An Efficient Deep Learning with Optimization Algorithm for Emotion Recognition in Social Networks

Ambika G N[1], Dr. Yeresime Suresh[2]
Assistant Professor, CSE Dept., BMS Institute of Technology and Management, Bangalore-560064, India[1]
Associate Professor, CSE Dept., Ballari Institute of Technology & Management, Ballari-583104, India[2]

***Abstract*—Emotion recognition, or computers' ability to interpret people's emotional states, is a rapidly expanding topic with many life-improving applications. However, most image-based emotion recognition algorithms have flaws since people can disguise their emotions by changing their facial expressions. As a result, brain signals are being used to detect human emotions with increased precision. However, most proposed systems could do better because electroencephalogram (EEG) signals are challenging to classify using typical machine learning and deep learning methods. Human-computer interaction, recommendation systems, online learning, and data mining all benefit from emotion recognition in photos. However, there are challenges with removing irrelevant text aspects during emotion extraction. As a consequence, emotion prediction is inaccurate. This paper proposes Radial Basis Function Networks (RBFN) with Blue Monkey Optimization to address such challenges in human emotion recognition (BMO). The proposed RBFN-BMO detects faces on large-scale images before analyzing face landmarks to predict facial expressions for emotional acknowledgment. Patch cropping and neural networks comprise the two stages of the RBFN-BMO. Pre-processing, feature extraction, rating, and organizing are the four categories of the proposed model. In the ranking stage, appropriate features are extracted from the pre-processed information, the data are then classed, and accurate output is obtained from the classification phase. This study compares the results of the proposed RBFN-BMO algorithm to the previous state-of-the-art algorithms using publicly available datasets derived from the RBFN-BMO model. Furthermore, we demonstrated the efficacy of our framework in comparison to previous works. The results show that the projected method can progress the rate of emotion recognition on datasets of various sizes.**

Keywords*—*Blue monkey optimization (BMO); deep learning; electroencephalograph (EEG); emotion recognition; human-computer interaction (HCI); radial basis function networks (RBFN)

I. Introduction

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Language, text, action, and other means are all ways that people can express themselves. How to recognize and accurately detect human facial expressions has emerged as a hot research area given the rapidly expanding artificial intelligence field [1]. Numerous businesses including amusement, security, online education, and intelligent medical care, use facial expression detection technologies [2]. Facial expression is a critical factor in human emotion recognition. Since a person's facial expressions convey their emotions, "facial recognition" [3] and "emotion recognition" are often used synonymously. Significant progress has been made in the automotive industry, augmented robotics, reality, neuromarketing, and interactive games. There is growing interests in enhancing all facets of human-computer interaction, particularly in recognizing human emotions.

Facial expression recognition can be used to monitor driver fatigue. An alarm is sent when the driver's face exhibits signs of drowsiness, and a camera records the driver's expression in real time while also analyzing the driver's mental state. This can assist with avoiding traffic accidents induced by fatigued driving. The elderly can benefit from installing a human-computer interaction system with a recognition of facial expressions feature in nursing homes or elderly homes. Facial expression recognition technology can track how each student responds to the lecture and provide the instructor with immediate feedback, which can, to some extent, advance the superiority of education [4]. During the online teaching process, it can be difficult for the instructor to keep track of each student's reaction, but it is still important to make timely adjustments to the course progress.

In the conventional method for recognizing facial expressions, a photograph is taken, its attributes are extracted, and then the image is identified using machine learning [5]. The difficult feature extraction method and the identification performance being easily influenced by the environment and a person's facial activity are some drawbacks of this strategy.

One of today's most vital and challenging techniques is emotional recognition. Applications for emotion recognition include helping to measure stress levels and blood pressure, among other things. When using emotional techniques, one can apply the functions of happy, sad, calm, and neutral facial features. The human body's inner workings can be detected using various methods and algorithms. Real-time emotional recognition can pick up on human thought processes. Identifying diseases early using emotional recognition shields can save humans from severe infections or illnesses. Emotional recognition has the main benefit of assisting in identifying human mentalities without using questions.

Machine learning algorithms accurately predict facial emotions like stress and sadness. The results for emotion recognition, such as sadness and rage, were improved when the ECG and PPG were merged with the 28 features take out from algorithms using machine learning [6]. Without knowledge sharing, facial expressions are essential for determining human mentality. In a few articles, datasets from 2010 to 2021 are combined, along with the majority of the features collected and categorized using deep learning and to support vector machine approach, hence increasing classification accuracy and outcomes.

A subset of machine learning methods called "deep learning" can be used to analyze facial expressions and identify emotions. However, the amount of data will affect how well it works. As data volume rises, performance gets better. Deep learning cannot be applied to facial expression datasets because they are too small. Several studies have found that augmentation techniques like cropping, scaling, translating, or mirroring during the pre-processing stage increase the alteration and, subsequently, the quantity of information.

In various pattern recognition and classification issues, neural networks have been used because they have the best approximation capability. Along with the back-propagation algorithm, face recognition has also used convolution neural networks and multilayer perceptron (MLPs) [7]. Because of its slow convergence rate and uncertainty about whether it will reach global optimums, the back-propagation learning procedure is computationally intensive. Due to their outstanding approximation accuracy and quick processing, radial basis function neural networks (RBFN) with a single hidden layer have been used for facial recognition applications. Radial basis functions in the hidden layer nonlinearly map the contribution face information to linearly divisible information in hidden hyperspace. Some enterprise challenges for hidden layers include defining the RBF unit centers of hidden neurons, their numbers, and the selection and shape of fundamental functions. Second, the success of blue monkey swarms naturally inspired the development of the Blue Monkey (BM) approach, a cutting-edge metaheuristic optimization method. The total number of men in a group is determined via the BM process. Like other forest guenons, blue monkey groups typically only contain one adult male outside the breeding season. With constraints and an unknown search space, this algorithm effectively finds solutions to practical problems. The BM method has some variables and the potential to produce better results [8].

Radial Basis Function Networks (RBFN) with Blue Monkey Optimization is suggested in this paper (BMO). The proposed RBFN-BMO first recognizes faces on large-scale imageries after assessing face landmarks to approximate representations for reaction acknowledgment. The two stages of the RBFN-BMO are convolutional neural networks and patch cropping. The proposed perfect is composed of four categories: feature extraction, ranking, preprocessing and organization. After preprocessing the dataset's collected data for data cleansing, the information is classified, the relevant attributes are extracted from the preprocessed data in the ranking phase, and the correct information is obtained. This study compares the results of the recommended RBFN-BMO method to earlier state-of-the-art methodologies using publicly accessible datasets inferred from the RBFN-BMO model. Furthermore, we have demonstrated that our structure is more efficient than earlier ones.

The projected work is defined in detail below. Section II goes into more excellent aspects of the work associated with the projected outcome. Section III goes over the proposed framework in depth. Section IV goes into great detail about experiment design and performance evaluation. Section V concludes the discussion of future work.

A. Contribution

- Data cleaning and pre-processing are performed on the dataset's collected data.
- The pre-processed data are given the appropriate characteristics during the ranking phase, and the information is then categorized.
- Pre-processing, feature extraction, ranking, and categorization are the four categories that make up the suggested model.
- Before looking at face landmarks to predict facial expressions for emotion detection, the Radial Basis Function Networks (RBFN) - Blue Monkey Optimization (BMO) proposed method first recognizes faces on large-scale images.

II. Literature Survey

Chen et al. [9] used a deep sparse auto-encoder network based on Soft-max regression to identify facial expressions of emotion during human-robot interaction. This work minimizes distortion, learning efficiency is determined, and dimensional complexity is measured using the SRDSAN technique. The soft-max simple regression perfect will help categorize the input signal, while the DSAN technique helps with accurate feature extraction.

Babajee et al. [10] suggested using deep learning to recognize human expressions from facial expressions. This paper uses deep knowledge and a convolutional neural network to offer seven methods for identifying facial emotions. This study uses the Facial Action Coding System (FACS) to collect 32,398 facial expressions to identify various types of emotion. The identification approach's failure to be an effective optimization technique is the sole justification for this research.

Satyanarayana et al. [11] used deep learning and cloud access to implement emotional acknowledgment in this study. One of the most effective methods in many presentations is facial emotion recognition. Face recognition makes extensive use of the deep learning algorithm. Her thesis paper examines a variety of emotions, such as sadness, joy, serenity, and rage. The Python code generates a particular IP address for each technique to send this data.

Jayanthi et al. [12] used deep classifiers to develop an organizing strategy for emotional categorizations utilizing speech and static images. One of the most crucial methods for determining someone's stress level is emotion identification. The two traits of emotion perception and speech modulation are essential in determining the stress level in the human body.

Sati et al. [13] used NVIDIA to implement face detection, recognition, and emotion recognition in his paper. In this study by Jetson Nano, face emotion recognition and detection are combined. Facial emotional identifications have historically been among the most challenging techniques to master. This technique's accuracy and classification outcomes can be improved by adding some features. The ANN technique assists in recognizing and classifying facial expressions of emotion.

Wang et al. [14] applied a recently developed deep learning technique in this paper. The four-category deep learning model is used in this paper. Convolutional neural networks and deep architectures fall under the first category. The deep learning model has a significant impact on deep neural networks. This component of the machine learning algorithm is essential. The classification, which includes both linear and nonlinear special functions, is necessary for the accuracy of the data.

The multi-label convolution neural network was implemented by Ekundayo et al. [15] to identify facial expressions and estimate ordinal intensity. This was completed because, while many features, like FER, are consistent with the emotional recognizing method, only one is ideal for the multi-class dynamic classification method. This study utilized a multi-label convolutional neural network.

Using facial expressions, EEG, and machine learning techniques, Hassouneh et al. [16] developed a real-time emotional recognition system. The system could distinguish between smiling, remaining neutral, and losing control. In this study, virtual markers detect facial regression using the optical flow algorithm, since it acknowledges a lower level of computational complexity, the optical flow algorithm system aids in providing people with a physical challenge.

Neuro-sense was used by Tan et al. [17] to implement short-term emotion recognition and comprehension. Spiking neural network simulations of the spatiotemporal EEG patterns served as the foundation for their strategy. The SNN method is used for the first time in this paper. It aids in comprehending how the brain operates. One of the two methods used to analyze the EEG data is arousal-valence space. The various types of segments that make up the arousal-valence space include low arousal, high arousal, high valence space techniques, and standard valence space methods.

A deep facial expression recognition survey was carried out by Li et al. [18]. One of the system's most significant challenges is recognizing a person's facial expression. The two main challenges to accurate facial expression recognition are a need for training sets and undesirable emotion variations (FER). The data set is first organized using the neural pipeline technique. Consequently, the FER technique's complex problems will be reduced.

Yang et al. [19] used a staked auto-encoder to implement three-class profound learning-based emotional expressions. This paper demonstrates that discrete entropy calculation can be used to measure the EEG signal. The deep learning algorithm's auto-encoder technique results are more accurate than those from the encoding system's calculation methods. To use the alpha, beta, and gamma values, this method assesses emotions. Classification results are produced more accurately when a deep learning procedure is used. The deep learning procedure typically yields acceptable outcomes for the various classes of emotional recognition.

Yadahalli et al. [20] used a deep learning technique to recognize facial micro expressions. This study uses six different emotional expressions—happy, sad, angry, scared, neutral, and surprised faces—to collect the eight layers of the dataset. Because it has started collecting datasets that contain the FER perfect, the paper assumes that the FER with a CNN improves accuracy and that the removed consequence produces the multimodal facial expression using a single method. Using a single algorithm, the multimodal facial expression is also added to the dataset that has been gathered.

Asaju et al. [21] used a temporal method to recognize facial emotional expressions. This study introduces a CNN-based deep learning procedure that can implement numerous kinds of emotional acknowledgment in the human body. To extract features, VGG-19 methods are used. Both the accurate mapping technique and the recognition of facial emotions method use the BiLSTM architecture.

Yolcu et al. [22] suggested a deep learning-based method for tracking consumer performance patterns that measured head pose assessment and analyzed facial expressions to gauge the level of interest in the product. To follow customer interest, this was done. Deep structured learning was suggested by Walecki et al. [23] as a technique for determining the level of facial expression intensity. Face physics and other pre-processing methods are less critical in deep learning-based face recognition. CNN's convolution layers convolve the input image using various filters. It generates a feature map with fully connected networks to recognize facial expressions.

To identify emotional expressions on faces, Asaju et al. [24] employed the temporal method. This study integrates a CNN with a deep learning technique to create dissimilar kinds of emotional identification in the human body. Use the VGG-19 methods for obtaining features. The title and precise mapping of facial expressions are then carried out using the Bi-LSTM architecture.

Ekundayo et al. [25] implemented a multilabel convolution neural network to recognize facial expressions and estimate ordinal intensities. Although many features can be used with sentimental character segmentation techniques like FER, they are only suitable for some of them for the ideal categorization emotional classification method. Convolutional neural networks with multiple labels are used in this study.

III. Proposed System

This study suggests combining RBFN and Blue Monkey Optimization (BMO) to acknowledge faces and emotions in high-resolution images. Modules for pre-processing, feature extraction, ranking, and classification can be seen in the block diagram of the proposed system in Fig. 1.

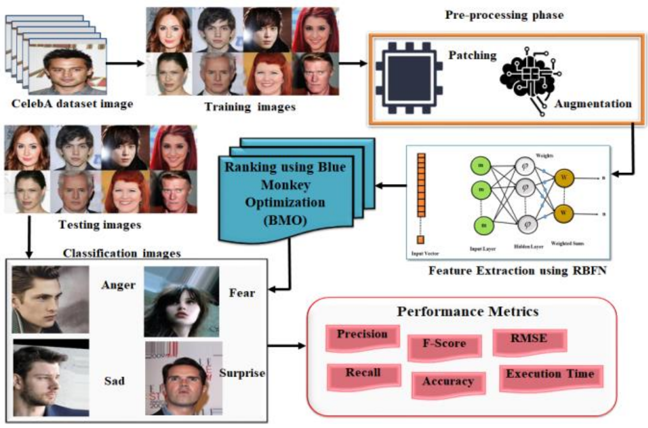

Fig. 1. Proposed method of RBFN-BMO method.

A. Pre-Processing of the Images

Before using the pyramid images approach, the original photographs are downscaled by a feature of 2 until they are 128×128 in dimensions. Additionally, each pyramid image is split into 128×128 pixel-sized patches to simplify processing and reduce memory allocation.

1) Data augmentation: Dawn sampling was performed on the input photos using a ratio of 2 up to an image size of 128×128. There was no overlap between the 128×128 patches created from the pyramid photos. If the picture segment is too long for the patches, zeros will be added to make up the difference. Additionally, we employ a data augmentation technique that involves rotating, translating, and flipping the images on their axes at 45-degree perspectives. The data augmentation method increases the number of training examples and progresses the network's ability to simplify under challenging circumstances. The images have been edited to resemble actual facial recognition scenarios. Due to the GPU's memory capacity, we use a batch size of 16 pictures during training. As a result, various combinations of patches for the same image might be created. The initial photo incorporates all sensing forecasts on the same image's patches.

B. Feature Extraction using RBFN

Feed forward neural networks comprise RBFN. The three layers that make up the RBFN's design are the input, hidden, and output layers, as depicted in Fig. 2. Data is sent from the user's input layer to the concealed layer [26]. Radial basis function (RBF) units, known as hidden neurons, comprise the hidden layer. Each jth RBF unit has a related basis function (φ_j), spread (∂_j), and centre (A_j).

The nonlinear basis functions φ_j are affected by how far the input is from the center of the jth RBF unit. RBFN frequently employs the basic functions Gaussian, multiquadric, inverse multiquadric, and thin spline. The most often used Gaussian basis function was signified in this study as

$$\varphi_j(x) = e^{\frac{\|m - A_j\|^2}{2\partial_j^2}} \tag{1}$$

The restriction r, which also denotes the function's width, characterizes the spread of the radial basis function, where Cj stands for the jth RBF unit's center. You can think of RBFN as a mapping from (2).

$$\boldsymbol{R}^d \rightarrow \boldsymbol{R}^u (u \gg d) \tag{2}$$

Where u is the amount of RBF units and $P \in \boldsymbol{R}^d$ is the d-dimensional input feature vector. The ith output of the RBFNN, $n_i(m)$), is

$$n_i(m) = \sum_{j=1}^{u} \varphi_j(x) \times w_{i,j} \tag{3}$$

Where wi,j denotes the degree of connectivity between the ith output neuron and the jth RBF unit.

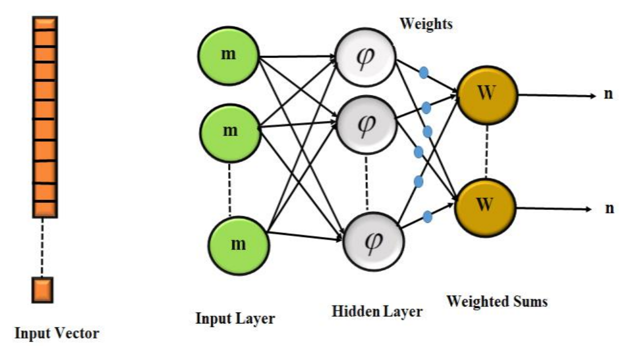

Fig. 2. Structure of RBFN.

C. Ranking with Blue Monkey Optimization (BMO)

Blue Monkeys are different from the other species. They frequently live in societies where women are the majority, meaning females stay in their natal groups. However, as soon as they reach the mature stage, the males leave their groups [27]. There are usually a lot of females and young in each group of blue monkeys, but only one male. This problem exacerbates the problem of inbreeding. The men leave the group and join another one when they're older. However, finding a new group might take some time, so the males might initially seem to be by themselves. Regarding social interactions, blue monkeys don't have a perfect sense of intuition [28]. Social interaction only lasts for a short time, typically when playing with and grooming other people.

Babies also connect with the other adults in the group and their mothers. The source of those newborns typically avoids their male counterparts. Baby handlers are the ones who do all the work. The young females tend to the babies and carry and protect them. From this habit, infants pick up how to react like all monkeys.

1) Group division: The BMO algorithm imitates the actions of Blue Monkey. Each group of monkeys had to travel through the search area to simulate these interactions. Earlier, it was mentioned that when the monkeys are divided into groups, they start searching for food sources far away in an area where more robust monkeys are out of sight of conventional vision. The young Cercopithecus mitis and the male have little to no interaction. Because Cercopithecus mitis is a territorial species, young males should venture outside as soon as possible. The dominant male of another family will challenge them. If they succeed in eliminating him, they will assume control of the family and be able to provide young men with food, shelter, and socialization. Blue monkey groups typically consist of a sizable number of females and young, with only one male [29].

2) Position update: Each blue monkey in a group updates to the position in the best place within that group. Equations like the ones below describe this behavior:

$$Power_{m+1} = \left(0.7 * Power_m\right) + (W_{lea} - W_m) * rand * (Y_{best} - Y_m) \quad (4)$$

$$Y_{m+1} = Y_m + Power_{m+1} * rand \quad (5)$$

Wlea stands for the leader weight, Wm for the monkey weight, Ybest for the leader location, which can take any value between [0,1], Power for the monkey power rate, and so on.

Using the following equations, the blue monkey's offspring are also updated.

$$Power^C_{m+1} = \left(0.7 * Power^C_m\right) + (W^C_{lea} - W^C_m) * rand * (Y^C_{best} - Y^C_m) \quad (6)$$

$$Y^C_{m+1} = Y^C_m + Power^C_{m+1} * rand \quad (7)$$

W^C_m is the child weight at which all weights are random amounts among [4, 6], Y^C_{best} is the child position, Ychis the leader child position, Ratechneeds to stand for the child power rate, is the leader child weight, and "rand" denotes an arbitrary amount among [0, 1]. Every cycle, the location needs to be reorganized.

Algorithm for Blue Monkey Optimization

Initialize the Blue Monkey and their children population Bm (m=1….,n)

Initialize power rate and weight of Blue monkey as Power and W

Where (Power ϵ [0, 1]) (W ϵ [4, 6])

Randomly Distribute Blue Monkey into T groups and children in one group.

Evaluate the fitness of blue monkey and children in each group

Select Worstfit and Best fit in Y^C_{lea} Children group

T=1

While (T≤ maximum number of group)

Swap Worstfit = Y^C_{lea}

Update Power and Y position of all blue monkey by Eq. (4,5)

Update Power and Y Position of children by Eq. (6,7)

Upgrade the fitness of all blue monkeys and kids.

Most recent Update

If (New best> Current best) then

New best = Current best

End if

T=T+1

End While

The best blue monkey should be returned.

D. Classification of Emotions Recognition

The centers of hidden neurons or RBFN units can be found using the sub-clusters produced by the proposed RBFN-BMO technique. Since the method evolves the sub-clusters based on the given training statistics, providing the number of sub-clusters for each participant as input for face recognition is unnecessary. Emotion recognition aims to identify a person's emotions. The capacity to perceive emotions varies significantly among people. A significant area of research is emotion recognition with technological assistance. Analyzing facial landmarks, with a focus on the lips, nose, and eyes, is the foundation for identifying emotions. Facial expressions are a huge help in recognizing emotions. The shapes of those sections represent the person's emotions. One can infer a person's emotional state from the points' locations and the distance between them. The main objective was to create the proposed methodology for finding 68 spots; A potential area for emotion detection in each of the locations. The jawline is depicted in points 1 through 17, the left and right brows in points 18 through 22, the left and right eyes in moments 37 through 48, the noise in points 28 through 36, the outer lip area in matters 49 through 60, and the inner lip structure in points 60 through 68. In studies of facial expressions, the location of those points is crucial.

In this study, we suggest using facial features as annotations for emotion recognition. The proposed RBFN-BMO accepts inputs such as high-resolution photos, facial feature annotations, and the face's position. The seven emotions portrayed in this piece are anger, disgust, fear, joy, sadness, surprise, and neutrality. More details about the data set used to train the recommended RBFM-BMO are provided in the following section.

IV. Experimental results

Details about the experimental setting that was used to develop and evaluate the suggested RBFN-BMO are provided in this section. The experiment was run on a Linux desktop with an Intel i7 processor, 32 GB RAM, and a 4 GB Nvidia GTX960 graphics card. The suggested RBFN was developing using the TensorFlow deep learning framework, cuDNN, and CUDA vibration libraries. For image manipulation, the OpenCV library was used.

A. Dataset Description

We suggest using the celeb datasets [30] to train the suggested RBFN-BMO. There are 202,599 RGB images of well-known people in this dataset. Face, attribute, and landmark acknowledgment was considered when creating the dataset. The CelebA dataset's images are summarised in Fig. 3. This work advocates using facial landmarks and distinctive analysis for face detection and expression acknowledgment.

A training set, a validation set, and a testing set were created from the collected data. The training set consisted of 70% of the data, the validation set of 10% of the training set, and the testing set consisted of 30% of the data.

While pre-processing reduces filter noise, 70% of the data are used as training input. The high dimensionality of the filter is reduced with the help of feature extraction. To decrease the size of the problem space, our work employs various methods for extracting features, such as edge detection. As a result, it generates clear output images with precise dimensional quality. In the data, categorization and part extraction happen simultaneously.

B. Performance Metrics

The effectiveness of the suggested work is assessed using the recognition rate. The classification performance is calculated by dividing the total amount of images into the data sets by the number of facial expressions successfully identified. It is shown as:

The percentage of accurate classifications is measured by precision (Prec). It can be indicated using (8):

$$\mathrm{Precision} = \frac{TP}{TP + FP} \tag{8}$$

Fig. 3. Celebrity images data set.

It is also possible to refer to the actual positive rate as the recall rate or recall. It assesses how frequently a classifier gives the right category a favorable result. It is described in (9).

$$\mathrm{Recall} = \frac{TP}{TP + FN} \tag{9}$$

The F-Measure represents the harmonic mean of sensitivity and precision (F). It is crucial since higher accuracy typically interprets into lower sensitivity. It can be calculated using (10).

$$F - Score = 2 * \frac{precision * recall}{precision + recall} \tag{10}$$

Accuracy: To calculate the precision of our predicted value, divide all values by the total of true negatives and true positives.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

Root Mean Square Error (RMSE)

The only departure from RMSE is the square root sign. The mean absolute error equation is given in (12).

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{\left(y_i - y_i\right)^2}{n}} \tag{12}$$

The messages TP, TN, FP, and FN are confirmed positive, true negative, true positive, and false negative, respectively. The outcome should improve as a component of precision, recall, f-measure, and sensitivity.

1) Precision analysis: In Fig. 4 and Table I, the precision of the RBFN-BMO strategy is contrasted with that of other methods currently in use. The graph demonstrates the increased efficiency and precision of the deep learning approach. In comparison to the GRU, LSTM, RNN, DNN, and ANN models, which have precision values of 89.029%, 85.536%, 90.927%, 88.435%, and 93.983% for the 1000 data, the RBFN-BMO model has a precision value of 96.425%. With different data sizes, the RBFN-BMO model has shown its greatest performance. The RBFN-BMO's precision value is 97.927% under 6000 data, compared to the GRU, LSTM, RNN, DNN, and ANN models' precision values of 89.827%, 86.324%, 93.782%, 87.625%, and 95.029%, respectively.

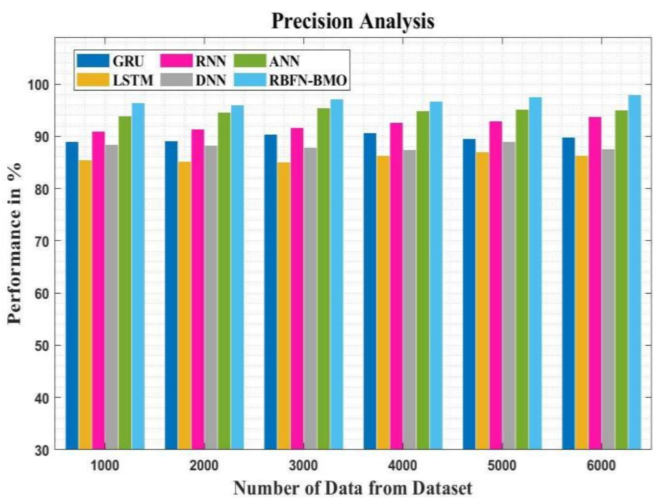

Fig. 4. Precision analysis for RBFN-BMO method with existing systems.

TABLE I. RBFN-BMO METHOD PRECISION ANALYSIS USING EXISTING SYSTEMS

Data from dataset	GRU	LSTM	RNN	DNN	ANN	RBFN-BMO
1000	89.029	85.536	90.927	88.435	93.983	96.425
2000	89.214	85.234	91.425	88.323	94.626	96.029
3000	90.425	85.029	91.728	87.922	95.435	97.182
4000	90.627	86.324	92.637	87.425	94.928	96.728
5000	89.526	86.973	92.938	88.937	95.227	97.632
6000	89.827	86.324	93.782	87.625	95.029	97.927

2) Recall analysis: Fig. 5 and Table II illustrate how the RBFN-BMO approach compares to other current methods in terms of recall. The figure demonstrates how the recall performance was enhanced by the deep learning approach. The RBFN-BMO model, for example, has a recall value of 93.827% with 1000 data, while the GRU, LSTM, RNN, DNN, and ANN models have recall values of 79.637%, 80.928%, 84.938%, 86.927%, and 89.627%, respectively. However, the RBFN-BMO model worked most effectively with various data sizes. For 6000 data points, the recall value of the RBFN-BMO is 95.737% as opposed to the GRU, LSTM, RNN, DNN, and ANN models' respective recall values of 81.924%, 84.536%, 87.736%, 90.326%, and 92.413%.

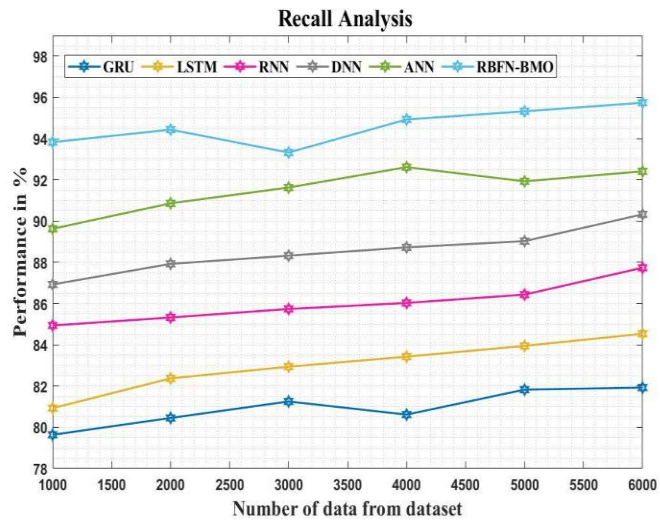

Fig. 5. Recall analysis for the RBFN-BMO method with existing systems.

TABLE II. RECALL ANALYSIS FOR THE RBFN-BMO METHOD USING EXISTING SYSTEMS

Data from dataset	GRU	LSTM	RNN	DNN	ANN	RBFN-BMO
1000	79.637	80.928	84.938	86.927	89.627	93.827
2000	80.452	82.373	85.324	87.926	90.862	94.435
3000	81.252	82.938	85.738	88.322	91.627	93.324
4000	80.615	83.425	86.029	88.726	92.617	94.928
5000	81.827	83.948	86.435	89.028	91.928	95.324
6000	81.924	84.536	87.736	90.326	92.413	95.737

3) F-Score analysis: Fig. 6 and Table III display an f-score contrast of the RBFN-BMO strategy with other existing methods. The graph shows that the deep learning method has produced better performance regarding the f-score. The RBFN-BMO model, for example, has an f-score of 92.536% with 1000 data, while the GRU, LSTM, RNN, DNN, and ANN models have f-scores of 87.928%, 85.435%, 81.526%, 83.425%, and 90.324%, respectively. The RBFN-BMO model, on the other hand, has performed best over a range of data sizes. Similarly, the f-score value of RBFN-BMO under 6000 data is 94.627%, while for GRU, LSTM, RNN, DNN, and ANN models, it is 89.928%, 87.435%, 82.213%, 85.324%, and 91.928%, respectively.

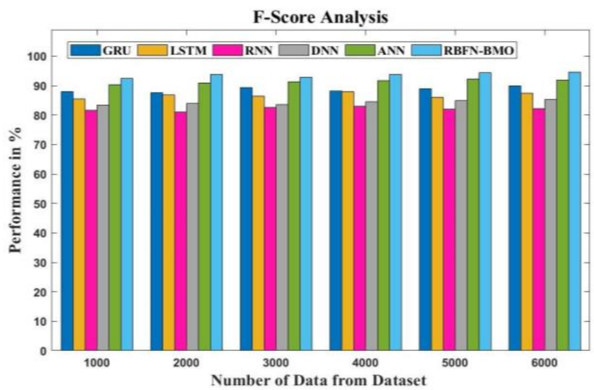

Fig. 6. F-Score analysis for the RBFN-BMO method using existing systems.

TABLE III. F-SCORE ANALYSIS USING TRADITIONAL SYSTEMS USING THE RBFN-BMO METHOD

Data from dataset	GRU	LSTM	RNN	DNN	ANN	RBFN-BMO
1000	87.928	85.435	81.526	83.425	90.324	92.536
2000	87.526	86.928	81.029	83.928	90.928	93.727
3000	89.432	86.425	82.536	83.526	91.243	92.927
4000	88.214	87.928	82.938	84.525	91.627	93.826
5000	88.921	86.029	81.937	84.928	92.173	94.324
6000	89.928	87.435	82.213	85.324	91.928	94.627

4) Accuracy analysis: Fig. 7 and Table IV shows the accuracy of the RBFN-BMO approach as compared to that of other currently utilized approaches..The graph shows how deep learning improves performance with accuracy. The RBFN-BMO model, for example, has a 1000-data accuracy of 97.627%, whereas the GRU, LSTM, RNN, DNN, and ANN models have accuracy of 89.536%, 90.917%, 92.524%, 94.526%, and 96.425%, respectively. The RBFN-BMO model, on the other hand, fared well with varying data sizes. Similarly, the accuracy of the RBFN-BMO under 6000 data is 99.546%, while the accuracy of the respective GRU, LSTM, RNN, DNN, and ANN models is 90.716%, 92.817%, 93.926%, 95.736%, and 97.125%.

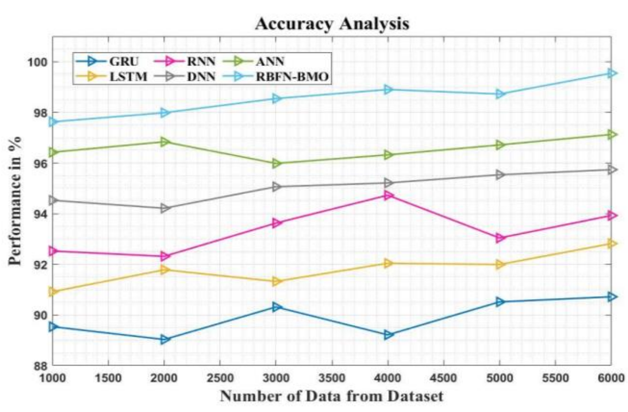

Fig. 7. Accuracy analysis for RBFN-BMO method with existing systems.

TABLE IV. ANALYSIS OF RBFN-BMO METHOD ACCURACY WITH EXISTING SYSTEMS

Data from dataset	GRU	LSTM	RNN	DNN	ANN	RBFN-BMO
1000	89.536	90.917	92.524	94.526	96.425	97.627
2000	89.029	91.783	92.314	94.213	96.837	97.983
3000	90.314	91.324	93.627	95.063	95.983	98.546
4000	89.213	92.039	94.728	95.213	96.322	98.902
5000	90.516	91.992	93.039	95.536	96.714	98.724
6000	90.716	92.817	93.926	95.736	97.125	99.546

5) RMSE analysis: Fig. 8 and Table V display an RMSE similarity between the RBFN-BMO strategy and other earlier techniques. The graph shows that the deep learning strategy has produced better results with a lower RMSE value. For instance, the RMSE value for the RBFN-BMO is 25.637% with 100 data, while the RMSE values for the GRU, LSTM, RNN, DNN, and ANN models are slightly higher at 30.526%, 26.928%, 33.626%, 36.536%, and 43.737%, respectively. The RBFN-BMO model, on the other hand, has demonstrated that it performs best with diverse data sizes while keeping a low RMSE. The RMSE value for the RBFN-BMO model under 6000 data is 26.324%, whereas it is 32.933%, 29.322%, 35.342%, 42.627%, and 47.326% for the GRU, LSTM, RNN, DNN, and ANN models, respectively.

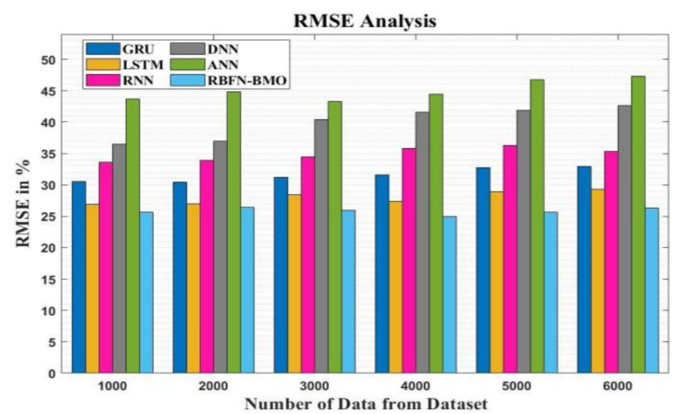

Fig. 8. RMSE analysis of the RBFN-BMO method with existing systems.

TABLE V. RMSE ANALYSIS OF THE RBFN-BMO METHOD USING EXISTING SYSTEMS

Data from dataset	*GRU*	*LSTM*	*RNN*	*DNN*	*ANN*	*RBFN-BMO*
1000	30.526	26.928	33.626	36.536	43.737	25.637
2000	30.425	27.029	33.928	36.928	44.863	26.435
3000	31.252	28.425	34.526	40.425	43.324	25.926
4000	31.627	27.425	35.827	41.627	44.432	25.029
5000	32.737	28.926	36.324	41.911	46.732	25.627
6000	32.933	29.322	35.342	42.627	47.326	26.324

6) Execution time analysis: The execution time analysis of the RBFN-BMO technique using existing methods is described in Table VI and Fig. 9. The information clearly shows that the RBFN-BMO method has outperformed the other techniques in every way. The RBFN-BMO process, for example, took only 2.738ms to execute 1000 data, while GRU, LSTM, RNN, DNN, and ANN took 12.837ms, 10.637ms, 8.526ms, 6.938ms, and 4.837ms, respectively. Similarly, the RBFN-BMO method takes 3.624ms to execute 6000 data, whereas the other existing techniques such as GRU, LSTM, RNN, DNN, and ANN have taken 15.526ms, 11.638ms, 9.553ms, 7.425ms, and 5.029ms, respectively.

TABLE VI. ANALYSIS OF RBFN-BMO METHOD EXECUTION TIME WITH EXISTING SYSTEMS

Data from dataset	GRU	LSTM	RNN	DNN	ANN	RBFN-BMO
1000	12.837	10.637	8.526	6.938	4.837	2.738
2000	12.536	10.827	8.928	6.324	4.213	2.324
3000	13.627	10.324	8.435	6.022	4.039	3.029
4000	13.829	11.526	9.073	7.425	4.637	3.927
5000	13.425	11.627	9.224	7.829	5.324	3.526
6000	15.526	11.638	9.553	7.425	5.029	3.624

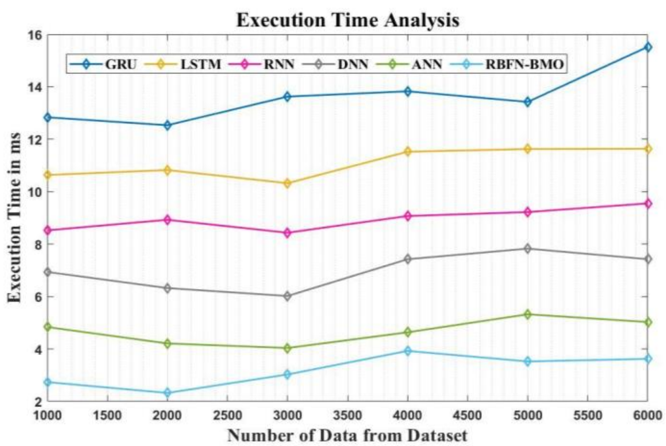

Fig. 9. Execution time analysis for the RBFN-BMO method with existing systems.

V. CONCLUSION

Facial expression analysis is one tool used to develop emotional intelligence, which is becoming increasingly important in many fields, including business and education. Numerous factors, such as visual contexts, point-of-view shifts, intra- and inter-class differences and more, impede the development of a reliable emotion recognition system. This paper suggests a convolutional neural network as a potential solution to the emotion recognition problem. To examine facial expressions in images, the proposed RBFN was made face-sensitive. The proposed RBFN-BMO can recognize people in high-resolution photos, evaluate facial expressions using facial features, and predict emotional states. The recognition during testing validates the proposed efficacy. Regarding output quality, the established RBFN-BMO classification algorithms perform better than those currently used. The RBFN-BMO uses every dataset used for the analysis and achieves the highest level of accuracy possible, which is 99.54%. To evaluate the effectiveness of the proposed classifier, the performance of proposed RBFN-BMO is compared with the existing Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), Deep Neural Network (CNN), Artificial Neural Network (ANN). As a result, the RBFN-BMO can produce better results for celebs datasets. Furthermore, it can be inferred that the Blue Monkey Optimization (BMO) meta-heuristic algorithm selects the input data features that are both the most informative and the most pertinent. It helps to achieve better categorization and reduces the error brought on by the Root Mean Square. The future of our research depends on adding new features, classifying facial emotions into their ten subcategories, and researching automatic facial emotion recognition.

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