Human Facial Emotion Recognition using Deep Neural Networks

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Abstract: *Humans experience a plethora of different, confusing and nearly indiscernible emotions. Interpreting and understanding these emotions is a rewarding challenge as they play an important role in developing and maintaining interpersonal relationships. Hence, extracting and understanding emotions is paramount to the interaction and communication between human and machine. This understanding aids applications such as brand humanization, sales, advertising and marketing by helping to gauge the response of existing or prospective clients, medical industry, e-learning, law enforcement, automatic counseling system, drunk-driving detection, pain or stress detection, brand value analysis from consumer reactions and the entertainment industry, social interactions and facilitate rational decision making and perception. The recognition of facial emotion is quite difficult problem since there will be a variation of same emotion of single person owing to occlusion, illumination, aging, pose, gender etc. This paper proposes a deep learning model to detect the seven basic emotion classes. The dataset used are CK+, JAFFE and it achieves higher accuracy when compared to the existing approaches*.

Keywords: *Neural Network, deep neural networks, facial expression, emotion recognition system*.

Received March 12, 2021; accepted March 27, 2022
https://doi.org/10.34028/iajit/20/3/2

1. Introduction

Facial emotion recognition plays a vital role in understanding the thought of person and it is used in daily applications [29]. The two types of emotions are basic and compound emotions. There are seven basic emotions and 23 compound emotions [20]. The basic emotions are anger, disgust, fear, happiness, sadness, neutral and surprise [2, 6]. The compound emotions are the combination of the basic emotions which is a temporal state of an individual person [31]. The facial emotion recognition is a very useful of human-human communication [18]. Efforts are being made to train the computer to classify the emotions as if humans do [28].

Automatic facial emotion recognition plays a major role in recent researchers in deep learning network and computer vision [22, 25]. The facial emotion recognition system is divided into static (frame-based) Facial emotion recognition and dynamic (video-based) facial emotion recognition for capturing the sequences of facial expression [10]. The data base plays a major role in the field of machine learning and the most advances include deep learning which achieves higher recognition accuracy [23, 27]. The subfield of machine learning which train system to perform naturally as humans is deep learning that deals with the artificial neural network [5]. The approaches [15] used in this paper for the facial emotion recognition system are

- Geometric based approach: this approach will focus on the extraction of feature points and the shape of the facial image [13].
- Appearance based approach: this approach will focus on facial appearance (texture) which is used for the classification of the facial image [13].

The main contributions of our work are as follows: to overcome the illumination variation in images and to detect the emotion when the same person differs in the way they portray the emotion. To solve the imbalance problem of the seven basic emotion classes in the CK+ and JAFFE datasets. To propose a deep learning model for facial emotion recognition and to calculate the efficiency of the proposed model and to compare the proposed model accuracy with the existing models.

2. Literature Survey

The researchers working in the field of the emotion recognition focus on recognizing emotion through various aspects such as speech signal, heartbeat rate, Electrodermal activity, gesture movement, static and dynamic images of the facial expression [3]. Based on the handcrafted techniques used for facial emotion recognition, we can divide the methodologies into two broad categories [7]: Conventional machine learning based approaches and deep learning based approaches [19]. Traditionally, [17] in the first approach, the recognition of facial emotion is done by extracting the facial features and then the facial images are classified. Happy and Routray [9] proposed a framework for facial emotion recognition based on the appearance based features in the selected facial regions (active regions) for feature extraction. Then one-against-one classification is used for classification. The dataset used are CK+ and JAFFE which achieves an accuracy of about 89.64% and 85.06%. Goyani and Patel [8] proposed a multilevel haar wavelet based approach for extraction of the appearance features in the face. Then for classification one vs all logistic regression model is used. The dataset used are CK+, JAFFE and Taiwanese Facial Expression Image Database (TFEID) which achieves an accuracy of 90.48%, 88.57% and 96.84%. Niu *et al*. [24] proposed an algorithm with combined oriented FAST and rotated BRIEF features. The effective features are first extracted using the face detection algorithm and then proposed algorithm is used for the extraction of the facial regions. Then detected features are then classified by support vector machine. The dataset used are CK+, JAFFE and MMI Facial Expression Database which achieves an accuracy of 93.2%, 88.5% and 79.8%. These are some of the Conventional machine learning methods where feature extraction and classification is done separately by some traditional methods. Kumar *et al*. [16] used the Improved Quantum Inspires Gravitational Search Algorithm for the feature selection and optimization. The dataset used are Karolinska Directed Emotional Faces (KDEF) and JAFFE which achieves an accuracy of 94.05% and 91.64%.

Recently used approaches are deep learning based methods where the features are learned automatically [30]. Jain *et al*. [11] proposed a single deep Convolutional neural network which has convolution layers and deep residual blocks. The images are first labelled for training and then they are given to proposed model. The CK+ and JAFFE dataset are used which achieves an accuracy of 93.24% and 95.23%. Jain *et al*. [12] proposed a hybrid convolution recurrent neural network for facial emotion recognition which contains the convolution layers and recurrent neural network. This model extracts the common features in the facial images and during the classification the temporal dependencies are considered. The JAFFE and CK dataset are used which achieves an accuracy of 94.91% and 92.07%. Chen and Hu [4] proposed a interclass relational learning method for assigning weight for individual pixels. The main goal is to predict the ratio of each emotion correctly and evaluated on five datasets CK+, JAFFE, TFEID, BAUM-2i and FER2013. This method works only when the inter class distance is increased and intra class distance is decreased. Abate *et al*. [1] proposed a combined center dispersion loss function for reducing the intra class and interclass similarities in the facial emotion dataset images. Then an incremental cosine annealing method is used for training multiple models for better learning and for achieving better accuracy. The Visual Geometry Group (VGG) Face model is used for training on FER2013 dataset and achieves an accuracy of 74.71%.

Still, facial emotion recognition system is a challenging problem for the research community [14]. Various Conventional machine learning methods and deep learning models for facial emotion detection are discussed in this section. Some of the challenges addressed are imbalanced distribution of emotion classes in the dataset, same person differs in the way they portray the emotion and the variations in face due to pose, age, facial hair, face glass, face mask, lighting and occlusions. Our objective is to classify the basic emotion classes on CK+ and JAFFE datasets. JAFFE is a small dataset and both the dataset JAFFE, CK+ have imbalanced nature of emotion classes. To address this issue the datasets are combined and the data augmentation approach is applied. In preprocessing stage, face detection algorithm is used for detection of face from image. Since the same person differs in the way they portray the facial emotion, by using contrast stretching techniques the image intensity and contrast are normalized. Then the preprocessed images are given to the proposed model for further processing. The proposed model has ability to recognize the emotions for low resolution images. So the proposed model can be used in real time applications like detection of facial emotion in real time web-cam and detection of facial emotion in dynamic images (Video).

3. Proposed Model

In the proposed deep learning model the data preprocessing is done by using the data augmentation technique and then the image is normalized where the face is detected. The preprocessed images are given to the proposed deep learning model for feature extraction and classification of the emotion classes. The input image size will be 256×256 when it is given to the deep learning model. The proposed model is shown in Figure 1 which has six Convolutional layers and three max pooling layers. There are two fully connected layers each consists of the Relu activation function and contains dropout for training.

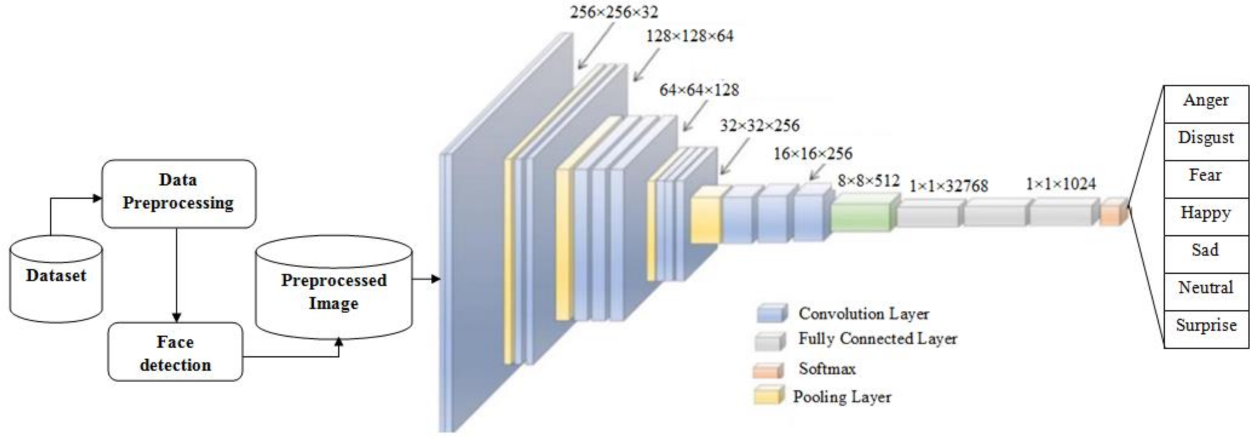

Figure 1. Architecture of the proposed model.

The proposed model makes the feature to be learned automatically and classification to be done efficiently. Some of the existing methods have some complexity in the facial emotion recognition task. The softmax activation function is used for classification. The dataset is trained using the proposed deep learning model. The images are first preprocessed and then trained and tested using the proposed model. There are two fully connected layers used and for training the model batch size was set as 64 which will be varied accordingly and the learning rate as 5e-5 which decreases for every 15epochs. The final output will be one of the seven emotion classes.

4. Methodology

The proposed model was evaluated on the benchmark dataset CK+ and JAFFE. Both the dataset are taken from a controlled environment. Some preprocessing techniques are used for improving the performance of the proposed model.

4.1. Dataset Description

Inorder to train the neural network, large amount of images are required. In this paper, the CK+ and JAFFE dataset are used. Both the dataset have imbalance problem. To address this issue, the CK+ and JAFFE are combined and data augmentation approach is used. The Cohn Kanade dataset is the first version of the facial emotion recognition dataset used for the purpose of the research for facial recognition of emotion. The large amount of the labeled images is required for training the neural network model. Here the images in the CK+ and JAFFE dataset are taken with constant lighting condition and head pose in the controlled environment. The CK+ dataset is taken from 97 different posers. The images obtained after preprocessing from CK+ dataset is a benchmark dataset used by researchers which has 593 sequences taken from 123 subjects. For experimentation the total images taken for training is 13467 and 700 for testing.

Few sample images of the CK+ dataset are shown in Figure 2.


a) Fear.


b) Surprise.


c) Disgust.


d) Happy.

Figure 2. Sample basic facial emotion images.

The Japanese Female Facial Expression (JAFFE) database as the name implies this dataset is a Japanese Female Facial expression database which is posed by 10 Japanese women models. The JAFFE dataset contains seven posed facial emotions with 213 images of resolution 256×256 pixels. The facial images in a dataset are imbalanced and there is problem of less data. Inorder to overcome this issue the data augmentation is done.

4.2. Pre-Processing

The illumination variation in the images will reflect in the interclass feature of the image. So inorder to reduce the mismatch in the interclass feature the image normalization technique is used in this paper. The mismatch in the interclass feature of the image is named as intensity offsets [12]. Since the intensity offset in the local region are uniform, the gaussian normalization is used. The normalized image can be computed using the equation

$$\omega(\eta,\varphi) = \frac{\Omega(\eta,\varphi) - \mu(\eta,\varphi)}{7\sigma(\eta,\varphi)} \quad (1)$$

Where $\omega(\eta,\varphi)$ is the input image, $\Omega(\eta,\varphi)$ is the normalized output image, where η and φ are the number of row and the column in the processed image. μ is the local mean and σ is the standard deviation computed for the image. To calculate the values of μ and σ when the value of a= (M-1)/2 is derived in Equations (2) and (3)

$$\mu(\eta,\varphi) = \frac{1}{P^2}\sum_{X=-\beta}^{\beta}\sum_{Y=-\beta}^{\beta}[\xi(X+\eta,\pi+\varphi)] \qquad (2)$$

$$\sigma(\eta,\varphi) = \sqrt{\frac{1}{P^2}\sum_{X=-\beta}^{\beta}\sum_{Y=-\beta}^{\beta}[\xi(X+\eta,\pi+\varphi)]^2} \qquad (3)$$

Where η and φ are the number of row and the column in the processed image. The pixel values are categorized by finding the standard deviation of the neighbor pixel value. Some of the facial parts very essential for emotion recognition are lips, eyes, eyebrows, and forehead. Now the mathematical representation for detecting the face accurately from the image based on the features in the face is done using the following Equation (4) as

$$\alpha(\eta,\varphi) = \sqrt{\frac{1}{Q^2}\sum_{X=-\alpha}^{\alpha}\sum_{Y=-\alpha}^{\alpha}[\tau(X+\eta,\pi+\varphi)]^2 - \alpha'(\eta,\varphi)} \qquad (4)$$

Where α' is the mean of the normalized image $\Omega(\eta,\varphi)$ and this value can be calculated using the Equation (5) as

$$\alpha'(\eta,\varphi) = \frac{1}{Q^2}\sum_{X=-\alpha}^{\alpha}\sum_{Y=-\alpha}^{\alpha}[\tau(X+\eta,\pi+\varphi)] \qquad (5)$$

The normalized image will overcome the illumination variation in images and used for detecting the emotion when the same person differs in the way they portray the emotion becomes easier. The preprocessing techniques used in this paper standardize the input to the proposed model. The average pooling is used in the proposed model for decreasing the spatial dimensionality of the images. During the preprocessing, the batch normalization is used for accelerating the training and thus provides the regularization which reduces the generalization error.

4.3. CNN based Model Construction

Inorder to predict the emotion class, a deep learning model has been proposed in this paper. There are six convolution layers and two fully connected layers are used dropout is used for training the dataset. The preprocessed image is given to the deep learning model and the feature extraction is done automatically. Two datasets are used for training and testing. Inorder to train the model more effectively the proposed deep learning model can be used. One of the issues in deep learning model is over fitting. This issue may be due to the lack of the data. Inorder to overcome this issue, we have varied the size of the filter, channel size and observed the performance of the model. The dropout of 0.2 is used. By varying the epoch, batch size, learning rate we have observed the performance of the proposed model.

For training the preprocessed images in the dataset are given to the proposed deep learning model. The fully connected layers were used for approximating the valence label. The stochastic gradient has been used and the batch size has been set to 512. The learning rate has been varied from the value 5e-5 and the loss function used is categorical cross entropy. We have trained the dataset by varying the epoch upto1000. The proposed model is implemented by Pytorch and all the experimentations were carried out in Nvidia. The test data which is used for testing the model after it has been trained. The testing is performed on the CK+ and JAFFE dataset. The precision, recall, f1 score are calculated and test accuracy is also calculated for the proposed model.

5. Experimental Results and Analysis

The proposed model has been developed to classifying the emotion classes and makes it efficient for real world applications. The data preprocessing is done where the dataset is augmented. The face is detected and then given to the proposed deep learning model. The proposed model is trained and tested using CK+ and JAFFE dataset.

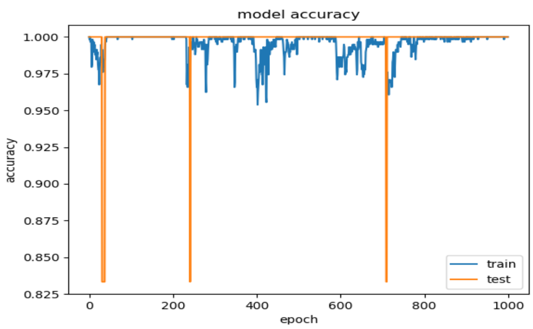

Figure 3. Model Accuracy of CK+ dataset.

The dataset is preprocessed, and then the images are given to the deep learning model. The dataset is augmented first and then the face is extracted from the image. The illumination variation is normalized. Then the images are trained and tested using the proposed model.

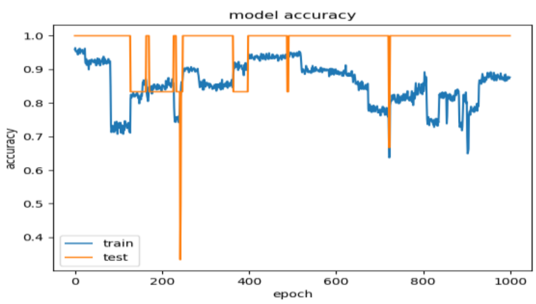

Figure 4. Model Accuracy of JAFFE dataset.

In our proposed work, we use an initial learning rate of 4e-2, batch size of 8 and varied accordingly, and weight decay of 1e-5. First the code is set for 10 epochs. Then by increasing the epoch, the accuracy of every performance is being observed. Then readings are noted by varying epochs until 1000 epochs, batch size is set as 512 by varying the hyperparameters.

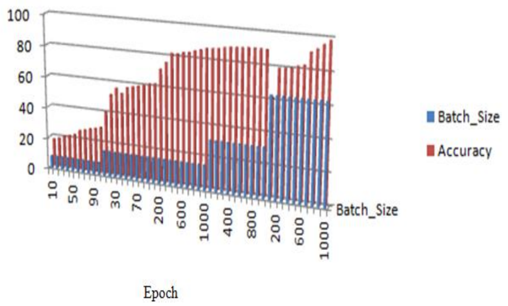

Figure 5. The Recognition accuracy of CK+ dataset based on varying epoch and batch size.

The Figure 5 shows the recognition accuracy of the CK+ dataset by varying the parameters like epoch, batch size. The overall emotion recognition task accuracy is obtained by the averaging of the values. The figure shows that on increasing the epoch, the accuracy increases accordingly.

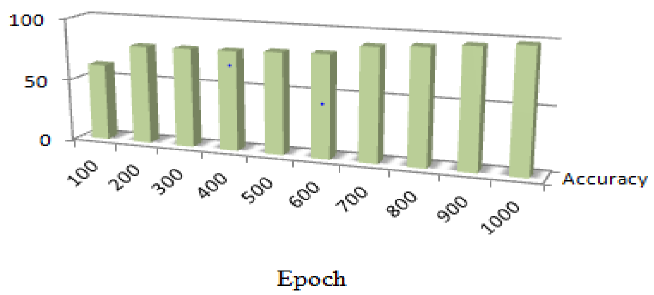

Figure 6.The Recognition Accuracy of JAFFE dataset based on varying parameters by setting batch size fixed.

By varying the epoch and setting the batch size fixed as 64, the recognition accuracy of the JAFFE dataset is shown in Figure 6. The accuracy increases when the number of the epochs is increased. By training the dataset using the proposed model it is clear that the accuracy of the dataset is efficient when compared with the state of the art techniques.

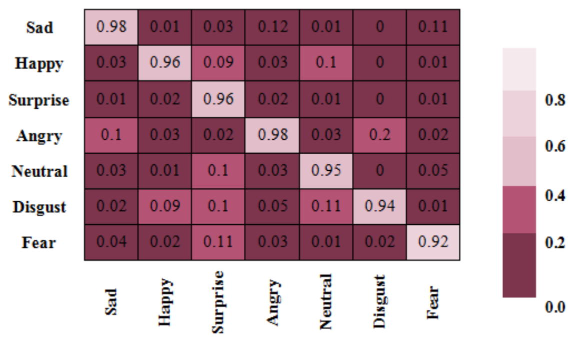

Figure 7. Confusion Matrices on JAFFE dataset.

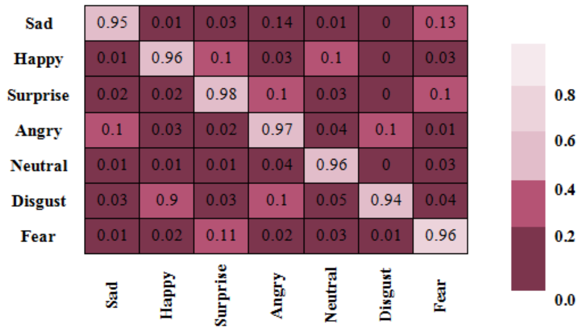

Figure 8. Confusion Matrices on CK+ dataset.

The Confusion matrix for JAFFE and CK+ dataset are presented in Figures 7 and 8. The proposed model increases the accuracy of the dataset and reduces the false detection of emotions in the dataset which is clearly visible in Figures 7 and 8.

Table 1. Comparison of performance with other models.

Method	**Recognition Rate**	
	JAFFE	**CK+**
Jain *et al.* [11]	95.23%	93.24%
Happy and Routray [9]	92.22%	94.14%
Goyani and Patel [8]	88.57%	90.48%
Minaee *et al.* [21]	92.8%	98.00%
Sun *et al.* [26]	96.57%	97.43%
Niu *et al.*[24]	88.5%	93.2%
Proposed Model	**96.91%**	**98.49%**

From the Table 1, it is clear that the accuracy of the proposed model is raised when compared to other existing models. As the results of the proposed model in CK+ dataset has better performance of 0.73% than Sun *et al*. [26] and 0.49% than Minaee *et al*. [21]. The proposed model in JAFFE dataset performs 0.34% better compared to Sun *et al*. [26] and 0.77% better compared with model in Jain *et al*. [11]. The proposed model in this paper for the facial emotion recognition has higher accuracy compared to the other models. The Figures 3 and 4 shows graphical representation of the prediction accuracy of the proposed model in the CK+ and JAFFE dataset.

6. Conclusions

In this paper, a deep learning model was proposed for the facial emotion recognition. The proposed model has been trained and tested on two benchmark dataset inorder to evaluate the concert of the model. The proposed model can be extended for detection of compound emotions and micro emotions also. The extension of this work will focus on handling occlusions, improving the accuracy of the predicted emotions. By specifically handling a specific emotion, facial emotion recognition can be used in the crime branch. The proposed model performs much better than existing models and this work can be extended for addressing the strength of the emotion. In this paper, the facial emotion recognition has been detected only for few basic emotions and the overall result shows the efficiency of the proposed model.

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