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An efficient way of text-based emotion analysis from social media using LRA-DNN

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ABSTRACT

Text devices are effectively and heavily used for interactions these days. Emotion extraction from the text has derived huge importance and is upcoming area of research in Natural Language Processing. Recognition of emotions from text has high practical utilities for quality improvement like in Human-Computer Interaction, recommendation systems, online education, data mining and so on. However, there are the issues of irrelevant feature extraction during emotion extraction from text. It causes mis-prediction of emotion. To overcome such challenges, this paper proposes a Leaky Relu activated Deep Neural Network (LRA-DNN). The proposed model comes under four categories, such as pre-processing, feature extraction, ranking and classification. The collected data from the dataset are pre-processed for data cleansing, appropriate features are extracted from the pre-processed data, relevant ranks are assigned for each extracted feature in the ranking phase and finally, the data are classified and accurate output is obtained from the classification phase. Publically available datasets are used in this research to compare the results obtained by the proposed LRA-DNN with the previous state-of-art algorithms. The outcomes indicated that the proposed LRA-DNN obtains the highest accuracy, sensitivity, and specificity at the rate of 94.77%, 92.23%, and 95.91% respectively which is promising compared to the existing ANN, DNN and CNN methods. It also efficiently reduces the mis-prediction and misclassification error.

1. Introduction

With the rapid growth of social media, users tend to share their emotions, opinions, and feelings on social media platforms, such as Twitter, Facebook, YouTube, etc. [1]. Although the users of social media reveal their emotions through audio and videos, preferred way to express the sentiments is through text [2]. People tend to express the sentiments through social media in the form of posts, status, comments and blogs. These posts need to be analyzed to know what emotion is conveyed through these posts [3]. The ability to recognize emotional cues is fundamental in social interactions, as these signals are necessary in the decoding of others' mental state and behavioural responses [4]. Emotion recognition has been important because emotions are taking different forms like stress [5]. In order to cure the patients' even health psychologists are studying for emotion extraction for establishing the link between physical health, stress and emotions [6].

Neurocognition has several areas of growing research towards extraction of emotional intelligence through different modalities be it text, audio or video. There exists strong relationship between emotional intelligence and neurocognition in severe mental disorders. If the machines be made enough intelligent to recognize the emotions, it will be helpful in studying the factors related to emotional intelligence, with special interest in neurocognitive deficits [7].

Prototypes developed for emotion recognition have several merits in neurocognition field. For example, period of adolescence is of high emotional reactivity. If the machines can be made to understand the emotions of a particular adolescent group, it opens

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up several avenues for the research in neurocognition regarding adolescent-specific behaviours and its related evidences [8].

Emotion detection is being studied in order to provide indications for future interactions between people, permitting computers to operate as social agents and produce more trustworthy results. Over the last decade, much effort has been invested towards identifying users' emotional states utilizing multimodal inputs such as voice, gestures and eye gazes, in addition to text detection [9,10]. Emotion detection is closely related to Sentimental analysis, which uses natural language processing [11]. The Sentimental analysis deals with identifying the positive, negative, and neutral nature of the text whereas the Emotion Analysis deals with seven basic emotions like disgust, fear, joy, anger, guilt, sadness and shame [12,13]. Thus, the recognition of emotions from the text can be used to improve customer services, business sectors, marketing and also serves as a measure of social media performance [14].

The COVID 19 outbreak also had an impact on individuals all across the world. Individuals have been subjected to preventative measures such as physical isolation and words like "lockdown," "emergency," and "curfew" has been coined in various countries. It has had a huge influence on society, not just physically and financially, but also emotionally. Financial implications, family member behaviour and support, country-specific lockdown measures, media influence, and pandemic fear all contribute to this discomfort in the human emotional quotient. Understanding the emotional differences between individuals is critical for effective pandemic management because it provides insight into public attitudes about various government pandemic control tactics [15,16].

Text-based emotion recognition has a key role in human-computer interaction [17]. For the efficient detection of emotions from the text, it undergoes various steps, such as preprocessing, feature extraction, ranking, classification, and validation [18]. In preprocessing, the input data are transformed into an understandable form by neglecting unwanted data [19]. In the feature extraction phase, the most appropriate and relevant features are extracted. The rank assigning process for each extracted feature is done in the ranking phase [20,21]. Then the data are classified in the classification and provides the accurate output. Finally, the validation phase validates the final outcome and checks whether the data is correctly classified or not. However, the emotion detection faces many issues when a comment contains multiple emotions [22]. Decision- is heavily influenced by emotions. Affective computing takes this into account in order to tailor decision support to distinct emotional states. However, because of the richness and complexity of language, precisely identifying emotions within narrative elements is a tough undertaking [23,24]. There are also the challenges like implicit emotion expression in a comment or the comment containing the sarcastic piece of text [25,26].

In an attempt to conquer such challenges, various existing techniques, such as RNN [27], CNN [28], LSTM [29] and SVM [30] are introduced. However, the traditional algorithm has its applications. On the other hand, it also possesses various issues in the recognition of emotions from the short text and abbreviated text, inadequate for effective feature extraction for emojis and special symbols which may cause analysis errors [31].

There are many complexities in the recognition of emotions from the text and many issues are to be addressed [32]. Unsupervised learning, on the other hand, is a machine learning strategy for constructing emotion classification models in which the underlying pattern in unlabelled training data is analyzed to reach a judgement. Unlike supervised machine learning, unsupervised learning methods employ unknown and unmarked input and output data [33]. So, the work has developed an efficient way of emotion detection from the text using the LRA-DNN technique. A novel technique has been introduced for the ranking evaluation of the extracted features. A meta-heuristic algorithm Elephant Heard Optimization (EHO) is merged with the Brownian Motion (BM) technique for the selection of the most relevant ranks to the extracted features. It has increased the performance and accuracy rate of the classifier.

Organization of the paper: Section 2 provides the literature review of the associated works, Section 3 explains the proposed methodology of text-based emotion detection and Section 4 illustrates the results and analysis for the proposed system based on performance metrics. Finally, Section 5 provides the conclusion of the associated work.

2. Literature survey

Dongliang Xu et al. [34] developed a microblog emotion classification model, named CNN_Text_Word2vec, based on the convolutional neural network (CNN). The method effectively extracted the significant features and also achieved a good classification effect. The experimentation results showed that the emotional classification accuracy of the scheme is 7%, 6.9% and 2.91% higher than that of SVM, RNN and LSTM, respectively. But, it had a limitation of improper ranking between the features.

Srishti Vashishtha et al. [35] developed the sentiment analysis of social media posts based on a set of fuzzy rules, which involved multiple lexicons and datasets. The fuzzy system integrated the Natural Language Processing (NLP) techniques and Word Sense Disambiguation based on a novel unsupervised nine fuzzy rule-based system for classification. The scheme provided the exact sentiment values and also dealt with the linguistic problems. Experimentation result showed that the scheme achieved higher performance as compared to the other state-of-the-art methods. However, the scheme exhibits a high error rate, which leads to inaccurate classification.

Jun Li et al. [36] introduced a multi-label maximum entropy (MME) model for user emotion classification over short text. MME generated rich features based on the multiple emotion labels and valence scored by numerous users. Thus, the scheme successfully identified the entities and provides the relevant social emotions for the generated lexicons. The experimentation results validated the effectiveness of the method on social emotion classification over the sparse features. However, the scheme had over fitting issues.

Fazeel Abid et al. [37] developed a scheme, which concatenated the distributed word representations DWRs through a weighted mechanism on Recurrent Neural Network (RNN) variants joint with Convolutional Neural network (CNN), which involved in weighted attentive pooling (WAP). The scheme addressed the issues of syntactic and semantic regularities as well as out of vocabulary (OOV) words. The experimentation analysis revealed that the scheme achieved an accuracy rate of 89.67%. But, it had a limitation of inadequate feature extraction which led to analysis error.

Peng Wu et al. [38] developed an Ortony-Clore-Collins (OCC) model and a Convolutional Neural Network (CNN) based opinion summarization method for Chinese microblogging systems. The scheme highlighted the potential of combined emotion cognition with deep learning in sentiment analysis of social media data. The experimental result demonstrated that the scheme outperformed the other state-of-the-art methods in terms of classification and recognition performance. But, the scheme had a complexity of microblog sentiment classification.

Muhammad Asif et al. [39] implemented the sentimental analysis of social media multilingual textual data, and discovered the intensity of the sentiments of extremism. Thus, the scheme effectively found the extreme sentiment from multilingual data. The experimentation result shows that the scheme achieves an overall accuracy at the rate of 82%. Thus the scheme outperforms the existing technique in terms of scalability and reliability. However the

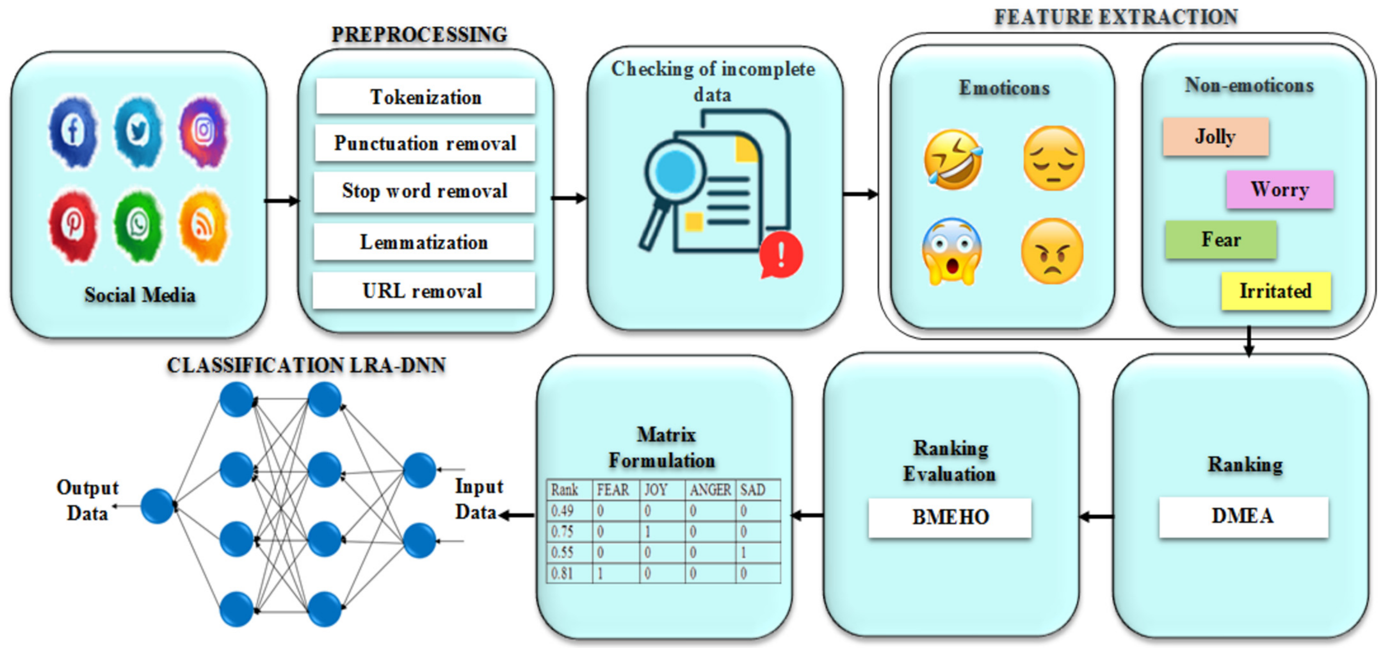


Fig. 1. Architecture of the proposed work.

scheme had performance degradation in the recognition of multimodal sentiment.

Currently, the process of identifying appropriate keywords for extracting emotions relies on the availability of human experts which does not scale well considering that different areas are rapidly evolving. This problem prompted [40] to develop a tool to automatically filter the most likely terms preferred by human experts.

3. Proposed methodology

Emotion detection is the process of understanding the true meanings and emotions, such as joy, sadness, anger, disgust, guilt, fear, and shame behind the text and the emojis. The emotion analysis technique uses natural language processing and information extraction techniques for the effective analysis of the text. Thus, the emotion analysis from text contributes towards knowing a person's opinion or mindset through their post on social media. However, recognizing textual emotions is a major challenge that often led to the misprediction of emotions. So the work deals with a proficient emotion analysis on social media data using LRA-DNN. Initially, the preprocessing step is carried out in which the input social media data from the publicly available database are transformed into the most appropriate and understandable format. Secondly, the most relevant features are extracted and certain ranks are assigned for each feature. Then, the ranks are optimized using BMEHO, and it is represented in the matrix format. Finally, the classification is done using LRA-DNN; it classifies the accurate emotions of the input data. Hence, the work achieves efficient emotion detection from the text. The architecture of the proposed work is shown in Fig. 1.

Fig. 1 depicts the architecture of the proposed algorithm. It includes the various blocks which defines the reactions of the persons on social media. However, following subsections explain each block in the architecture in detail.

3.1. Preprocessing

There is always unwanted part in the social comments. The preprocessing stages remove those parts from the comments which ultimately helps in improving the accuracy. In this study, the pre-processing undergoes six different steps, such as tokenization, punctuation removal, stop word removal, lemmatization and URL removal. Mathematically, representation of pre-processing function can be done as:

$$p_r = \lambda_p[I_t] \tag{1}$$

Where, p_r is the output of pre-processing function. I_t is the input data and λ_p is the pre-processing function that is represented by

$$\lambda_p = [\lambda_{tk}, \lambda_{pr}, \lambda_{sr}, \lambda_{lm}, \lambda_{ur}] \tag{2}$$

Where λ_{tk} is the tokenization function, λ_{pr} is the punctuation removal function, λ_{sr} is the stop words removal function, λ_{lm} is the lemmatization function, and λ_{ur} is the URL removal function.

3.1.1. Tokenization

Initially, the input text is subjected to a tokenization process in which the entire text is separated into smaller units called tokens. The tokenization process helps the machine to understand the text easily. The tokenization function is given by

$$\lambda_{tk} = [I_{t1}, I_{t2,} I_{t3,\ldots..} I_{tn}] \tag{3}$$

3.1.2. Punctuation removal

After the tokenization, the removal of the punctuation process is carried out in which the punctuation marks (';!.,":?) are removed from the tokenized data for a better analysis of the text. The removal of the punctuation process is given by

$$\lambda_{p_1} = \lambda_{pr}[I_t] \tag{4}$$

3.1.3. Stop word removal

Stop words are frequently used words that hardly contributes any meaning in any language. To name the few are "the", "a", "is", "are", "or" etc. These stop words have very little amount of information for emotion analysis from the text, such words are discarded so that the quality of the text gets improved.

3.1.4. Lemmatization

After the removal of the stop word, the lemmatization process is carried out in which the root words are analyzed. The root words are nothing but the meaningful base form of the text, which is called the lemma. For example exciting, excites, excited, excitement exhibits the same meaning in which the root word or lemma is “excite”.

3.1.5. URL removal

Finally, the URL removal process takes place. The URL mentions the location of the resource that does not provide any required information for sentiment analysis.

3.2. Checking of incomplete data

Even a small percentage of incomplete data can cause misprediction of emotions in the text in order to deal with such an issue; the checking of incomplete data is done. In which, it checks the presence of incomplete or irrelevant data from the preprocessed data. If any incomplete data are present, then it replaces such data with complete meaningful data so that the data can be synthesized correctly and provides relevant emotions.

For example “gd mrng” can be replaced as “good morning”, “c u tmrw” can be replaced as “see you tomorrow”, “Lol” can be replaced as “Laugh out loud”, “b4” can be replaced as “before”, “2day” can be replaced as “today”. Thereafter, the completed data undergoes a feature extraction process.

3.3. Feature extraction

In feature extraction method, it extracts the features that are more appropriate to the data and the redundancy of the data is also reduced. In the proposed method, the feature extraction is done by extracting both emoticons and non-emoticons features. Emoticons feature represents the icons that express the emotions, for example, smilies and non-emoticons features represent simple text without any icons or smilies. The mathematical expressions of the extracted features are given by

$$F_{ex}(p_r) = (F_i^E, F_i^{nE}) \tag{5}$$

$$F_i^E = [F_1^E, F_2^E, F_3^E, ...F_n^E] \tag{6}$$

$$F_i^{nE} = [F_1^{nE}, F_2^{nE}, F_3^{nE}, ...F_n^{nE}] \tag{7}$$

Where, F_i^E and F_i^{nE} is the emoticon feature and non-emoticon feature respectively and $i = 1, 2, 3, ..., n$.

After extracting the emoticon and non-emoticon features, the rank assigning process is carried out. In which the relevant ranks are assigned for each feature based on some criteria. For emoticon features, the ranking has been done on the basis of their polarity. For non-emoticon features, the rank assigning process is done by using the Depeche mood emotion analysis technique. A brief explanation of the ranking process is given in the below section.

3.3.1. Ranking of emoticon features

For the emoticon features, certain rank values are assigned for each emojis based on their polarity. In the proposed method, the emojis are classified under seven different classes and specific rank values are given to each class, respectively. The emojis that come under the class “Joy” is ranked as 1. The rank value of the emojis under the class “sad” is assigned as 0, the ranks of the emojis under the class angry are assigned as 0.5, and the emojis that come under the class “disgust” is assigned as 0.75. For the class “guilt”, the rank value is given as 0.25, the emojis under the class “fear” is assigned as 0.65, and finally, the emojis that are categorized under the class shame is assigned as 0.32.

Table 1
List of emoticon features with their ranks.

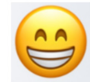
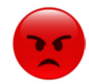
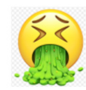
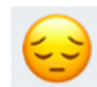
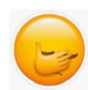
Emoticon	Meaning	Rank	Class
	Big grin	1	Joy
	Crying	0	Sad
	Angry face	0.5	Anger
	Vomiting	0.75	Disgust
	Pensive face	0.25	Guilt
	Fearful face	0.65	Fear
	Ashamed	0.32	Shame

Table 1 depicts the list of emojis with their specific meaning, their rank values as well as their corresponding classes. The tabulation comprises seven different classes, such as joy, sadness, anger, disgust, guilt, fear and shame along with their rank values. The emojis like big grin comes under the class joy with the rank value of 1 and the emojis like crying, angry face, vomiting, pensive face, fearful face, ashamed are categorized under the classes sad, anger, guilt, fear and shame respectively, with their corresponding rank values.

3.3.2. Ranking of non-emoticon features using Depeche mood

After extracting the non-emoticon features, the extracted features are ranked using the Depeche mood emotion analysis technique (DMEA) in which the rankings are done on the basis of emotion score.

In the DMEA technique, each term is annotated with its corresponding numerical score value, which indicates the emotion class of the information. Among them, the highest predominant numerical score value of the class is considered as the final rank value of a word. The tabulation comprises seven different classes, such as fear, joy, angry, sad, guilt, disgust, and shame. The word sorry contains seven kinds of numerical score values such as 0.11, 0.19, 0.04, 0.13, 0.49, 0.08, and 0.32 that indicates seven different classes like fear, joy, angry, sad, guilt, disgust, and shame respectively. From this, the value 0.49 is the highest predominant score value and that mentions the class guilt. So, the term sorry comes under the class guilt with the rank value of 0.49. Likewise, the ranking has been done for the other terms like fun, upset, nervous, nausea, shut up, and ashamed (see Table 2).

3.4. Ranking evaluation

The extracted features contain more amount of information; hence, there is the chance for the occurrence of computational complexity as well as time complexity in classifying the emotions. In order to rectify such issues, the evaluation of ranking has been

Table 2
List of non-emoticon features with their rank values using Depeche mood emotion analysis technique.

Words	FEAR	JOY	ANGRY	SAD	GUILT	DISGUST	SHAME
sorry	0.11	0.19	0.04	0.13	**0.49**	0.08	0.32
Fun	0.21	**0.75**	0.15	0.06	0.42	0.17	0.25
upset	0.16	0.35	0.02	**0.55**	0.43	0.31	0.30
nervous	**0.81**	0.72	0.63	0.18	0.09	0.48	0.56
nausea	0.62	0.51	0.64	0.36	0.45	**0.90**	0.62
Shut up	0.43	0.21	**0.79**	0.19	0.52	0.10	0.28
ashamed	0.56	0.46	0.61	0.33	0.41	0.58	**0.95**

done, in which the most relevant and informative features are selected. For better feature selection, the proposed methodology uses the developed version of EHO that is named BEHO. The developed algorithm alleviates the computational complexity and also improves the accuracy of the classification model.

3.4.1. BMEHO for ranking evaluation

Elephant Heard Optimization (EHO) is a meta-heuristic algorithm that was based on the herding behaviour of the elephant. Naturally, the elephant group consists of several groups of clans under the guidance of the matriarch. Often, the clan consists of one female with her calves or certain related females. Females prefer to live in family groups, whereas male members tend to live elsewhere. Even though the male elephants live away from their family group, they can stay in contact with elephants in their clan through low-frequency vibrations. The EHO algorithm is used in many application fields due to its advantage of excellent global optimization ability. However, there is still an insufficiency in the EHO algorithm regarding its random replacing of worst individual and lack of exploitation, which leads to slow convergence. In order to rectify these issues, the EHO is merged with the Brownian Motion (BM) technique, which significantly reduces such issues and increases the performance and accuracy rate of the method. So that, in the proposed work, the developed version is named BMEHO. In BMEHO, the elephants represent the features. The overall steps that are involved in the BMEHO technique are explained below.

Step 1: In the initial step, the new position of each elephant is updated based on the matriarch. The elephant β in a clan ξi can be updated as

$$\aleph_{n,\xi i,\beta} = \aleph_{\xi i,\beta} + \alpha \times (\aleph_{b,\xi i} - \aleph_{\xi i,\beta}) \times \Re \tag{8}$$

Where $\aleph_{n,\xi i,\beta}$ and $\aleph_{\xi i,\beta}$ represent the new and old positions of an elephant β in a clan ξi respectively, $\aleph_{b,\xi i}$ denotes the matriarch, ξ_i denotes the best elephant in the clan, $\Re \in [0, 1]$, and $\alpha \in [0, 1]$ indicates the scale factor.

Step 2: The best elephant for each clan can be calculated as follows

$$\aleph_{n,\xi i,\beta} = \Im \times \aleph_{c,\xi i} \tag{9}$$

Where $\Im \in [0, 1]$ is the factor that defines the influence of the $\aleph_{c,\xi i}$ on $\aleph_{n,\xi i,\beta}$. A new individual $\aleph_{n,\xi i,\beta}$ is formulated by the information obtained by all the elephants in a clan.

Step 3: The centre of the clan is represented as $\aleph_{c,\xi i}$. The mathematical representation for the calculation of dimension is expressed as follows.

$$\aleph_{c,\xi i,\vartheta} = \frac{1}{\eta_{\xi i}} \times \sum_{\beta=1}^{\eta_{\xi i}} \aleph_{\xi i,\beta,\vartheta}, \quad \textit{where } 1 \le \vartheta \le D \tag{10}$$

Where $\eta_{\xi i}$ represents the number of elephants in clan, $\aleph_{\xi i,\beta,\vartheta}$ represents the ϑth dimension of an individual elephant $\aleph_{\xi i,\beta}$.

Step 4: In the clan of elephant, the adult male elephant leaves their family and live anywhere. This separating process can be modelled into separating operators when solving the optimization problems. To improve the searching ability of the EHO approach, the separating operator has been implemented by the elephant individual with the worst fitness in each generation, as given in equation

$$\aleph_{w,\xi i} = \aleph_{mn} + (\aleph_{mx} - \aleph_{mn} + 1) \times \wp_d \tag{11}$$

Where $\aleph_{mn}$ and $\aleph_{mx}$ indicate the upper bound and lower bound of the individuals respectively, $\aleph_{w,\xi i}$ represents the worst individual in clan, $\wp_d$ is a stochastic distribution between 0 and 1. In which $\wp_d$ is a variable that is randomly selected between 0 and 1, which leads to the limitations like random replacing of worst individual and lack of exploitation. So, the slow convergence problem occurs. In order to balance this, the EHO is combined with the BM technique. Brownian motion is the random motion of particles suspended in a liquid or a gas resulting from collisions with fast-moving molecules in the fluid. The Brownian motion is expressed as follows.

$$B_W = \partial * r_d(.) * \lambda_\ell \tag{12}$$

$$\partial = \sqrt{\frac{\tau}{\mu}} \tag{13}$$

$$\mu = 100 * \tau \tag{14}$$

$$\lambda_\ell = \frac{1}{\partial\sqrt{2\pi}} \exp\left(-\frac{(\dim ension - agent)^2}{2\partial^2}\right) \tag{15}$$

Where τ indicates the motion time period in seconds of an agent, μ denotes the number of sudden motions for the same agent in proportion to time.

The improvement of Elephant Heard Optimization with Brownian motion (BMEHO) is obtained by merging equation (4) with equation (5) and equation (9) is re-written as follows.

$$\aleph_{w,\xi i} = \aleph_{mn} + (\aleph_{mx} - \aleph_{mn} + 1) \times \partial * r_d(.) * \lambda_\ell \tag{16}$$

Therefore, the high exploitation ability is achieved due to the updation mechanism of elephant heard optimization. In addition to that, convergence speed gets enhanced and the high accuracy of classification is also achieved. The pseudo-code of the BMEHO is demonstrated in Fig. 2.

3.5. Matrix formulation

The most relevant ranks as well as classes have been obtained from the previous phase. The final outcome from the ranking evaluation phase is presented in the form of matrix representation that is given as follows.

Table 3 demonstrates the matrix representation of the rank and their classes. In which, the rank that represents the exact class is marked as 1 whereas the other classes are denoted as 0. For example, the rank value 0.49 indicates the class guilt so it is indicated as 1, and other classes are mentioned as 0. Likewise, the rank 0.75 indicates the class "sad" so that is mentioned as 1 and other classes are represented by 0 and so on.

3.6. Classification

After the matrix formulation phase, the classification technique called Leaky ReLU Activated-Deep Neural Network (LRA-DNN) is performed for the classification of emotions from the text.

Input: Ranks of the extracted features
Output: Selection of most relevant ranks

Begin
Initialize the population size p_s and set maximum generation Mx_g of BMEHO
Calculate the fitness of each elephant
    Sort each elephants according to their fitness
    For $\xi i = 1\, to\, n$ do
        For $\beta = 1\, to\, n$ do
            If $(\aleph_{\xi i,\beta} = \aleph_{b,\xi i})$ then
                Update $\aleph_{\xi i,\beta}$ and **generate** $\aleph_{n,\xi i,\beta}$ by computing,
                    $\Im \times \aleph_{c,\xi i}$
            Else
                Update $\aleph_{\xi i,\beta}$ and **generate** $\aleph_{n,\xi i,\beta}$ by computing,
                    $\aleph_{\xi i,\beta} + \alpha \times (\aleph_{b,\xi i} - \aleph_{\xi i,\beta}) \times \Re$
            End if
        End for β
    End for ξi
    For $\xi i = 1\, to\, n$ do
        Replace the worst elephant in clan ξi using,
            $\aleph_{n,\xi i} = \aleph_{mn} + (\aleph_{mx} - \aleph_{mn} + 1) \times \partial * r_d() * \lambda_\ell$
    End for
    Evaluate each elephant individual according to the newly updated positions.
End

Fig. 2. Pseudocode for BMEHO.

Table 3
Matrix representation of the rank with their respective classes.

Rank	Classes						
	FEAR	JOY	ANGER	SAD	DISGUST	GUILT	SHAME
0.49	0	0	0	0	0	1	0
0.75	0	1	0	0	0	0	0
0.55	0	0	0	1	0	0	0
0.81	1	0	0	0	0	0	0
0.90	0	0	0	0	1	0	0
0.79	0	0	1	0	0	0	0
0.95	0	0	0	0	0	0	1

The Deep Neural Network (DNN) consists of three main layers namely, the input layer, hidden layer and the output layer. The input layer brings the input data into the classifier structure for further processing by subsequent layers. The next layer is the hidden layer; the hidden layer is also known as the dense layer. In which, it performs the function of addition the product of the input values and the weight vector of all the input nodes that are connected to it. Activation function is applied on this result. Finally, the output layer is responsible for producing the final result. However, in the hidden layer of DNN, the invoking of activation function causes various flaws like the death of neurons and vanishing gradient problems. In order to avoid such issues, the work has used the improved version of Rectified Linear Unit (ReLU) called Leaky Rectified Linear Unit (Leaky ReLU), which significantly addresses the gradient vanishing problem, prevents the death of neurons, and avoids the misclassification error. In the proposed work, Leaky ReLU (LR) activation function is used in DNN so that it is named LRA-DNN. Fig. 3 depicts the general structure of the DNN.

The procedure that is involved in the design LRA-DNN of technique is explained as follows;

- In an initial step, the matrix formulation is given as an input to the classifier, $\hbar_i$ and the corresponding weights ϖ_i are represented as follows.

$$\hbar_i = \{\hbar_1, \hbar_2, \hbar_3, \hbar_4, \ldots\ldots, \hbar_n\} \tag{17}$$

$$\varpi_i = \{\varpi_1, \varpi_2, \varpi_3, \varpi_4, \ldots\ldots, \varpi_n\} \tag{18}$$

- Then the output of the input layer is further fed into the hidden layer, in which the given inputs are multiplied with the weight vectors, and then the bias vectors are selected randomly and then summed up together. The mathematical representation of the input layer is given as follows.

$$\delta_i = \sum_{i=1}^{n} \hbar_i \varpi_i + \alpha_i \tag{19}$$

Where δ_i denotes the input of the hidden layer, the input value is denoted as $\hbar_i$, weight value is denoted as ϖ_i and the bias value is represented as α_i.

- The outcome of the hidden layer is performed along with the activation function. The mathematical representation of the hidden layer outcome is expressed as follows.

$$\zeta_i = f\left(\sum \delta_i \varpi_i + \alpha_i\right) \tag{20}$$

Where, $f(.)$ represents the activation function.

- The activation function which is used in the proposed work is Leaky ReLu, which efficiently overcomes the existing drawback like dying of neurons and prevents performance degradation. The Leaky ReLU function is mathematically represented as

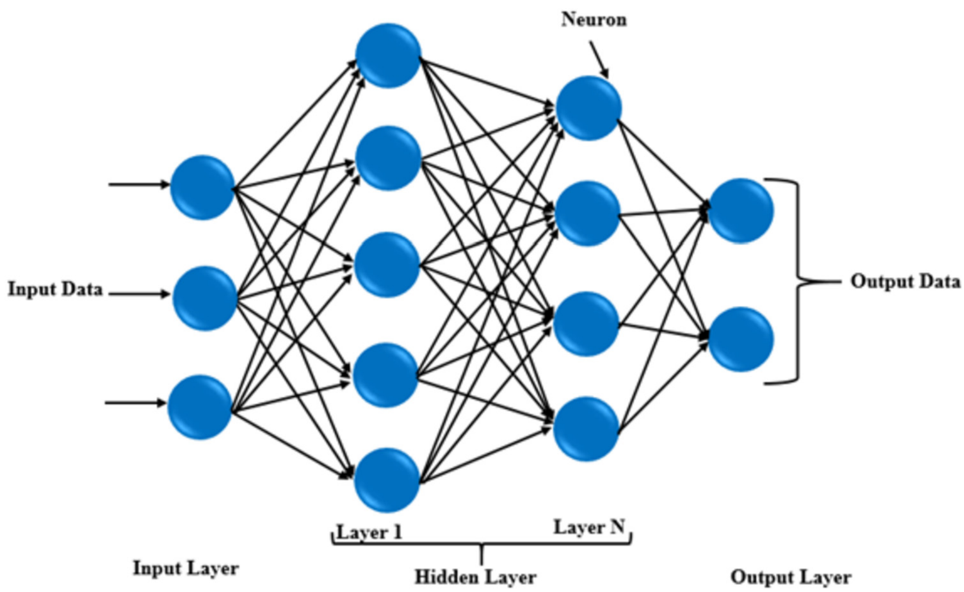


Fig. 3. General Structure of the DNN.

$$f(\delta) = \begin{cases} \delta, & \delta \geq 0 \\ \rho\delta, & \delta < 0 \end{cases} \tag{21}$$

Where, ρ is a small value that is selected randomly. This modification provides a non-zero value. Hence, it would no longer encounter the dead neurons.

- For each layer in the LRA-DNN, the above-mentioned three steps are performed. At last, we calculate the output unit thereby addition of all the weights of the input signals.

$$\Psi_i = f_s\left(\sum \zeta_i \varpi_i + \alpha_i\right) \tag{22}$$

Where Ψ_i is the output unit, the ϖ_i shows the weights of the hidden layer, ζ_i is the value of the layer that precedes the output layer. f_s represents the softmax activation function.

- At the later stage, comparison is done between the output of the network and the target value of output. Result of the subtraction is the error value. Error is mathematically represented as:

$$\varepsilon_v = \Gamma_i - \Psi_i \tag{23}$$

Where ε_v is the error value, Γ_i is the target output and Ψ_i is the current output of the classifier. Now, if the value of error $\varepsilon_v = 0$ then the model gives the exact value, but the value of error $\varepsilon_v \neq 0$ then the backpropagation is performed by updating the weights. Finally, the output of the classifier provides the accurate emotions of the input data.

4. Result and discussion

The experimental analysis of the proposed work is done in this section. The analysis is carried out based on the various performance metrics and further, a comparative analysis has been done to state its efficiency. The proposed methodology is employed in the working platform of PYTHON and the data are gathered from the publically available dataset.

4.1. Performance analysis

Evaluation of several performance metrics is performed for detail analysis of the proposed LRA-DNN. Study is compared with various existing techniques, such as Deep Neural Network (DNN), Convolutional Neural Network (CNN), and Artificial Neural Network (ANN) in terms of evaluation metrics such as precision, recall, F-Score, accuracy, sensitivity, specificity, and execution time. The performance metrics which is used in the evaluation of the proposed work are briefly explained in the below sections.

(*a*) *Precision*

Precision represents the exactness of the classifier. This metric is mathematically expressed as

$$p_{rn} = \frac{\Im_{TP}}{\Im_{TP} + \Im_{FP}} \tag{24}$$

Where, p_r denotes the precision, $\Im_{TP}$ denotes the true positive values and $\Im_{FP}$ denotes the false positive values.

(*b*) *Recall*

The next performance metric is the recall. Formula for the calculation of the recall is the number of true positives divided by the total number of true positives and false negatives. The term recall is calculated as follows.

$$r_{cl} = \frac{\Im_{TP}}{\Im_{TP} + \Im_{FN}} \tag{25}$$

Where, r_{cl} denotes recall metrics, and $\Im_{FN}$ denotes the false negative value.

(*c*) *F-Score*

The F-Score (F_s) value is computed by

$$F_s = 2.\frac{(presicion)(recall)}{precision + recall} \tag{26}$$

(*d*) *Accuracy*

Accuracy is defined as the percentage of correct predictions for the model. The accuracy (A_c) is calculated as:

$$A_c = \frac{\Im_{TP} + \Im_{TN}}{\Im_{TP} + \Im_{FP} + \Im_{TN} + \Im_{FN}} \tag{27}$$

Where, $\Im_{TN}$ denotes true negative value

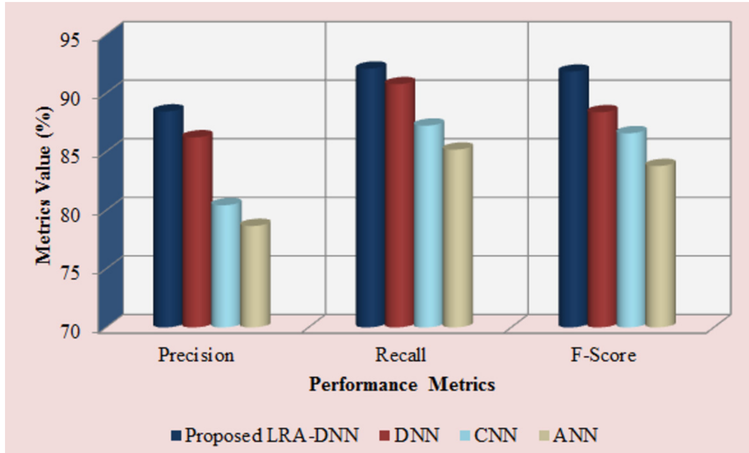


Fig. 4. Comparative analysis of proposed LRA-DNN based on precision, recall and F-Score.

Table 4
Evaluation of proposed LRA-DNN based on precision, recall and F-Score.

Performance metrics (%)/Techniques	Precision	Recall	F-Score
Proposed LRA-DNN	88.45	92.11	91.85
DNN	86.24	90.78	88.38
CNN	80.44	87.24	86.59
ANN	78.67	85.19	83.79

Table 5
Evaluation of proposed LRA-DNN based on accuracy, sensitivity, and specificity.

Performance metrics (%)/Techniques	Accuracy	Sensitivity	Specificity
Proposed LRA-DNN	94.77	92.23	95.91
DNN	92.13	90.89	93.45
CNN	90.42	88.41	90.52
ANN	87.69	86.33	87.64

(*e*) *Sensitivity*

Sensitivity is the metric that is used to evaluate a model's ability to predict true positives by a test. The term sensitivity S_t is mathematically expressed as follows.

$$S_t = \frac{\Im_{TP}}{\Im_{TP} + \Im_{FN}} \tag{28}$$

(*f*) *Specificity*

Specificity is the metric that is used to evaluate a model's ability to predict true negatives by a test. The term sensitivity S_p is mathematically expressed as

$$S_p = \frac{\Im_{TN}}{\Im_{TN} + \Im_{FP}} \tag{29}$$

Table 4 demonstrates the analysis of various performance metrics, such as precision, recall, and F-Score of the proposed LRA-DNN with the various existing techniques, such as DNN, CNN and ANN. The high range of precision, recall and F-Score reveal the effectiveness of the proposed work. From the table, it is clearly known that the proposed LRA-DNN achieves the precision at the rate of 88.45%, recall of 92.11% and F-Score at the rate of 91.85%, whereas the existing techniques like DNN, CNN and ANN obtain the metrics' value that overall ranges between 78.67% and 90.78%. Hence, the proposed LRA-DNN effectively recognizes the emotions from the text with a minimized error rate as compared to the existing methods. The graphical representation of Table 4 is shown in Fig. 4.

This comparative analysis states that the proposed LRA-DNN is more efficient than the existing techniques. From the graph, it is known that the proposed LRA-DNN techniques outperform the existing technique by achieving high rate of precision, recall and F-Score. Therefore, the proposed work significantly mitigates the issues like misprediction and misclassification error and delivers the optimum result. The Evaluation of proposed LRA-DNN in terms of accuracy, sensitivity, and specificity is given in Table 5. These parameters were evaluated and compared with other techniques.

Table 6
Evaluation of proposed LRA-DNN in terms of execution time.

Execution time (sec)/Technique	1000	2000	3000	4000	5000
Proposed LRA-DNN	12.57	15.33	20.66	25.27	31.36
DNN	15.43	20.36	22.67	27.57	33.79
CNN	17.19	22.49	25.31	30.51	35.26
ANN	20.69	25.83	29.91	34.45	38.72

It was found that the proposed technique showed best results in terms of all the three parameters.

The Table 5 shows that the proposed LRA-DNN shows a high-performance value, which increases the classification accuracy by achieving the high range of accuracy, sensitivity and specificity at the rate of 94.77%, 92.23%, and 95.91% respectively. But the existing techniques like DNN, CNN, and ANN obtain the accuracy rate at an average of 90.08%, sensitivity at an average of 88.54%, and specificity at an average of 90.53%. Therefore, the proposed work yields better performance when compared to the existing techniques. Fig. 5 depicts the graphical representation of comparative analysis of the proposed LRA-DNN with existing techniques, such as DNN, CNN, and ANN.

The comparative analysis reveals that the proposed work achieves better evaluation metrics and provides the accurate recognition of emotions from the text under various circumstances. Thus, the proposed methodology outperforms the existing techniques in terms of accuracy, sensitivity, and specificity. Table 6 demonstrates the total execution time taken by the proposed LRA-DNN technique for executing a certain number of data.

From Table 6 it is known that the proposed technique has an execution time of 12.57 s, 15.33 s, 20.66 s, 25.27 s, and 31.36 s for 1000, 2000, 3000, 4000, and 5000 data respectively. But the existing techniques, such as DNN, CNN, and ANN obtain execution time for executing 1000 number of data at an average of 17.77 s, for the execution 2000 data, it takes nearly 22.89 s, for executing 3000 data, it takes an average of 25.96 s, for 4000 data, it takes an average of 30.84 s, and for executing 5000 data, it takes an average

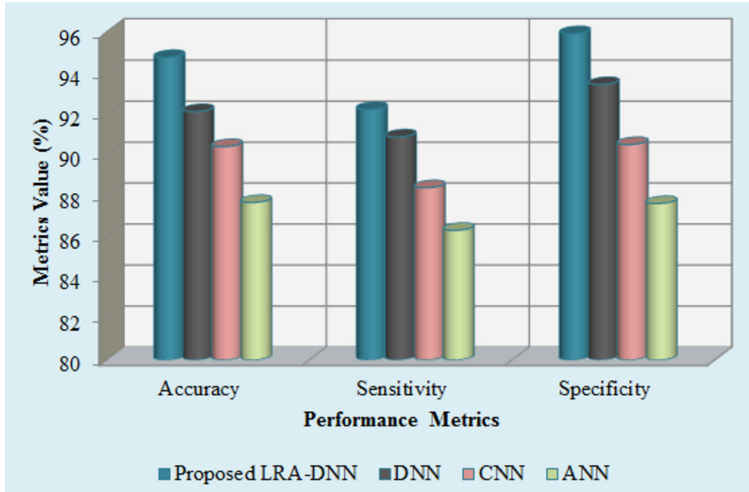


Fig. 5. Comparative analysis of the proposed LRA-DNN based on accuracy, sensitivity, and specificity.

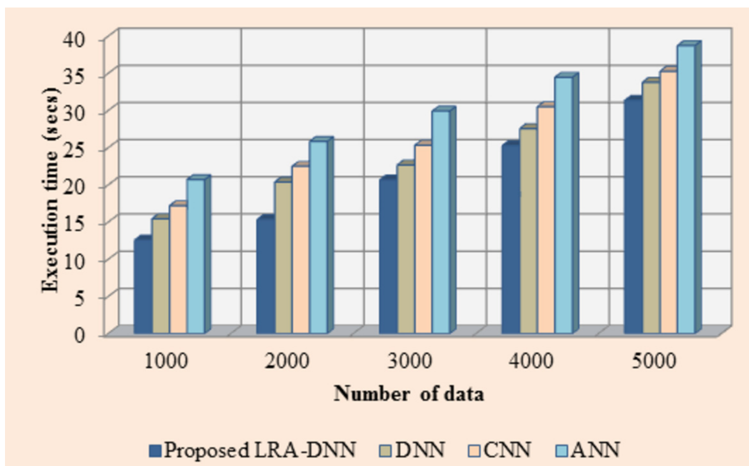


Fig. 6. Comparative analysis of the proposed LRA-DNN based on execution time.

of 35.92 s, which is relatively high as compared to the proposed LRA-DNN technique. Therefore, the proposed LRA-DNN technique tends to achieve faster execution of the entire emotion detection process than the existing techniques. The graphical representation of Table 6 is given in Fig. 6.

From Fig. 6, it is conveyed that the proposed LRA-DNN technique exhibits low execution time than the existing techniques. Therefore, the proposed technique completes the entire process quickly and reduces the complication. This represents the noteworthy efficiency of the proposed technique as compared to the existing techniques. From the Tables 4, 5 and 6 it can be concluded that proposed technique is giving promising results on all the evaluation parameters. One of the reasons for such promising results can be the rigorous pre-classification tasks regarding the extraction of features, ranking evaluation of the extracted features till the selection of most relevant ranks to the given feature. Proper feature pruning and its ranking helps the classifier for avoiding confusion for the classification and the faster execution time.

5. Conclusion

In this paper, a novel deep learning approach, namely LRA-DNN, is proposed for text-based emotion detection in social media content. The approach includes several operations, such as pre-processing, feature extraction and ranking, for the classification of the input collected documents. After classification, the experiments are carried out and the comparative analysis of the proposed and existing techniques is done in terms of some performance metrics to know the performance efficiency of the proposed algorithms. The proposed LRA-DNN classification algorithms obtain better results when compared with the existing algorithms. From every dataset, which is used for the analysis, the LRA-DNN attains the highest accuracy. Therefore, the LRA-DNN obtains superior results for publically datasets. Moreover it can be concluded that merging of Elephant Heard Optimization (EHO) meta-heuristic algorithm with the Brownian Motion (BM) technique selects the more informative features and relevant features from the input data. It helps in achieving a better classification and reduces the misclassification error. In the future, the work will be extended with some advanced deep learning algorithms to perform the emotion classification of the data with multimedia contents, such as audio and image.

Compliance with ethical standards

The authors declare that the work described has not involved experimentation on humans or animals.

Declaration of competing interest

We have no conflict of interest.

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