Facial Emotions Recognition using Convolutional Neural Net.

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Abstract—Human beings displays their emotions using facial expressions. For human it is very easy to recognize those emotions but for computer it is very challenging. Facial expressions vary from person to person. Brightness, contrast and resolution of every random image is different. This is why recognizing facial expression is very difficult. The facial expression recognition is an active research area. In this project, we worked on recognition of seven basic human emotions. These emotions are angry, disgust, fear, happy, sad, surprise and neutral. Every image was first passed through face detection algorithm to include it in train dataset. As CNN requires large amount of data so we duplicated our data using various filter on each image. The system is trained using CNN architecture. Preprocessed images of size 80*100 is passed as input to the first layer of CNN. Three convolutional layers were used, each of which was followed by a pooling layer and then three dense layers. The dropout rate for dense layer was 20%. The model was trained by combination of two publicly available datasets JAFFED and KDEF. 90% of the data was used for training while 10% was used for testing. We achieved maximum accuracy of 78% using combined dataset.

Index Terms—Facial expressions recognition, Facial emotions detection, CNN

I. INTRODUCTION

Observing human emotion is interesting psychological from long ago. Darwin wrote a book “The expression of Emotions in Man and Animals” in 1899 about emotions [1]. In this book, Darwin stated that humans living in different cultures develop different distinct facial expression for different type of emotions. These particular expressions are passed on to them as heredity hence they are not in control of humans. These emotions are produced when humans face various life difficulties and they have evolved with evolution. Darwin as an example wrote that fear reaction helped living organisms to run away from danger, the anger emotion helped them to fight enemies.

Human facial expressions has a significant role in involvement, engaging or communicating with each other. Through facial expressions are the emotion state can be easily figured out. With the advancement of technology, we tend to solve problem with machines. In computer vision field we are interested to help the machine learn to identify and classify objects. Recognizing an emotion or facial expression recognition from a facial image is an interesting and challenging problem in computer vision field. A machine with high accuracy and powerful expression recognition intelligence will better interpret human emotions and interact more naturally. Real world applications such as commercial call center, system of emotions screening during interview, screening behavior of student in a class or in MOOCs and affect-aware game development will greatly benefit from such a system. The objective of having machine vision systems that can recognize human emotions has been pursued for a very long time now.

Many people have studied and carried out experiments to come up with better results and ultimately a system that recognize emotions. Those system can be classified into two categories: A system which identify emotions in a still image and a system which works on videos, which are basically a sequence of images.

In 1978 Suwa et al. [2] tried to develop facial expression system by analyzing twenty known areas of image structure. Facial emotion detection system can be split up into three parts. The first part is to detect faces in an image or track face in a video. The second part is to preprocess those images to obtain visible face features and extract them, the final part is emotion classification [3, 4].

Face detection is studied in computer vision from long ago and many researchers have developed high performance face detection and recognition systems. Vaillant et al. [5] used neural networks for face detection. They trained a convolutional neural network and then scanned the image with a window to locate the face. Rowley et al. [6] developed a connected neural network for detection of face in image. Publicly available benchmarks such as Face Detection Database and Benchmark [7], wilder Face- Face Detection Benchmark [8], PASCAL FACE [9] also have much have contribution in advancement of face detection problem. Generally, the latest face detection...
algorithms can be classified into these categories: cascade based algorithms [10, 11], part based algorithms [12, 13], channel feature based algorithms [14, 15], and NN based algorithms [16, 17]. Extensive work has also been done on facial expression recognition. Many researches have worked on the said systems and they have used Facial Action coding [23,24,25]. In this methodology the emotions are classified based on Action units displayed on face. Combination of multiple units leads to an expression. These methodologies have proven quite better results. Hidden Morkov Model Neural Network based models has also been proposed in several studies for facial emotion detections [26].

In our project we are using Convolutional neural network. We will first detect face in an image and then estimates its exact area and extract it. Further we will do intensity normalization and contrast enhancement so that our neural network may recognize those features with high accuracy. As our dataset is very limited so we have used preprocessing stage to achieve multiple images set of the same image. Using those images set we have trained a convolutional neural network for emotion classification. Finally using that model, we have developed our application for facial emotions detection from both live video as well as still images.

The rest of the paper is organized into 5 parts. Part 2 explains dataset. Part 3 gives the details of preprocessing which is further subdivided into face detection, face extraction, image enhancement and duplication and image image resizing. Part 4 explains architecture of neural network, part 5 gives the detail overview of results. Parts 6 concludes the work and explain future possibilities in the study.

II. DATASET

We have combined two datasets Japanese Female Facial Expression dataset and Karolinska Directed Emotional Faces dataset[18,19].Japanese Female Expression dataset contain 213 static images of 10 models. The images are gray scale and resolution is 256*256. All the images are posed. The Dataset contain 4900 pictures from different models. All images are grayscale with resolution 572*762. The dataset contain images of 70 models. There is an equal distribution of males and females. The images are taken in same lightening conditions with no makeups, glassed and earrings. Each model is photographed from 5 different views (frontal, full left, half left, full right and half right). The mouth and eyes are positioned at a specific place on a grid and then images were cropped at specified resolution. Age of the model is in between 20 to 30 years. Both the dataset contain seven facial expressions (Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral), which we labelled as (0, 1, 2, 3, 4, 5, 6) respectively. We have combined 2 datasets according to each emotion label. After preprocessing and duplication of data in these datasets, the data were classified into training and testing sets. The testing data is almost 11% that of training data. Train data contain 14200 images and test data contain 1580 images. Images whose faces were not detected in pre-processing stage were removed from the dataset. As our main focus is on expression recognition rather face detection problem. The dataset is almost balance. Statistics of each emotion set of final datasets are shown in fig 1.

![Fig. 1. Training and Testing Data Statistics](image)

### III. PRE-PROCESSING

Before feeding the data into Convolutional Neural Network, the images were pre-processed. The preprocessing stage includes face detection, face extraction and histogram equalization, duplication of data using various filters and resizing of images. Figure 2 shows overall preprocessing.

![Fig. 2. Pre-Processing](image)

A. Face detection and Face Area Estimation

Face can be detected using different algorithm like Haar cascade algorithms, HOG + Support vector machine object detector or using a deep learning trained model. In our system, we used a pre-trained model of facial landmark detector included in Dlib library for detection of face [20]. This model finds the locations of 68 (x, y)-coordinates. Each of which represent a location of region of interest on face. Those 68 points are shown in figure 2. The algorithm used in Dlib library is the implementation of [21]. This algorithm uses training set of labeled facial points on an image. These images are manually labeled. Those labels are (x, y)-coordinates which specify
regions of face. Points 1-17 specifies the jaw line, 18-22 specifies left eye brow, 23-27 specifies right eye brow, 37-42 encircles left eye region, 43-48 encircles right eyes region, 28-36 specifies region of nose, 49-60 specifies outer lip area while 60-68 specifies inner lip structure. We applied convex hull to those 27 points to create an enclosed structure boundary of face. Figure shows convex hull of 0-27 points.

To make a mask for extracting the face we filled the convex hull using opencv function cv2.fillConvexPoly. The mask size is same as that of original image. Figure 4.b shows mask obtained after convex filling.

Fig. 5.a Convex hull of 0-27 facial landmarks. 4.b Mask obtained after filling of convex hull

The mask was then applied to images to extract the face area. Figure 5 shows the extracted face images.

This data is then used for training of a model of regression trees to find these facial landmark points directly from the pixel intensities. There is no feature extraction in this method hence the detection is very fast i.e. in real time and high accuracy and quality. We do not need ear regions and regions above mid of fore head. As emotion mainly deals with eyes, nose, eyebrows regions and some facial regions. So this face detection algorithm gives us the exact facial regions which we are interested in. Figure 3. shows some results of our detected faces and regions according to 68 points model.

Fig. 3. Visualizing the 68 facial landmark coordinates [22]

B. Face Extraction

After detecting next step is to extract that face region from original image. We first extracted 1-27 points location from 68 points facial landmarks. 1-27 points covers overall face which deals with facial expressions. To find minimum enclosed structure of a set convex-hull is used. The opencv function cv2.convexHull(params) finds the minimum possible enclosed structure of set of points. We applied convex hull to those 27 points to create an enclosed structure boundary of face. Figure shows convex hull of 0-27 points.

C. Image Enhancement and Duplication

Fives copies of each image were obtained through a series of filters. Histogram equalization was applied to cropped face image for intensity normalization and contrast enhancement. Histogram equalized image is first image of the five images set. Opencv function cv2.equalizeHist() was used for obtaining histogram equalized image. figure The second image was obtained by applying bilateral filter to the cropped face image. Bilateral image removes noise efficiently while preserve the edges. Bilateral filter combines both domain and range filtering. Fig.7 shows how bilateral filter remove noise and preserve high frequency edges. Opencv function cv2.bilateralFilter(params) was used d=9, sigmacolor=75 and sigmaspace=75. Third image was obtained by applying a convolutional 2D filter with kernel shown in fig.8 to the bilateral filtered image. The fourth image was obtained by again applying histogram equalization to the filtered image. Finally, fifth image was obtained by applying a bilateral filter with d=9, sigmacolor=100 and sigmaspace =100. At the end of the process five images set for each image was obtained.

Fig. 5. Visualizing the 68 facial landmark coordinates [22]

Fig. 4. Face Detection and Face Area Estimation

Fig. 6. Face Extraction

Fig. 7. Convolutional 2D filter with kernel

Fig. 8. Convolutional 2D filter with kernel
Fig. 7. Histogram Equalization of Image

Fig. 8. Bilateral Filter Noise Removal and Edge Preserving

\[
\begin{array}{ccc}
-1 & -1 & -1 \\
-1 & 9 & -1 \\
-1 & -1 & -1 \\
\end{array}
\]

Fig. 9. Kernel for Convolutional 2D Filter

\( D. \) Image resizing

All the images were resized to 80*100. An array of training and test images were made to pass it into Convolutional Neural Network. Fig. 2 block diagram of pre-processing shows the set of images obtained after Image Enhancement and duplication step.

IV. CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE

Our network has five convolutional layers, one max pooling layer, two average pooling layers and three dense layers. Max pooling chooses the maximum response, while average filter calculates average of the responses. The dense layers contain dropout of 20%. This dropout in connected layers prevents the model from overfitting.

We have train data of shape (14210,100,80) and test data of shape (1580,100,80). The shape tells us that there are 14210 training instances and 1580 test instances, each of which has dimension of 80*100 which is size of our image.

The input layer accepts 80*100-dimension image and passes the same dimensions data to first convolutional layer. The convolutional layer has 64 filter and kernel of size (5,5) and has activation function RELU. The layer gives output (76,96,64), which is passed to max pooling layer with pool size of (5,5) and strides of (2,2). An output of size (36,46,64) is obtained which is then passed to two convolutional layers in series. Both has 64 filters and kernel size (3,3) and RELU as activation function. The output of second convolutional layer in the series has size (32,42,64). An average pooling layer is (15,20,64). It is further connected with two consecutive convolutional layers with 128 filters and kernel size (3,3) and has activation function RELU. The output of these last convolutional layer has size of (11,16,128). To this output average pooling with same pool size and stride as earlier one, is applied. The output of this layer has size (5,7,128) which is then flattened 5*7*128=4480. Which is passed to three fully connected layers with 1024 filters each. The drop out rate of each layer is 0.2. Finally layer is dense layer with activation function softmax which gives output of size 7. These 7 instances represents probability of each class. Fig. 10. Shows the detail of our convolutional neural network architecture.

In the convolutional layer activation function RELU is used instead of sigmoid because it reduces the likelihood of gradient to become too small and almost go disappear, and also RELU results in sparse representation while sigmoid results in dense representation. The earlier is much better than the later.

\( \text{Fig. 10. CNN Architecture} \)
V. RESULTS

We trained the network with batch size of 100 with epochs size of 100. Epochs is one complete pass over training set instances. An accuracy of 70% percent was achieved. Later when we increased the epochs to 200 the accuracy increased to 72% and with epoch size of 300 the accuracy reached to 78%. Our current tables here describe training with epoch 300. We calculated Precision, recall, F1-score and Support for all the seven type of emotions and also calculated the average value. These metrics were calculated using sklearn library. Each metric scores with respect to each emotion is shown in fig 11. The labels 0 represent angry, 1 represent disgust, 2 represent fear, 3 represent happy, 4 represent sad, 5 represent surprise, 6 represent neutral.

For each type of emotion we also draw the receiver operating characteristic curve (ROC). ROC curve is a tradeoff curve between true positive rate and false positive rate. The area under the curve shows the accuracy. The more the area and the more the curve away from diagonal line the better the results are. Fig. 12 shows 7 ROC curves. Each of which shows accuracy of each motion.

| Emotion | Precision | Recall | F1-Score | Support |
|---------|-----------|--------|----------|---------|
| 0       | 0.84      | 0.56   | 0.67     | 230     |
| 1       | 0.82      | 0.86   | 0.84     | 225     |
| 2       | 0.60      | 0.60   | 0.60     | 225     |
| 3       | 0.90      | 0.88   | 0.89     | 225     |
| 4       | 0.79      | 0.83   | 0.81     | 230     |
| 5       | 0.87      | 0.84   | 0.85     | 220     |
| 6       | 0.67      | 0.85   | 0.75     | 225     |
| Total/Avg | 0.78   | 0.77   | 0.77     | 1580    |

VI. GRAPHICAL USER INTERFACE

The trained model was then used to implement an application. PYQT5 library was used to develop the interface. The application developed is dual mode, which work on both still images and live video feed. User has to select between each mood. Pre-Processing and then labelling of each image takes about 20-30ms time, that is why the video feed performance drops. The Interface shows the original image or frame of video and also shows the cropped face image. Two labels has been included in interface. One label shows probabilities of all the labels while another shows the predicted emotion. During preprocessing we obtain five images. Average Probability of the related emotions of all the images is calculated to increase the chances of accurate label selection i.e accuracy. Fig.13(a) shows a happy face so the corresponding emotion is shown on the label at top-right. Fig. 13(b) is a continuation frame in which the emotion is angry so the angry is shown on the label. Fig.13(c) shows a disgust emotion, the corresponding label is shown on the left. The probabilities in all three images is displayed at bottom.
VII. CONCLUSION AND FUTURE WORK

The results and live display shows that system has quite promising performance. Pre-processing stage is important. Loss of many feature in pre-processing may lead to poor result. We have also observed that with increase of training epochs the system performance is increasing more. In future the network can be further optimized and the further evaluated for high performance. Complex Network lead to heavy models which gives low performance during live video. The overall system will be extended to emotion scanning in live interview system.

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