An Integrated CNN-BiLSTM Approach for Facial Expressions

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Abstract—**Deep learning algorithms have demonstrated good performance in many sectors and applications. Facial expression recognition (FER) is recognizing the emotions through images. FER is an integral part of many applications. With the help of the CNN-BiLSTM integrated approach, higher accuracy can be achieved in identification of the facial expressions. Convolutional neural networks (CNN) consist of a Conv2D layer, dividing the given images into batches, performing normalization and if required flattening the data i.e. converting the data in a 1D array and achieving a higher accuracy. BiLSTM works on two LSTMs i.e. one in the forward direction and the other in a backward direction. One can use LSTM to process the images (datasets) however, it is suggested with the help of BiLSTM can predict the expressions with more accuracy. Input data is available in both the direction (forward and backward) which helps maintaining the context. Using LSTM CNN and BiLSTM always helps increasing the prediction accuracy. Application areas where a BiLSTM can give more prediction accuracy are the forecasting models, text recognition, speech recognition, classifying the large data and the proposed facial expression recognition. The integrated approach (CNN and BiLSTM) increases the accuracy significantly as discussed in the results and discussion section. This approach could be categorized as a fusion technique where two methods (approaches) are integrated to get higher accuracy. The results and discussion section elaborates the effectiveness of the integrated approach compared to HERO: human emotions recognition for realizing the intelligent internet of things. As compared to the HERO approach CNN-BiLSTM gives good results in terms of precision and recall.**

Keywords*—*CNN (Convolutional Neural Network); BiLSTM (Bi Directional Long Short Term Memory); facial expression recognition; deep learning; flattening

I. Introduction

A convolutional neural network (CNN) can be used to extract the features from images. Emotions like anger, sadness, happiness, disgust etc. can be extracted using CNN. CNN helps in accurately predicting the emotion from the given images. CNN consists of a few layers such as a convolutional layer, a pooling layer and a fully connected layer. With the help of the CNN, the model can successfully get the probability of the image being a certain class [5, 6, 11].

The convolutional layer is quite similar to extracting the features from given images. "Convolution" is the key term used in CNN which means multiplying 02 functions to generate 3rd function. In a similar way feature extraction in CNN works. The pooling layer processes the image and divides it into sub-regions. According to this division, there could be max-pooling and mean-pooling. The system processes a large volume of data.

However, data could be labeled or unlabeled. A fully connected layer takes input from the previous layers and predicts the desired class for the given images. LSTM – Long Short Term Memory is a method of deep learning used in many applications. To increase the prediction accuracies in the proposed model one can use long short-term memory which is based on an artificial neural network. With the help of LSTM, it is possible to process complex data. It is known as long short-term memory because it consists of a "memory unit" to store information for a long period. With the help of these memory units, model can learn further dependencies. LSTM can be used for forecasting purposes where it could deliver results with better accuracy.

LSTM [12, 17] consists of 03 gates namely forget gate, Input and output gate. A sigmoid layer is an important layer in LSTM that helps in binding the input to the output. Based on the concept of LSTM, BiLSTM can be developed where each training sequence (input) is given in both the direction i.e. backward and forward directions. BiLSTM is the extended version of LSTM and results in better accuracy. BiLSTM uses 02 LSTMs to train the input data where the first LSTM processes the input data and second LSTM works on the reverse of the input data. The benefit of the second LSTM is that it brings additional context to the processing environment, increases speed and accuracy of the proposed model.

II. Literature Review

Being human one can express different emotions like happiness, anger, neutral reaction etc. in different situations. Facial emotion/expression recognition is the current need in many applications such as health care, crime, finance and places with more crowds like shopping malls. Deep learning methods can be used to identify different emotions by processing 'n' images or real-time videos. Authors [1] have developed a model which extracts features from given images and trained the model to process the upcoming features automatically. Authors in study [2] suggested using support vector machines (*SVM*), naïve Bayes and lexicon methods can be used to know different emotions from images. The proposed model generates 'n' vectors as there could be different emotions. A model emphasizes knowing the sentiments according to different conversations. Robots are trained to process images and give appropriate feedback once analyzed all the captured images. Authors [3] have proposed PEIS model trains the robots to process real-life images. Features are extracted from the captured images using the FERW model to give correct feedback.

Authors in [4] have integrated CNN and auto-encoders to extract different features from images. This set of features will be used for classification purposes. Authors have proposed 06 architectures out of which 02 are trained on Japanese female facial expressions and 04 with Berlin database. Convolutional neural network (CNN) architecture consists of convolution layers, pooling layers and dense layers with output. These convolution and pooling layers help in extracting different features from emotions whereas the auto-encoder reduces the dimensions. Authors [5, 6, 11] deep learning methods can be used to extract the features from images. Even though there are complex features associated with different images those are also extracted and classified using different deep learning techniques. "Gabor Filter" can be applied to analyze the textures, edge detection, and extract different features from the images. Gabor filter helps in accurately detecting edges of the images and therefore in the proposed model there are 02 Gabor filters. Output from the Gabor filter is given as input to the convolutional neural network layer (CNN). Human feelings can be classified into different categories like sadness, happiness, fear, anger, surprise etc. Authors [7, 13, 24, and 27] used a JAFEE dataset with these emotions and used MATLAB processes the same. The data set consists of 213 images with .tiff format. The proposed model consists of layers like the input layer, CNN layer, pooling layer, activation layer and fully connected layer. Captured data can be classified into 02 categories 'labeled' and 'unlabeled'. The proposed model [8, 23] focuses on 'unlabeled data'. Idea is to reduce human intervention and automatically process the 'unlabeled data'. "LLEC"- label-less learning for emotion recognition is the proposed model which predicts the probable label for unlabeled data. To assess the model's accuracy and prediction uncertainty in labeling authors have suggested using an 'entropy mechanism'. It is also possible to train the robots and IoT devices to process the images, extract features and identify the emotions. The proposed model [9] uses HAAR- a feature-based cascade classifier. A motion sensor senses the motions of humans and activates the camera which captures real-time images. The model also consists of a 'cropping' mechanism where captured images will be cropped to select the human face. Once the images are cropped, the next phase is to know the emotion. All the cropped images will be processed, emotions will be identified and classified results will be stored in the database. Authors [10] have used 02 datasets Cohn-Kanade and JAFEE Japanese female facial emotions. In the proposed model "Keras" is used for recognizing emotions. Authors also used pre-trained models like VGC-16, ResNet 152V2, Inception V3 and Xception etc. These pre-trained models process the datasets and their accuracies are compared in the proposed model.

A framework based on LSTM is proposed [12, 17, 18] to identify different emotions. The model gives ratings (1 to 9 scales) to emotions like anxiety, anger, sadness, joy etc. Authors have also suggested features can be extracted using EEG signals and the application of thresholding schemes to gain better accuracy in classification. To reduce the errors, authors [14] have suggested one can use a backpropagation algorithm [14]. ReLu – rectified linear unit can be embedded to make negative values zero. The model also deals with over-fitting by introducing a dropout layer to achieve accuracy. In an image, some micro-expressions can be identified with the application of deep learning methods [15, 19, 25-26]. The authors have used the FER-2013 dataset to know different micro-expressions. This proposed model consists of a cross-entropy loss function and Adam optimizer to train the features, providing the best results and helping to reduce the losses. A model is proposed [16] based on LDL- a label distribution learning with conditional probability to reduce the errors. Authors have used JAFEE dataset to know the emotions like happiness, sadness, fear, anger, surprise and disgust. The proposed system consists of a convolutional layer, a local binary convolutional layer, a fully connected layer and an output layer to generate the feature map. Authors in [20] have proposed a pose-guide estimation model using the pyramid histogram orientation gradient method, edge histogram descriptor and local binary pattern (LBP). LBP helps convert images into an integer array. Authors have used CK+, JAFEE, CASIA, and AR datasets. Pose estimation, template generation, and target matching are the few steps involved in the proposed model.

Authors in [21] have proposed a model based on landmark-based spatial attention to know the crucial regions of images. It is possible to focus on key regions of the images. Additionally, the temporal attention method is introduced to get the informative expressions from the images. Authors have used datasets like CK+, Olulu CASIA, and MMI. The model also gives the best results for the video inputs. A cascaded spatiotemporal attention network (CSTAN) is proposed [22] to integrate spatial and temporal emotional information. CSTAN helps in locating exact regions of interest for the given images. A deep learning- based BiLSTM model is proposed [23] to classify the given images. BiLSTM is an extended version of LSTM where training is given in both directions i.e. forward and backward to successfully separate the recurrent nets. The authors have used Berlin EMO-DB for simulation purposes with MATLAB. Authors have concluded that the BiLSTM classifier gives better accuracy more than 86% and hence it could be the best classifier for speech emotion recognition.

III. Methodology and Algorithmic Discussion

A. *Proposed Approach*

1) *Input an image or video*

   a) *Splitting the video in 'n' frames*

   b) *Processing the image or frames from the input video*

2) Application of *CNN* and *BiLSTM* approach

   a) Processing the image/frames through convolution layer, pooling and fully connected layers

   b) Application of BiLSTM

3) Generating the output

4) Categorizing the given set of images into

a) Sadness

b) Happy

c) Disgust

d) Fear

e) Neutral

f) Angry

A. *CNN*

CNN helps in achieving higher accuracy in facial expression recognition. CNN consists of 'n' convolution layers (see Fig. 1) and 'm' fully connected layers will help in batch formalization. The dataset (FER 2013) consists of grayscale images with 48*48 pixels. The dataset consists of images with different emotions like anger, disgust, happiness, fear, sad, surprise and neutral. The dataset consist of emotions, pixel values and usages based on which it is possible to classify the images among different groups. The initial step is to divide the dataset into training and testing categories. The proposed model successfully classifies the dataset in X_train, X-test which contains pixel values. Y_train, Y_test consists of emotions. Upon execution of encoding and reshaping data will be ready for training purposes. As discussed earlier, CNN based model consists of 'n' convolution layers, 'm' fully connected layers and ReLU. The next phase is to generate the batches with the desired size i.e. 64 in this approach. CNN consists of a few more steps after this batch normalization as follows-

- Batch-normalization
- Max-pooling
- Dropout
- Flattening

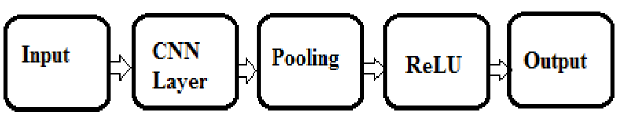

Fig. 1. Working of CNN.

Given data can be processed in 'n' epochs i.e. 100 in the proposed approach. It is nothing but training the neural network with all data from the given dataset. Epochs decide the accuracy after training the data and as the epoch increases output curve moves from underfitting to optimal and then moves to overfit. The steps included in this process can be decided with the help of the following equation-

$$\text{steps\_in\_epoch} = \text{Total\_TrainingSamples}/\text{Training\_BatchSize} \quad (1)$$

B. *BiLSTM*

Deep learning algorithms are very useful in facial expression recognition. It consists of 02 LSTMs to process the input in the forward direction and others to process in the backward direction. It is proved that BiLSTM gives better prediction accuracy than LSTM. Once the input is processed in both directions (i.e. forward and backward), the model executes encoding to concatenate the inputs. The proposed approach model consists of CNN and BiLSTM methods for better accuracy. The advantage of BiLSTM is given input can be fully utilized to gain better accuracy. One can say using BiLSTM it is possible to preserve the information from future to past and past to future.

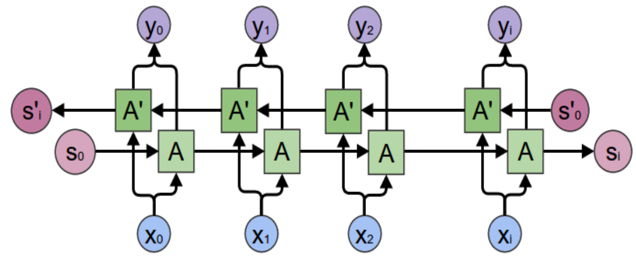

Fig. 2. BiLSTM.

BiLSTM learns (see Fig. 2) from a sequence of data i.e. processing the input forward and backward and works on the principle of maximum utilization of the available information. There is a Hidden layer to remembering the information between these steps. More the hidden layers, the model become overfits the training data. BiLSTM also consists of a learning rate parameter for input weights and depends on the following –

1) Input gate (Forward)

2) Forget gate (Forward)

3) Cell candidate (Forward)

4) Output gate (Forward)

5) Input gate (Backward)

6) Forget gate (Backward)

7) Cell candidate (Backward)

8) Output gate (Backward)

The proposed approach consists of a pre-training layer where a given set of images or input video will be processed and then passed to the next phase. The next subsequent layers of the proposed model are the attention layer and mapping of the extracted feature layer. One can integrate the HAAR cascade classifier to detect the face or specific region of the face from the given image to extract the features.

C. *Advantages of Proposed Approach*

The advantage of the integrated CNN-BiLSTM approach is that CNN is known for maximum feature extraction from the given set of images or video using a max-pooling layer. As discussed earlier, BiLSTM preserves the information in the memory cells to process it in both directions. BiLSTM also consists of hidden layers (states) to retain the information. To utilize the strengths of these models, an integrated approach is proposed. The output of the CNN model is given as an input to the BiLSTM. Output of this integrated approach is discussed in the result and discussion section of this paper with the application of quality parameters such as F1 score, precision and recall.

IV. RESULTS AND DISCUSSION

As discussed earlier the given dataset consists of images with different emotions. Those images are grouped under a separate label as shown in Table I.

TABLE I. ANALYSIS OF THE DATASET

	Emotion	Number
0	Angry	4953
1	Disgust	547
2	Fear	5121
3	Happy	8989
4	Sad	6077
5	Surprise	4002
6	Neutral	6198

Different emotions like anger, sadness, disgust, fear, happiness, surprise and neutral are detected from the given set of images. Table I is the count of images with different emotions.

TABLE II. SHAPE OF THE DATA

train shape	(28709, 3)
validation shape	(3589, 3)
test shape	(3589, 3)
train _X shape	{}
train _Y shape	(28709, 48, 48, 1)
val _X shape	{}
val _Y shape	(3589, 48, 48, 1)

Above Table II is the analysis of the given dataset. The proposed integrated approach initially divides the values in terms of training and testing data. Along with these values model also validates the dataset.

Table III elaborates the pixel values of the images available in the dataset that is used for training purposes. These pixel values plays important role in the analysis, classification and final prediction of the accuracy.

TABLE III. PIXEL VALUES

Emotion	Pixel values	Use pixel Values for
0	0 70 80 82 72 58 58 60 63 54 58 60 48 89 115 121...	Training
1	0 151 150 147 155 148 133 111 140 170 174 182 15...	Training
2	2 231 212 156 164 174 138 161 173 182 200 106 38...	Training
3	4 24 32 36 30 32 23 19 20 30 41 21 22 32 34 21 1...	Training
4	6 4 0 0 0 0 0 0 0 0 0 0 0 0 3 15 23 28 48 50 58 84...	Training
5	2 55 55 55 55 55 54 60 68 54 85 151 163 170 179 ...	Training
6	4 20 17 19 21 25 38 42 42 46 54 56 62 63 66 82 1...	Training
7	3 77 78 79 79 78 75 60 55 47 48 58 73 77 79 57 5...	Training
8	3 85 84 90 121 101 102 133 153 153 169 177 189 1...	Training
9	2 255 254 255 254 254 179 122 107 95 124 149 150...	Training

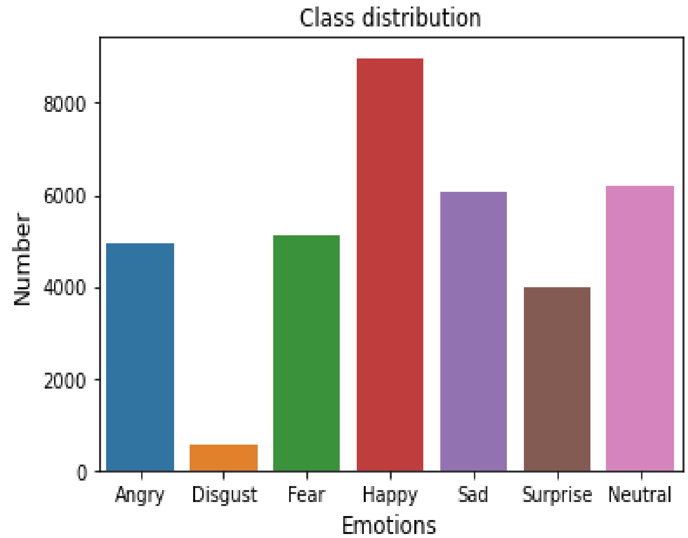

Fig. 3. Distribution of emotions.

Successful categorization of images into different emotions shows there are maximum images under the "happy" category. Fig. 3 shows the distribution of emotions.

Fig. 4. Analysis of images.

Model based on *testing, training and validated data* labels individual image with its "emotion category" as shown in Fig. 4 and Fig. 5. Results showed integration of the CNN with BiLSTM gave good accuracy. BiLSTM is useful where the analysis of sequences or series of sequences is required. Fig. 5 shows classification of data into training, testing and validating data.

Fig. 6 elaborates on the application of quality parameters like precision, recall and F1-score on different emotion categories. Precision helps in determining the prediction accuracy of the model. In the previous step, model evaluates the given dataset values into training data and testing data. Upon successful classification model validates the remaining data.

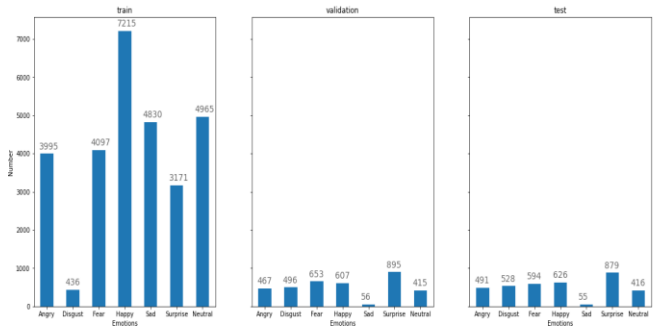

Fig. 5. Train-Test-Validate the dataset.

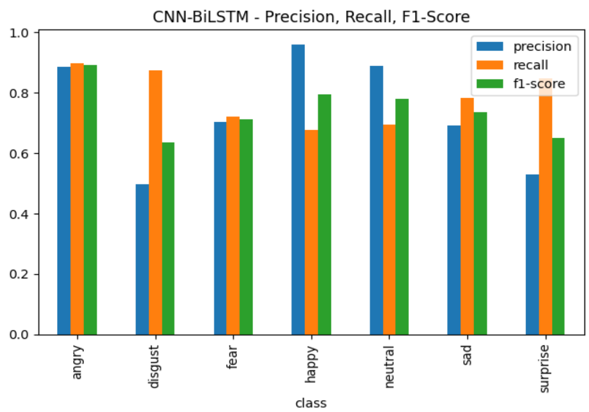

Fig. 6. Applying quality parameters - Precision, Recall and F1-Score.

Recall helps in error minimization and also helps in studying the model with different memory performance for different emotions.

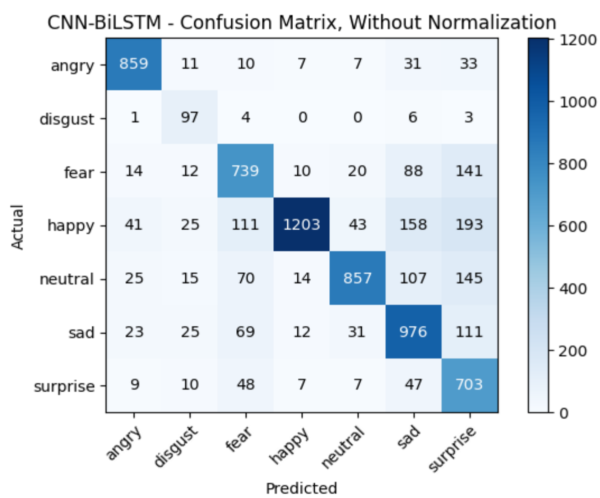

Fig. 7. Confusion Matrix for CNN-BiLSTM without Normalization.

It is good to consider F1-score for the proposed model as it includes both precision and recall. Precision, Recall and F1-score parameters were evaluated on different emotion categories available in the given dataset. Presentation of confusion matrix is shown in Fig. 7 (without normalization) for the proposed CNN-BiLSTM model and Fig. 8 is the confusion matrix for existing HERO approach.

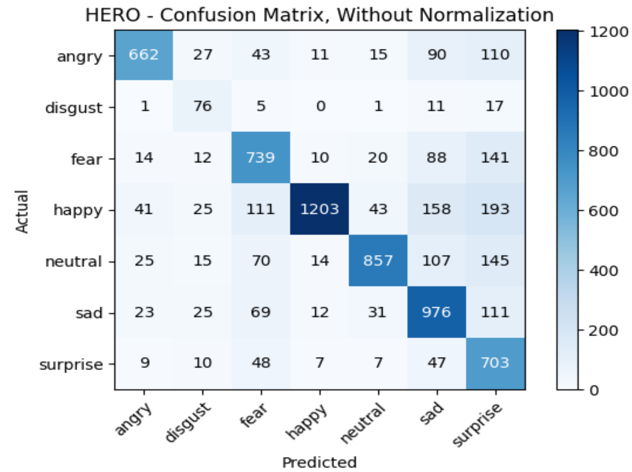

Fig. 8. Confusion Matrix for HERO (existing approach) without Normalization.

V. Conclusion

The proposed model gives best results using the CNN-BiLSTM approach for facial expression recognition. The proposed model evaluated the performance of both the approaches i.e. CNN, BiLSTM and the existing HERO approach. Results discussed demonstrated that, individual CNN and BiLSTM can give good results with improved accuracy in recognizing the facial expressions. Comparison of the existing and CNN-BiLSTM integrated approach presented with the help of different parameters like F1-score, precision and recall. Evaluating these parameters it is proved that proposed integrated CNN-BiLSTM approach is very effective.

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