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A Novel Grey Wolf Optimizer Tuned Bidirectional Gated Recurrent Unit Model for High Accuracy Facial Recognition Classification

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ABSTRACT: Facial recognition is an essential component of human communication, impacting interactions and decision-making processes. In order to facilitate more natural and efficient interactions between humans and machines, it is becoming more and more critical to include emotional awareness into machines. In this paper, a Bidirectional Gated Recurrent Unit classification is proposed to quickly recognise the facial reaction. Firstly, image resolution conversion is applied to CK+ facial recognition dataset to resize the image, then pixel values of an image based on its intensity histogram is adjusted using histogram equalization. Then it smoothen the image and removes the noise using Gaussian filter to get high quality image. Next, the processed image is given to feature extraction by Scale-Invariant Feature transform it is used to find the key points. After that image features are selected using Grey Wolf Optimization (GWO) designed for further analysis. Finally, a Bidirectional Gated Recurrent Unit (Bi-GRU) framework is processed to enhance the classification of face recognition. Using python software proposed framework have accuracy of 92% is accomplished when compared to other techniques.

Keywords: Bidirectional Gated Recurrent Unit (Bi-GRU), Grey Wolf Optimization (GWO), Scale-Invariant Feature Transform (SIFT), Gaussian Filtering, Image Resolution Conversion, Histogram Equalization, Face Recognition.

1. Introduction

Face recognition is the process of automatically recognizing or confirming a person's identification through the analysis of facial patterns [1].Now a days, one of the most important and a difficult method is emotion recognition. Emotion recognition have a number of applications, such as assisting in the assessment of stress levels, blood pressure, etc. [2]. Whereas, among the face features that employ emotional strategies are the applications of calm, neutral, sad, and cheerful. People are protected from dangerous infections or illnesses because emotional awareness helps detect diseases early. The key benefit of emotional recognition is its capacity to identify human mindsets without requiring direct conversation. [3]. However, the internet allows users to access the smart devices, which is used for various decision support systems and for surveillance purposes using sensors and cameras in smart cities and houses for facial reaction [4-5]. Moreover, anumber of factors, including position, face occlusion, scale, illumination, image infringement, facial expressions, and others, affect face identification. By using some of the facial expressions such as anger, contempt, disgust, fear, happy, sadness and surprise the face reactions are identified [6-7].

Using the Viola-Jones face detection the face region is detected. To improve the identification of the eye, nose, and mouth regions, a Butterworth high pass filter is used. Performance is poorer close to the cutoff frequency due to the slow roll-off than with a steeper roll-off from other filter types [8]. Conversely, to analyze the frequency and location a Gabor filter is used. Excellent spatial localization, frequency selectivity, and orientation selectivity, but they also have drawbacks, such as high processing costs and noise sensitivity [9].

In order to extract features from face eye, lip, brow and cheek both Histogram Oriented Gradients (HOG) and 2D-Discrete Wavelet Transform (2D-DWT) is utilized. It improves the accuracy and recognition process. Drawback is lack of period information, insufficient directionality, and shift sensitivity [10]. Whereas, Tree-structured Parzen Estimator (TPE)-based Bayesian optimization technique is used for facial recognition. By this optimization approach it successfully allows the system to adjust and improve its feature extraction capabilities. Low accuracy on complex issues, especially when working with high-dimensional search spaces [11]. However to identify the action element for establishing and expressing various facial expressions Principle Component Analysis (PCA) is used. To provide a face action unit, PCA have been misused to identify and build alternative facial expressions [12].

To increase facial recognition accuracy CNN is used. As a result, it eliminates the incorrect data from the face image caused by the function. Over fitting, and interpretability issues and high processing are drawback of CNN [13-14]. Moreover, to identify facial reaction the combination of Long Short Term Memory (LSTM) and Maximum Boosted Convolutional Neural Network (MBCNN) have revealed high accuracy value. It takes more intervals to access the process when identifying the facial reaction [15]. To overcome this limitation a Bi directional Gated Recurrent Unit (Bi-GRU) is used for face recognition.

2. Related Work

Sahan *et al* [16] (2023) have proposed a One-Dimensional - Deep Convolutional Neural Network (1D-DCNN) classifier joined by Linear Discriminative Analysis (LDA) methods to create a face recognition. The one-dimensional face feature set that LDA creates from the original image database for the 1D-DCNN classifier's training, enhances facial recognition performance. Low accuracy in complex issues, particularly when functioning with high-dimensional search places.

Kim *et al* [17] (2021) have developed an Xception algorithm to predict facial recognition. Here to improve the performance of system a Facial Image Threshing (FIT) machine is used as an advanced feature. The advantage of xception algorithm is easy to understand because they represent a solution to a problem step-by-step. With a larger number of parameters, Xception typically needs more training data to function.

Tan *et al* [18] (2021) have proposed a Spiking Neural Network (SNN) to detect the emotion recognition. It improves the facial reaction using the Spiking Neural Network. Benefits including dynamic behavior, real-time processing, and energy efficiency, but they also have training difficulties and fewer sophisticated tools than standard.

Sikkandar *et al* [19] (2021) have proposed Improved Cat Swarm Optimization (ICSO) algorithm and Deep Convolutional Neural Network (DCNN) to recognize the human facial expression. The ICSO and DCNN model is reliable enough to accurately and efficiently identify and classify face reaction. Slow convergence and local minima susceptibility are two drawbacks of ICSO and DCNN.

Yang *et al* [20] (2021) have proposed an Attentional Adversarial Attack Generative Network (A3GN), to identify the face recognition.

The A3GN model is reliable enough to accurately and efficiently recognise the face recognition. When identifying face reaction, several issues are increased; poor identification speed, high computation costs, and inadequate precision.
The contribution of this work is follows

- Introduces an image resolution conversion technique which is applied to the CK+ facial recognition dataset to resize the input face image
- Then the pixel values of an image based on its intensity histogram is adjusted using histogram equalization after that the unwanted noises are removed using the Gaussian filter to get high quality image.
- Subsequently, feature extraction by Scale-Invariant Feature transforms to find the key points.
- After that feature selection by GWO to optimize the image for further classification.
- Finally, a Bidirectional Gated Recurrent Unit (Bi-GRU) is treated to enhance the classification of face recognition.

3. Proposed Work

The proposed block diagram in figure 1 for face recognition using neural network technique is applied to CK+ facial recognition datasets.

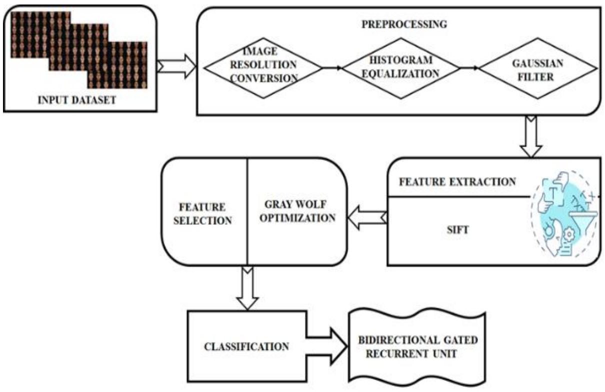

Figure 1: *Block diagram of proposed method*

Initially using image resolution conversion the face image is resized. After that using histogram equalization pixel intensities and the neighborhood's average intensity value are used to enhance the image contrast. Then using Gaussian filters the image smoothes and reduces noise. The processed face image is given as input to feature extraction here the Scale -Invariant Feature Transform (SIFT) is used to find the key points. After that using feature selection the image is optimized using Grey Wolf Optimization (GWO) for recognition. Finally using classification technique the Bidirectional Gated Recurrent Unit (Bi-GRU) the process is done in both forward and backward direction. A proposed Bidirectional Gated Recurrent Unit (Bi-GRU) is used to increase the accuracy and efficiency for facial recognition.

3.1 Pre-Processing

In the face recognition identification pre-processing have three methods image resolution conversion, histogram equalization and Gaussian filtering.

3.1.1 Image Resolution Conversion

In order to make it simpler to see the distribution and evolution of face recognition image, pre-processing aims to display a color image by mapping the gray scale image of the one-dimensional fluorescence value to the three-dimensional RGB value using a false color system.

3.1.2 Histogram Equalization

The histogram equalization is the relationship between a pixel's intensity and the neighborhood's average intensity value to enhance the image's contrast. Here, the joint histogram is constructed in order to obtain the correlation and a multidimensional histogram is constructed through selecting a set of local pixel points to produce a joint histogram. The amount of pixels in the image stated by a particular grouping of feature values is represented by each individual cell in the joint histogram matrix. The intensity levels of a specific pixel in a picture are

$\{0, \dots \dots, L-1\}$, whereas the regular intensity levels of its region are $\{0, \dots \dots, L-1\}$. There will be $L \times L$entries in the joint histogram.

3.1.3 Gaussian Filtering

A linear filter that smooth images and reduce noise is the gaussian filter and it is unknown however a low-pass filter. Gaussian noise typically affects the input face image. The white gaussian noise filter is used to identify this noise. Additionally, the Gaussian noise filter aids in removing image blur. It accurately forecasts the image fixation.

$$G(u,v) = \frac{1}{2*3.14*\sigma^2} e^{\frac{-(u^2+v^2)}{\sigma^2}} \qquad (1)$$

Where, u indicates u coordinate value, v indicates v coordinate value and σ stands for standard deviation, 3.13 indicates mathematical constant PI.

3.2 Feature Extraction

In feature extraction Scale-invariant feature transform is used for extracting the face reaction.

4. Scale-Invariant Feature Transform (SIFT)

Several significant descriptive image features are extracted using the scale invariant feature transform. These characteristics are invariant by illumination, rotation, and scale. These points are typically found in locations with extreme contrast, sometimes on the margins of objects. Figure 2 shows the scale invariant feature transform for face recognition.

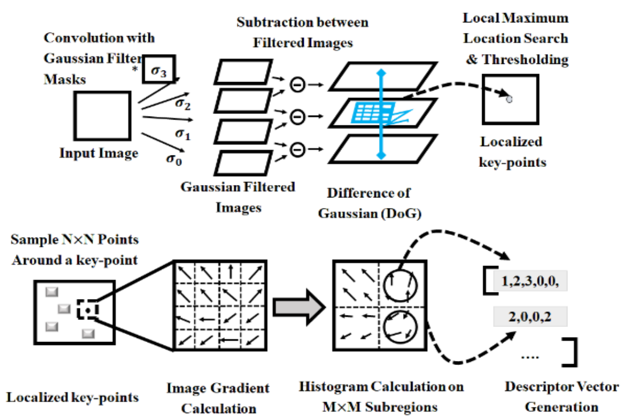

Figure 2: *Scale-Invariant Feature Extraction*

The primary steps in Scale-Invariant Feature Transform feature extractions for facial recognition. The first step, known as scale-space extrema extraction, involves searching for interest points that are both scale and rotation invariant. It makes use of the Difference of Gaussian (DoG) function. The location and filtering of the essential points are then carried out. The position and scale of the resulting interest spots are determined at this step. Important points that are resistant to image distortion are chosen. The Orientation Assignment step comes next, when each key point location is given one or more orientations based on local image-gradient directions. After that, the feature description is executed. Invariant to Scale is to find the local characteristics of an image that are not impacted by actions like object scaling and rotation; Feature Transform takes an image as input and converts it into a large collection of local feature vectors called the key points. In the neighbourhood of a key point, the local image gradients are measured at the chosen scale. Moreover, a 128D feature descriptor is produced. Figure 3 shows the flow chart of feature description.

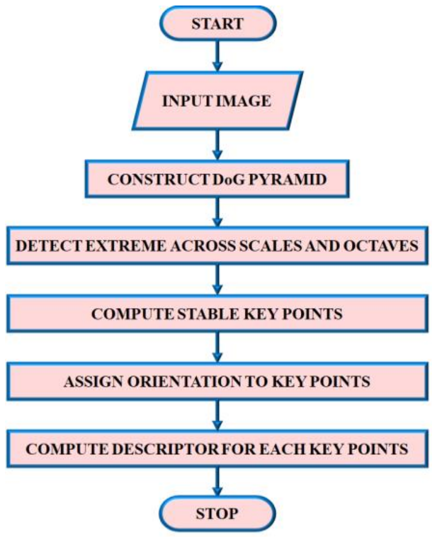

Figure 3: *Flow chart for feature description*

4.1 Feature Selection

To feature the facial recognition Grey Wolf Optimization (GWO) is used.

5. Grey Wolf Optimization

The Grey Wolf Optimization is optimized to get better classification for face recognition. One type of swarm intelligence is GWO system that chooses pertinent features from data by utilizing the social hierarchy and hunting behavior of grey wolves. Because wolves alive in sets and are at the top of the food chain, grey wolves are regarded as the largest predators. Five to twelve wolves make up the group. These are separated into four groups. Alpha is the first group, which is made up of a male and female couple who make all of the decisions. The fact that they take for the benefit of the herd rather than for individuals is a plus. Wolves at the beta level are subservient to alpha and assist in making decisions on other pack activities. In the event that one of the alpha pairs lives, these are the most suitable options for the alpha wind pipe. Figure 4 shows the Gray wolf optimization for face recognition.

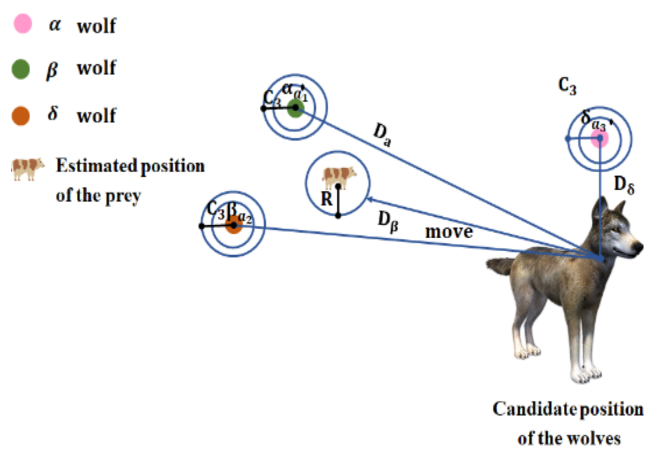

Figure 4: *Grey Wolf Optimization*

Even though it commands the other levels, this one respects the alpha. The final category, known as omega, falls under each of the abovementioned groups. They appear in the least significant group, but in addition to meeting the group's needs, they also uphold the hierarchy of dominance from the other groups, frequently acting as the group's children's guardians.

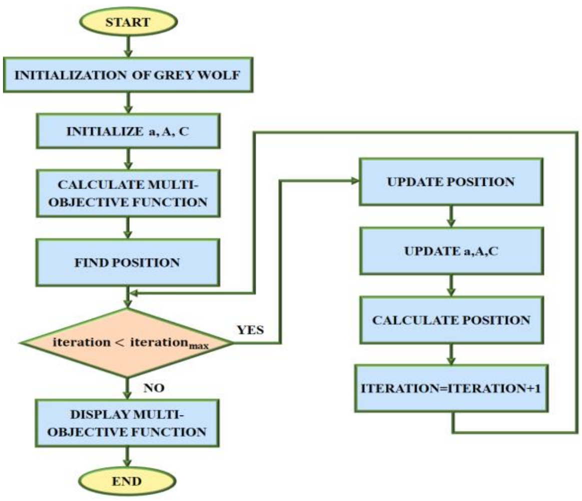

Figure 5: *Flow chart for GWO*

A category above omega is delta, which is the other group. It serves a number of purposes, including keeping an eye on the territory's boundaries, ensuring the group's safety, and advising the hunter and alpha. Hunting is the initial action, and it is modeled as follows:

$$X(t+1) = X(t) - A.D \qquad (2)$$

Where A is a coefficient, X (t+1) is the wolves' location, X (t) is their current position, and is a vector that is determined by the press's position X (p) and is computed as follows:

$$D = \left|C.X_p(t) - X(t)\right| ku\ C = 2.r_2 \qquad (3)$$

Where the random vector r_2 falls between 0 and 1 and the wolves must adjust their positions in the following ways in order to obtain the local optimum:

$$X(t+1) = \frac{1}{3}X_1 + \frac{1}{3}X_2 + \frac{1}{3}X_3 \qquad (4)$$

Where X1, X2, and X3 are determined in this way:

$$X_1 = X_\alpha(t) - A_1.D_\alpha \qquad (5)$$

$$X_2 = X_\beta(t) - A_2.D_\beta \qquad (6)$$

$$X_3 = X_\gamma(t) - A_3.D_\gamma \qquad (7)$$

The Pseudo code of grey wolf optimization algorithm is in table 1 to calculate the calculation technique.

Table 1: *Pseudo code of grey wolf optimization algorithm*

Set up the grey wolf population initially. $X_i(i = 1,2, \dots, n)$
Set up $a, A, and\ C$
Determine each search agent's fitness
Beast hunt agent is $\vec{X}_\alpha$
second hunt agent is $\vec{X}_\beta$
Third hunt agent is $\vec{X}_\delta$
while ($t <$,max amount of repetitions)
    for every hunt agent
        Use an equation to update the present hunt agent's position.
end for
Modernize $a, A, and\ C$
Determine the fitness of all hunt agents
Modernize $\vec{X}_\alpha\ \vec{X}_\beta\ \vec{X}_\delta$
t=t+1
end while
return $\vec{X}_\alpha$

5.1 Classification

To classify the facial recognition Bidirectional Gated Recurrent Unit (Bi-GRU) is used.

6. Bidirectional Gated Recurrent Unit

An enhanced form of RNN, the Gated Recurrent Unit (GRU) in facial recognition solves the problems of gradient explosion and vanishing gradients that conventional recurrent neural networks face. Gated recurrent units successfully address these issues by implementing update and reset gates. Because of this, the gated recurrent unit is less likely to over fit and performs better in terms of iteration and convergence time.

This uses a bidirectional gated recurrent unit to model the feature information of face sub regions in order to efficiently utilize contextual information across various facial areas in facial expression identification. Two distinct sets of hidden states are produced by applying a bidirectional gated recurrent unit to these feature sequences of facial sub regions in both forward and backward computations. By combining these two sets of states, bidirectional gated recurrent unit outperforms unidirectional gated recurrent unit in terms of fitting capability. Bidirectional gated recurrent units perform better in terms of fitting capabilities than unidirectional gated recurrent units by merging these two sets of states. Better use of the input sequence information is made possible by this mix of forward and backward computations, which helps the network better capture a minute changes in face expressions.

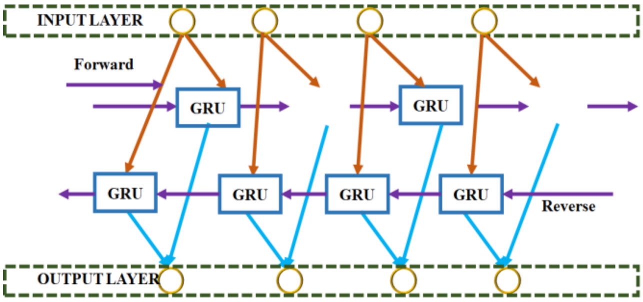

Figure 6: *Bidirectional GRU in both directions*

The forward-propagating and backward-propagating gated recurrent units' cell architectures are displayed in Figure 6, along with the related computational formulas, which are as follows:

$$z_t^{(p)} = \sigma(W_z^{(p)} x_t + U_z^{(p)} h_{t-1}^{(p)} + b_z^{(p)} \quad (8)$$

$$r_t^{(p)} = \sigma(W_r^{(p)} x_t + U_r^{(p)} h_{t-1}^{(p)} + b_r^{(p)} \quad (9)$$

$$\hat{h}_t^{(p)} = \varphi((W_h^{(p)} x_t + U_h^{(p)} h_{t-1}^{(p)} \odot r_t^{(p)} + b_h^{(p)} \quad (10)$$

$$h_t^{(p)} = \left(1 - z_t^{(p)}\right) h_{t-1}^{p} + z_t^{p} \odot \hat{h}_t^{(p)} \quad (11)$$

$$z_t^{(b)} = \sigma(W_z^{(b)} x_t + U_z^{(b)} h_{t-1}^{(b)} + b_z^{(b)} \quad (12)$$

$$r_t^{(b)} = \sigma(W_r^{(b)} x_t + U_r^{(b)} h_{t-1}^{(b)} + b_r^{(b)} \quad (13)$$

$$\hat{h}_t^{(b)} = \varphi((W_h^{(b)} x_t + U_h^{(b)} h_{t-1}^{(b)} \odot r_t^{(b)} + b_h^{(b)} \quad (14)$$

$$h_t^{(b)} = \left(1 - z_t^{(b)}\right) h_{t-1}^{b} + z_t^{b} \odot \hat{h}_t^{(b)} \quad (15)$$

$$h_t = h_t^{p} + h_t^{b} \quad (16)$$

The forward and backward GRU cells to which they belong are indicated by the letters $p\ and\ b$, respectively, and the step of the current iteration is indicated by the index t in the bidirectional gated recurrent unit formulation. The reset and update gates of the gated recurrent unit are represented by the letters r and $z,$ respectively. W_z, W_r and W_h are the starting weights of the current input sequence's neurons, U_z, U_r and U_h symbolize the hidden layer's starting weights from the previous step and b_z, b_r and b_h are the corresponding offsets.

In particular, each GRU unit first determines the hidden state $h_t - 1$ of the previous stage and the current input x_t in order to compute the states of the reset and update gates. When the sigmoid activation function is applied, a state vector in the 0– 1 range is produced. The state vector following forgetting is then calculated by $h_t - 1 \odot r_t$ calculating, where $\odot$ represents a multiplication operation between individual elements. The nonlinear activation function φ then activates the outcome of the previous step, which is then added to the bias and the appropriate weighted input vector xt. Which data should be retained as the final data is determined by the update gate in the current cell.

6.1 Result and Discussion

The aim of this work is improve the efficiency of various prospective DL algorithms and Bidirectional Gated Recurrent Unit is used. Using Python software the proposed work is illustrated. To assess the algorithms' performance, the CK+ facial recognition dataset is utilized.

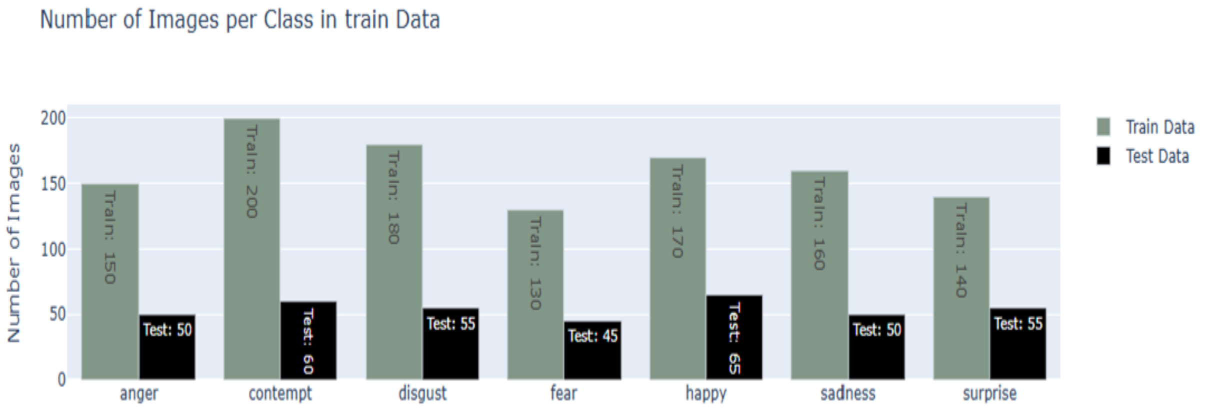

Figure 7: *Number of images per class in train data*

Figure 7 shows the number of per class in train data. Here number of images takes is 200 and seven classes of reactions are trained using the CK+ facial recognition dataset. The seven classes of images are anger, contempt, disgust, fear, happy, sadness and surprise. For anger test data is 50 and train data is 150, for contempt test data is 60 and train data is 200, for disgust test data is 55 and train data is 180, for fear test data is 45 and train data is 130, for happy test data is 65 and train data is 170, for sadness test data is 50 and train data is 160 and for surprise test data is 55 and train data is 140.

Figure 8: *Original face image*

Figure 8 shows the original face image. Here the input image is taken from the CK+ facial recognition dataset. Using the image processing techniques the input image is processed.

Figure 9: *Original image to resize image*

Figure 9 shows the original image to resize image. Here the input face image is resized using image resolution technique. The noises are removed and smooth's the original image.

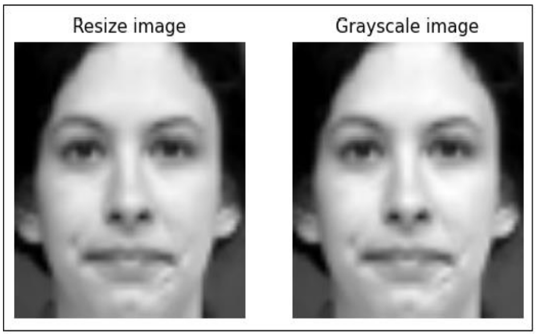

Figure 10: *Resize image to gray scale image*

Figure 10 shows the resize image into gray scale image. Here face image is converted an image to a gray scale or black and white representation is gray scale image.

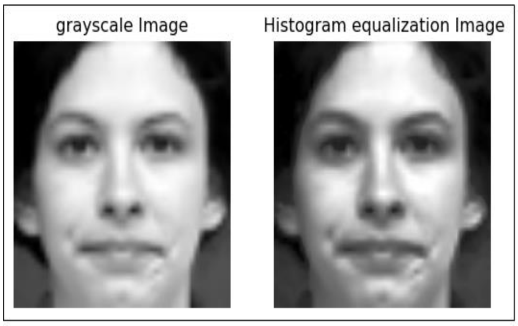

Figure 11: *Histogram equalization image*

Figure 11 shows the grayscale image into histogram equalization image. Here the image is enhanced and contrast by its pixel values.

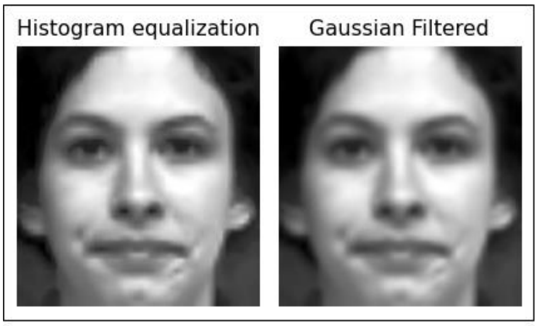

Figure 12: *Gaussian filter*

Figure 12 shows the histogram equalization into Gaussian filter. Here after the grayscale conversion the Gaussian filter is utilized. It smoothens the face image and reduces the noise using Gaussian filtering.

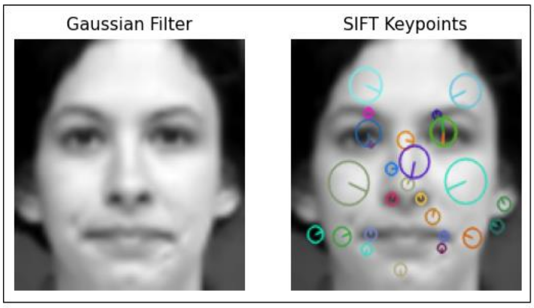

Figure 13: *Gaussian filter into SIFT key points*

Figure 13 shows the Gaussian filter into SIFT Key points. Here the Scale-Invariant Feature Transform fined the key points from the face image for further analysis.

7. Performance Metrics

By examining accuracy, precision, sensitivity, specificity, Area under the Curve (AUC), classification with "positive" and "negative" labels, the performance of each classification model in this study explained in table 2.

Table 2: *Performance Metrics*

Performance metrics	Formula
Accuracy	$\frac{(TN+TP)}{TS}$
Precision	$\frac{(TP)}{TP+FP}$
Recall	$\frac{(TP)}{(TP+FN)}$
$F1-score$	$\frac{(2 * \text{Precision} * \text{Recall})}{(Precision\ + Recall)}$

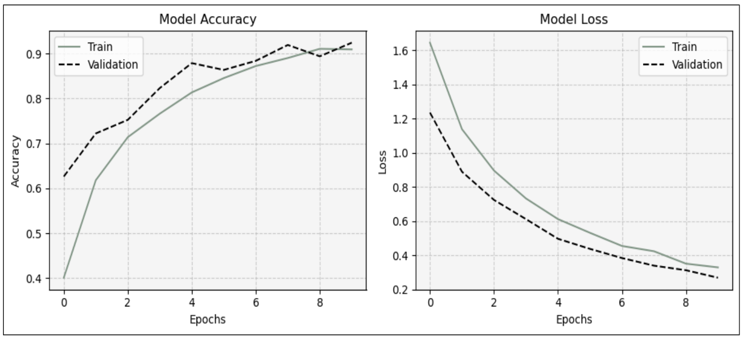

Figure 14: *Model accuracy and model loss*

Figure 14 shows the model accuracy and model loss. Here in model loss the training loss is going on decreasing and the validation loss is going on decreasing the decreased below training loss. The accuracy value is trained using the Bidirectional Gated Recurrent Unit (Bi-GRU) to classify the model to get the higher accuracy of 92%. When compared to the existing method.

8. Confusion matrix

Face recognition classes are predicted using confusion matrix. Anger, contempt, disgust, fear, happy, sadness and surprise are predicted from the seven classes.

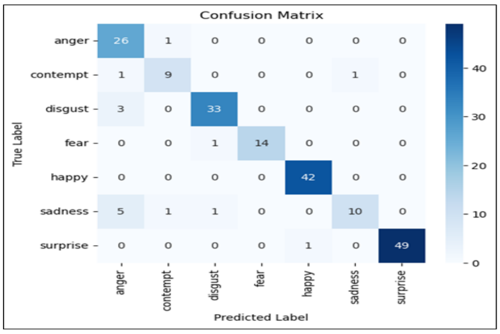

Figure 15: *Confusion matrix for proposed Bi-GRU*

The confusion matrix in figure 15 evaluates the model's performance in predicting different levels of face recognition. It shows high accuracy for all classes, with 26 faces of anger, 9 faces of contempt, 33 faces of disgust, 14 faces for fear, 42 faces for happy, 10 faces for sadness and 49 faces of surprise correctly classified.

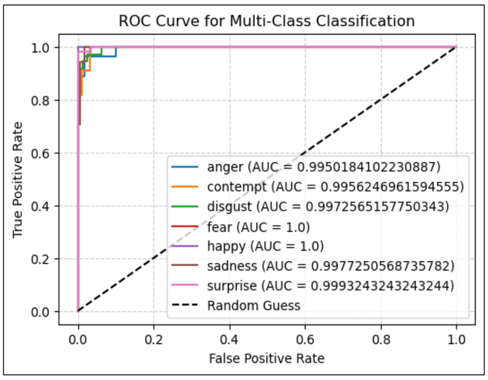

Figure 16: *Roc cure for Multi-class classification*

According to the results shown in Figure 16, the face recognition, the suggested Bi-GRU continues to have the highest AUC value of 1 for happy and fear, and for anger, contempt, disgust, sadness, surprise the AUC value of 0.99 demonstrating the unique overview and flexibility of this approach.

9. Comparison for the Proposed Method

The comparison of the proposed method with existing method is presented in table 3. The Xception algorithm have the classification accuracy of 79.39% [17] and Spiking Neural Network have the accuracy of 76.55% [18] The proposed Bi-GRU have the higher accuracy of 92% compared to the existing method in table 3. The proposed Bi-GRU have better performance.

Table 3: *Comparison for the proposed method*

Study	Method	Accuracy
Kim *et al.* [17]	Xception Algorithm	76.55%
Tan *et al.*[18]	SNN	79.39%
Proposed approach	Bi-GRU	92%

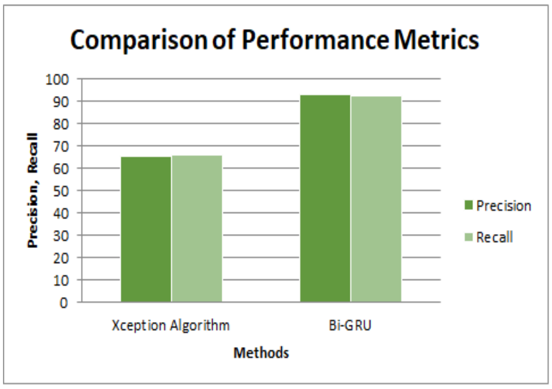

Figure 17: *Comparison for precision and recall*

The Precision and recall value for classifiers XG Boost and the proposed is presented in Figure 17. The Xception algorithms have the value of 65% and 65.5% [17] and proposed Bi-GRU methods have the precision value of 92% and recall of 93% respectively.

10. Conclusion

This research introduces a comprehensive and efficient framework for the detection and classification of face recognition using Bi-GRU. The integration of advanced data preprocessing techniques, such as image resolution conversion, histogram equalization and Gaussian filter, ensures that the input data are optimized for feature extraction. Then feature extraction for key point extractor. Additionally, the Grey Wolf Optimization for wolf hunt for food using pertinent features from data by utilizing the social hierarchy and hunting behavior of grey wolves capturing crucial patterns for effective classification. The performance evaluation, conducted on the CK+ facial recognition dataset, demonstrates the superior capabilities of the Bidirectional Gated Recurrent Unit compared to existing state-of-the-art methods. By using recurrent neural network the model focuses on critical features, resulting in improved accuracy of 92%.

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