinguishing between different levels of happiness or anger expressed in Arabic tweets. In addition, future work can explore techniques to account for dialectal variations in affect classification, ensuring the model's effectiveness across different dialects present in Arabic tweets.

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