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Visual Sentiment Analysis using Convolutional Neural Networks

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ABSTRACT: Study of visual sentiment examines complex emotional reaction and reflex behavior of visual expressions, such as pictures and videos. Our research aims to explain the high-level visual information content and obtain recognition results as seven emotional states (neutral, excitement, sorrow, surprise, outrage, fear, disgust), based on facial emotions. The project is divided into three phases: Face identification, which is the ability to recognize facial orientation in any input image or frame inside boundary box coordinates; Facial recognition, which deals with analyzing multiple faces together to recognize the faces belong to the same individual by matching facial embedding vectors and Emotion Detection to define the expression on the face and classify them as happy, neutral, surprise, disgust, fear, outrage or sad.

Keywords: Facial detection, Facial Recognition, Emotion detection, OpenCV, Image preprocessing, Feature Extraction, Convolution Neural Networks, Evaluation metrics.

I. INTRODUCTION

Emotion recognition is a process of detecting and classifying human emotions. Individuals differ greatly in their precision in understanding others' emotions. A relatively new field of study is the use of technology to aid people with emotion detection. Typically speaking, the technology performs better when it uses multiple contextual modalities. To date, much of the research has been performed on automating the identification of facial expressions from images, audio spoken expressions, text written expressions, and wearable-measured physiology.

Visual Sentiment Analysis is also a method for identifying human feelings from facial expressions. The human mind naturally identifies feelings and now a technology has been built that would identify emotions as well just like our brain. This technology is becoming more effective and accurate progressively, and will one day soon be able to interpret the sentiments as well as our thoughts and impulses in our mind by just reading our facial expressions. AI can interpret emotions by studying the significance of our body language, facial expressions and tone of the voice and apply this insights to the new information that is provided. Emotional artificial intelligence is a new technology that has an ability to articulate, replicate, evaluate and react to human face behaviors and emotions.

Recognition of feelings is a very relevant subject matter. The technology has a range of applications. Applications range from different fields such as medical, e-learning, accounting, marketing, entertainment and law. While emotion recognition technology is important one that has been demanding in different fields, it still remains as the unsolved problem. Detecting human emotion can be accomplished by the use of facial expression, voice, body form and so on. Among them, the facial image is the most common source for emotion detection. In particular, the facial frontal image is widely used to identify emotions. Recognition of emotions is not a simple but complex process because it requires complex steps to extract proper function and detect emotion. But, with the recent advance in machine learning and computer vision, emotions can be easily identified from images. Within this project we use convolutional neural networks (CNN) to introduce a novel technique called facial emotion recognition to perform visual sentiment analysis.

II. DATA DESCRIPTION

There are 35,888 images in this dataset which are classified into six emotions. The data file contains 3 columns — Class, Image data, and Usage.

The data consists of 48x48 pixel grayscale images of faces. The faces have been automatically registered so that the face is more or less centered and occupies about the same amount of space in each image. The task is to categorize each face based on the emotion shown in the facial expression in to one of seven categories (0=Angry, 1=Disgust, 2=Fear, 3=Happy, 4=Sad, 5=Surprise, 6=Neutral). The FER2013 dataset contains images that vary in viewpoint, lighting, and scale.

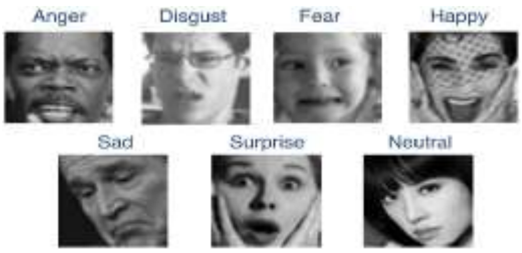
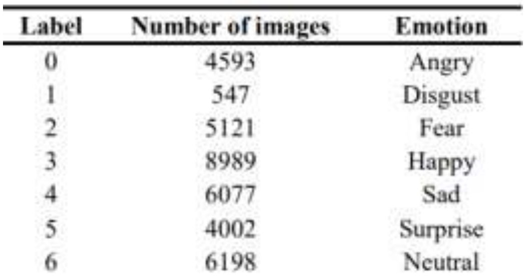


Figure 1: Sample Images from FER2013 dataset

Table 1. Description of the FER2013 dataset



Label	Number of images	Emotion
0	4593	Angry
1	547	Disgust
2	5121	Fear
3	8989	Happy
4	6077	Sad
5	4002	Surprise
6	6198	Neutral

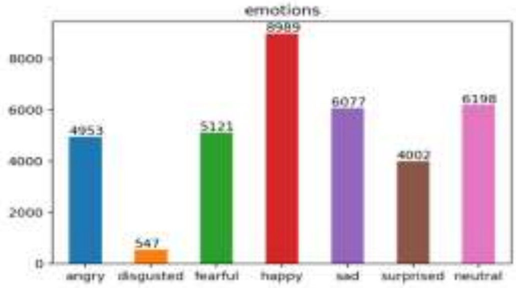


Figure 2: FER-2013 Expression Distribution

III. VISUAL SENTIMENT ANALYSIS

A. MODULES:

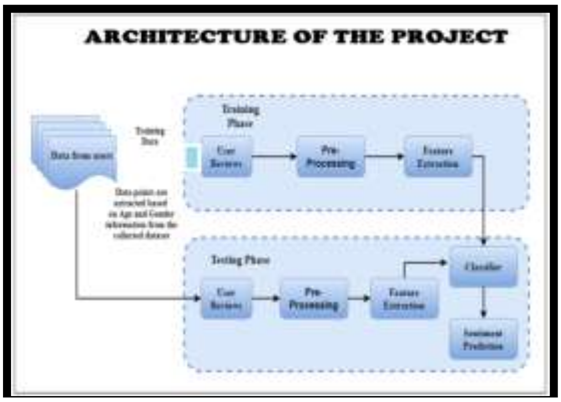


Figure 3: Architecture of the project

The entire project is divided into 3 modules namely,

1. **Data Preprocessing**: The input image from the FER2013 dataset may contain noise and have variation in illumination, size, and color. To get accurate and faster results on the algorithm, some preprocessing operations were done on the image. The preprocessing strategies used are conversion of image to grayscale, normalization, and resizing of image

a) The FER2013.csv consists of three columns namely emotion, pixels and purpose.

b) The column in pixel first of all is stored in a list format. Since computational complexity is high for computing pixel values in the range of （0-255), the data in pixel field is normalized to values between [0-1].

c) The face objects stored are reshaped and resized to the mentioned size of 48 X 48. The respective emotion label's and their respective pixel values are stored in objects.

d) We use scikit-learn's train test split()function to split the dataset into training and testing data, The test size being 02 meaning, 20% of data is for validation while 80%of the data will be trained.

2. **Facial Detection:** Here the face is detected in a image with bounding box coordinates. Face detection using Haar Cascades is a machine-based approach to learning where a cascade function is trained with a set of input data. OpenCV already includes many pre-trained classifiers for face, eyes, smiles, etc.

3. **Emotion Detection:** Here the face is studied and the emotion of the human face is given of the result.

B. PROPOSED ALGORITHM:

Convolutional Neural Networks (CNN):

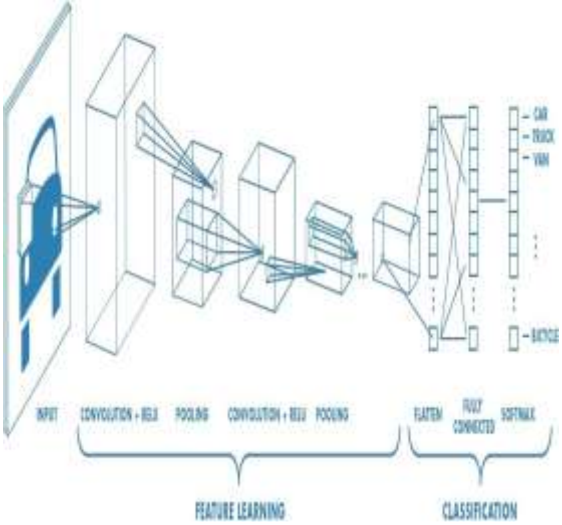


Figure 4: General Architecture of the Convolutional Neural Network

A Convolutional Neural Network is an artificial neural network that is so far been the most popularly used for analyzing images, although image analysis has been the most widespread use of CNN, they can also be used for other data analysis or classification problems as well. Most generally we can think of a CNN as something which has a type of specialization for being able to pick out or detect patterns and make sense of them. This pattern detection is what makes CNN so useful for image analysis. Here's what differentiates a CNN form a standard multi-layer perceptron or MLP, a CNN has hidden layers called convolutional layers and these layers are precisely what makes a CNN unique. CNNs usually do have other non-convolutional layers as well but the basis of a CNN is the convolutional layers. Like any other layer a convolutional layer receives input then transforms the input in some way and then outputs the transformed input to the next layer. With each convolutional layer we need to specify the number of filters the layer should have (these filters are actually what detect the patterns).

Multiple edges, shapes, textures, object etc. So one type of pattern a filter could detect could be edges or corners or circles other squares. These simple and kind of geometric filters are what we would see at the start of our network. The deeper our network goes the more sophisticated these filters become so in later layers rather than edges and simple shapes our filters maybe able to detect specific objects like eyes, ears, hair, nose etc.

In this step, the system classifies the picture as one of the seven universal expressions – Happy, Sadness, Anger, Surprise, Disgust, Fear, and Neutral – labeled in the FER2013 dataset. Training was carried out using CNN, which is a type of neural networks that has been shown to be effective in image processing. The dataset was first split into training and test datasets, and then trained in the testing collection. Feature extraction process was not completed on the data before it was fed to CNN. The approach followed was to experiment with different architectures on CNN, to achieve better accuracy with the validation set, with minimal over-fitting.

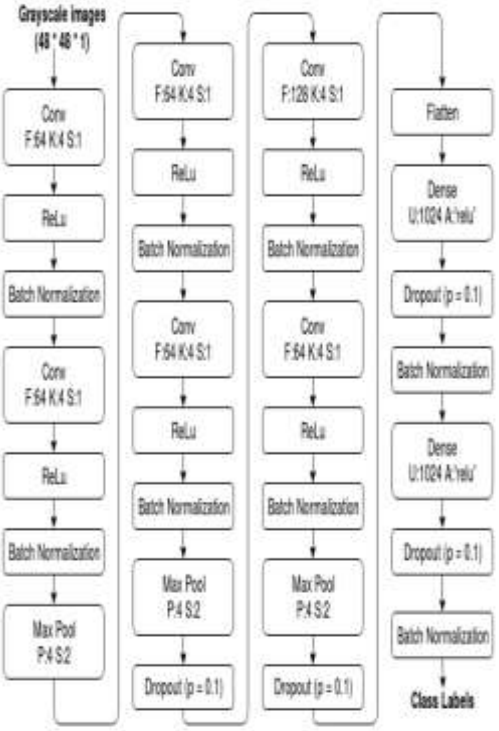
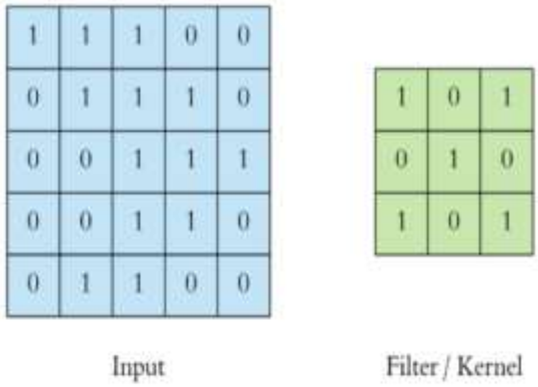


Figure 5: Flow Process of the proposed CNN

The Emotional Classification Step consists of the following phases:

(a) Convolution:

The core building block of CNN is the convolutional layer. Convolution is a mathematical operation to combine two sets of information. In our case, the convolution is applied to input data using a convolution filter to create a function map.

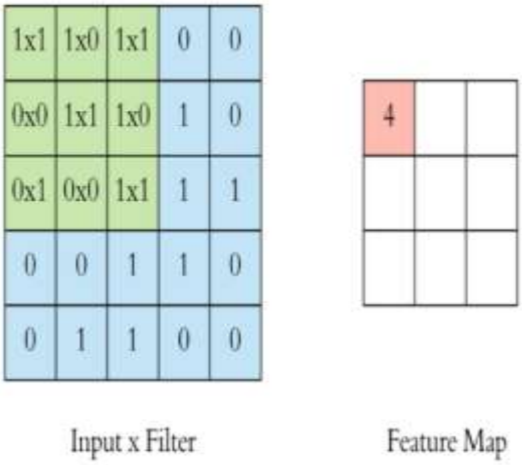


1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

1	0	1
0	1	0
1	0	1

Figure 6: On the left side is the input to the convolution layer, e.g. the input image. To the right, the convolution filter, also called the kernel, will be used interchangeably.

We perform the convolution process by sliding the filter over the data. At each position, we do a multiplication of the element-wise matrix and sum the result. This total is applied to the feature map. The green area where the convolution process is taking place is called the receptive field. Thanks to the filter scale, the receptive field is also 3x3.



1x1	1x0	1x1	0	0
0x0	1x1	1x0	1	0
0x1	0x0	1x1	1	1
0	0	1	1	0
0	1	1	0	0

4		

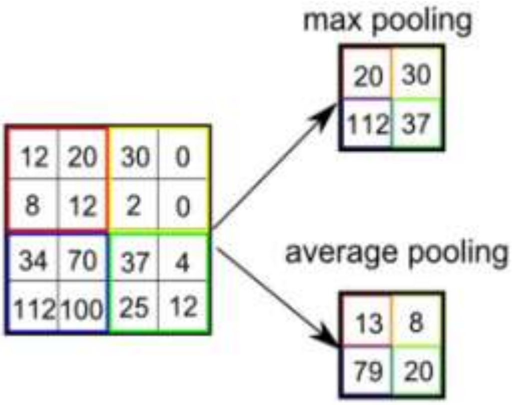
Figure 7: The output of the convolution operation "4" is shown in the resulting feature map where the filter is at the top left.

We then move the filter to the right and perform the same operation, adding the result to the feature map as well. We continue like this and aggregate the convolution results in the feature map.

(b) Pooling

Usually we do pooling after a convolution operation to reduce the dimensionality. It helps us to reduce the amount of parameters that both shorten training time and over-fit combat. Pooling layers down sample each of the features of the map individually, minimizing height and width, and keeping the depth unchanged.

The most popular method of pooling is max pooling, which only takes the max value in the pooling window. In comparison to the convolution process, there are no parameters for pooling. It slides the window over its entry, and it simply takes the full value in the window. Similar to the convolution, we specify the size of the window and the step.



12	20	30	0
8	12	2	0
34	70	37	4
112	100	25	12

20	30
112	37

13	8
79	20

Figure 8: Result of max pooling and average pooling using a 2x2 window and stride 2.

(c) Fully connected layer:

In the fully connected layer, each neuron from the previous layer is connected to the output neurons. The size of final output layer is equal to the number of classes in which the input image is to be classified.

(d) Activation function:

Activation functions are used in to reduce the over fitting. In the CNN architecture, the ReLu activation function has been used. The advantage of the ReLu activation function is that its gradient is always equal to 1, which means that most of the error is passed back during back-propagation.

(e) Softmax:

The Softmax function takes a vector of N real numbers and normalizes that vector into a range of values between (0, 1).

(f) Dropout:

Dropout is used to avoid over-fitting, and the principle is quite basic. In the training cycle, at each step, the neuron is momentarily "dropped" or disabled with a p probability. It means that at the current iteration, all inputs and outputs to this neuron will be disabled. The drop-out neurons are re-sampled with the likelihood p at each training phase, so the drop-out neuron at one point can be active at the next. Hyper parameter p is called the drop-out rate and is usually around 0.5, equivalent to 50 percent of the neurons being lost.

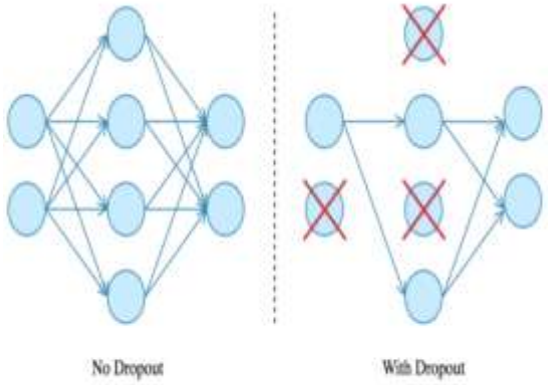


Figure 10: Visualization representation of Dropout method

(g) Batch Normalization:

The batch normalizer speeds up the training process and applies a transformation that maintains the mean activation close to 0 and the activation standard deviation close to 1.

C. TRAINING THE MODEL:

After the data is preprocessed and the required libraries are imported, create place holders for all the important features extracted by the CNN model and for the target variable. Then define a batch size and initialize the number of epochs in the backend. Initialize X_train and Y_train data as validation data. Combine all the functions above into a single CNN network and use mini-batch gradient descent for training. It is an iterative optimization algorithm used to find the best results (minimum of a curve) in machine learning. Gradient imply a slope's inclination rate or decay rate. Descent means the descending case. The iterative algorithm means we need to get the results several times in order to get the most efficient result. The gradient descent's iterative quality helps a graph that is under fit to make the graph fit optimally to the data.

D. CROSS VALIDATION:

Here, we use categorical entropy as the loss function. Categorical cross entropy is a loss function that is used for single label classification. Categorical cross entropy will equate the prediction distribution (activations in the output layer, one for each class) with the true distribution, where the true class likelihood is set at 1 and 0 for the other classes.

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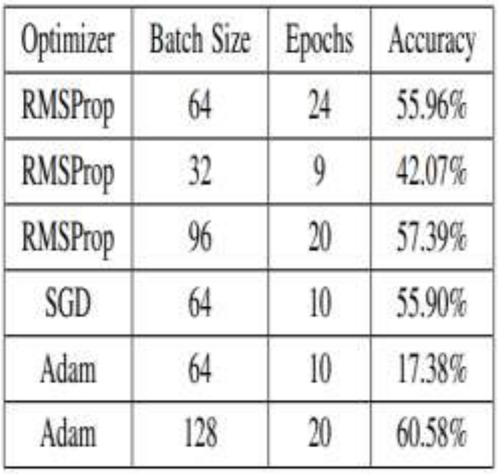
$$L(y,\hat{y}) = -\sum_{j=0}^{M}\sum_{i=0}^{N}(y_{ij} * \log(\hat{y}_{ij}))$$

where $\hat{y}$ is the predicted expected value and y is the observed value.

Figure 11: Algorithmic representation of categorical entropy (loss function)

E. HYPERPARAMETER TUNING:

Upon tuning the hyper parameters, the highest accuracy was achieved for each optimizer. Using the RMSProp optimizer, an accuracy of 0.57 was reached over 20 epochs and a batch size of 96. The Stochastic Gradient Descent optimizer gave an accuracy of 0.55 out of the box and it could not be increased significantly by further tuning of the hyper parameters. Using the Adam optimizer with the default settings, a batch size of 64 and 10 epochs lead to an astoundingly low accuracy of 0.17. However upon setting the learning rate to 0.0001 and the decay to 10e − 6, the highest accuracy of 0.60 was attained. A comparison of the various hyper parameters that were tuned can be seen in table below.



Optimizer	Batch Size	Epochs	Accuracy
RMSProp	64	24	55.96%
RMSProp	32	9	42.07%
RMSProp	96	20	57.39%
SGD	64	10	55.90%
Adam	64	10	17.38%
Adam	128	20	60.58%

Figure 12: Comparison of Hyper parameters

Results were achieved by experimenting with the CNN algorithm. The loss over training and test set decreased with each epoch. The batch size was 128, which was kept constant in all experiments. In order to produce successful performance, the following improvements have been made to the neural network architecture:

1) Number of epochs: it has been found that the accuracy of the model has improved with an increasing number of epochs. A high number of

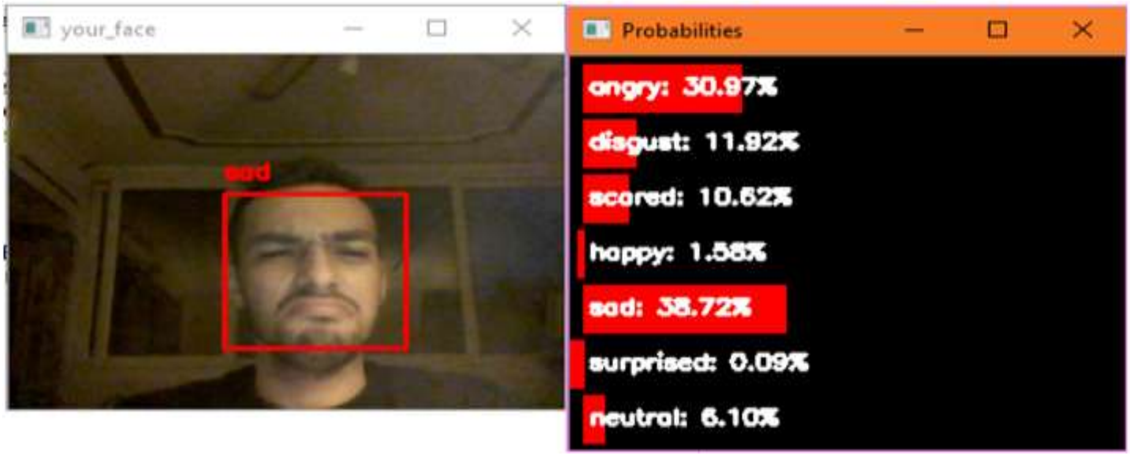
epochs, however, resulted in over-fitting. It was concluded that eight epochs resulted in minimal over-fitting and high accuracy.

2) Number of layers: the neural network architecture consists of three hidden layers and one fully connected layer. A total of six convolution layers were built using 'relu' as the activation function.

3) Filters: The accuracy of the neural network on the data set varied with the number of filters applied to the image. The number of filters for the first two layers of the network was 64, and 128 for the third layers of the network was maintained.

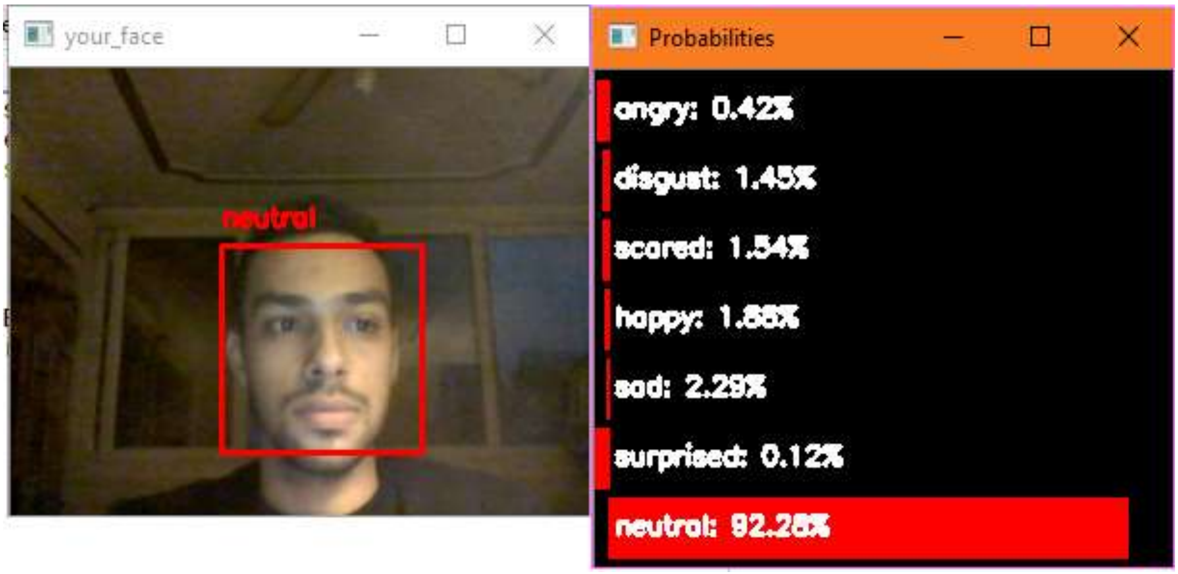
IV. OUTPUT ANALYSIS

The input of the program will be an image of a human taken with the help of the webcam. This human face will have to display one of the following emotions happy, sad, fear, disgust, anger, surprise. The program will then analyze the given image with the help of the CNN and compare the result with that of the dataset. The most similar emotion from the dataset is then delivered as the final result. This can be understood by viewing the given below images. The user can display a number of emotions as follows:



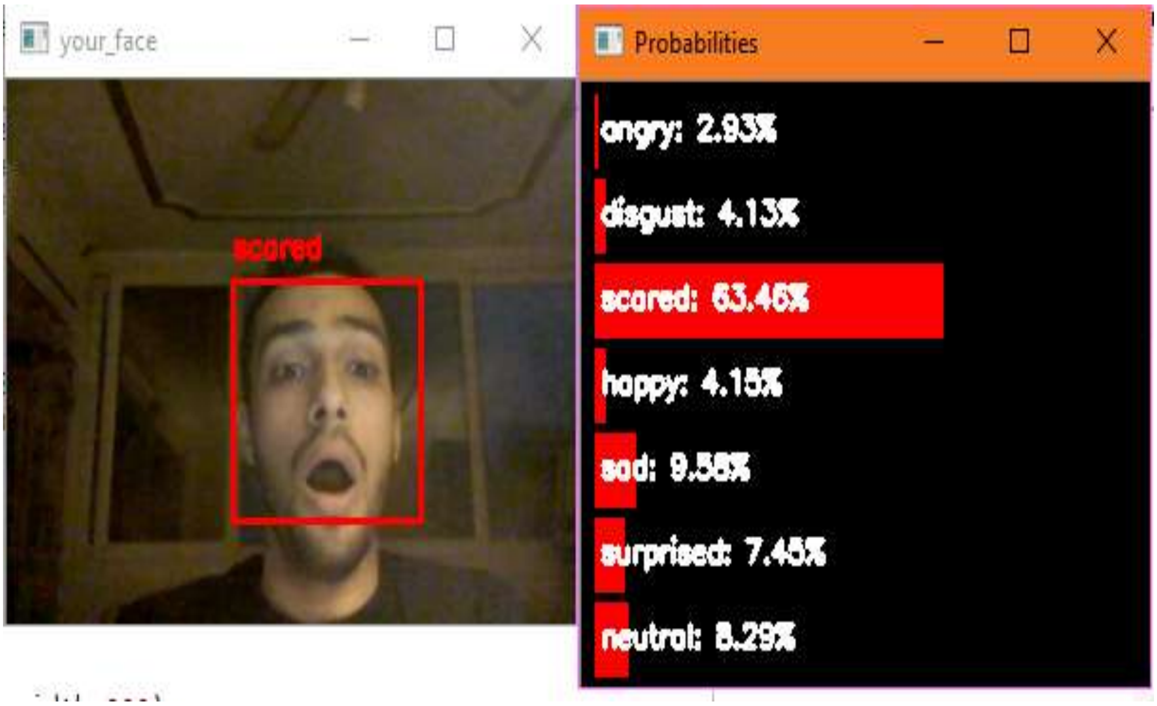
```
angry: 30.97%
disgust: 11.92%
scared: 10.62%
happy: 1.58%
sad: 38.72%
surprised: 0.09%
neutral: 6.10%
```

Figure 13: Sentiment analysis of Sad face



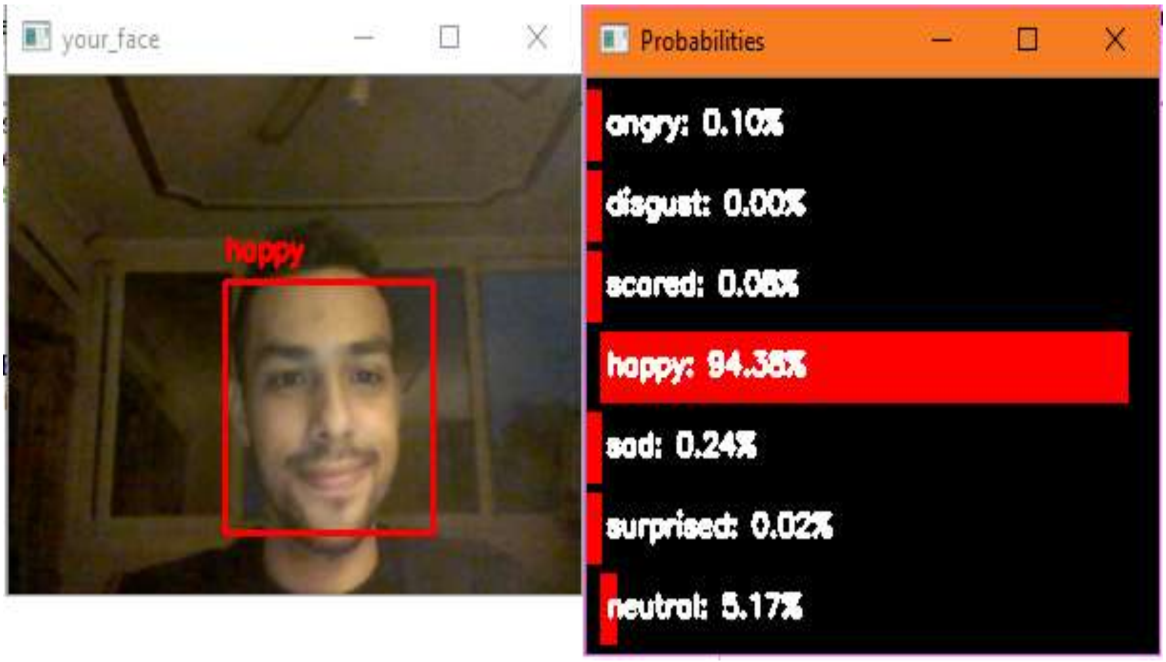
```
angry: 0.42%
disgust: 1.45%
scared: 1.54%
happy: 1.88%
sad: 2.29%
surprised: 0.12%
neutral: 92.28%
```

Figure 14: Sentiment analysis of Neutral face



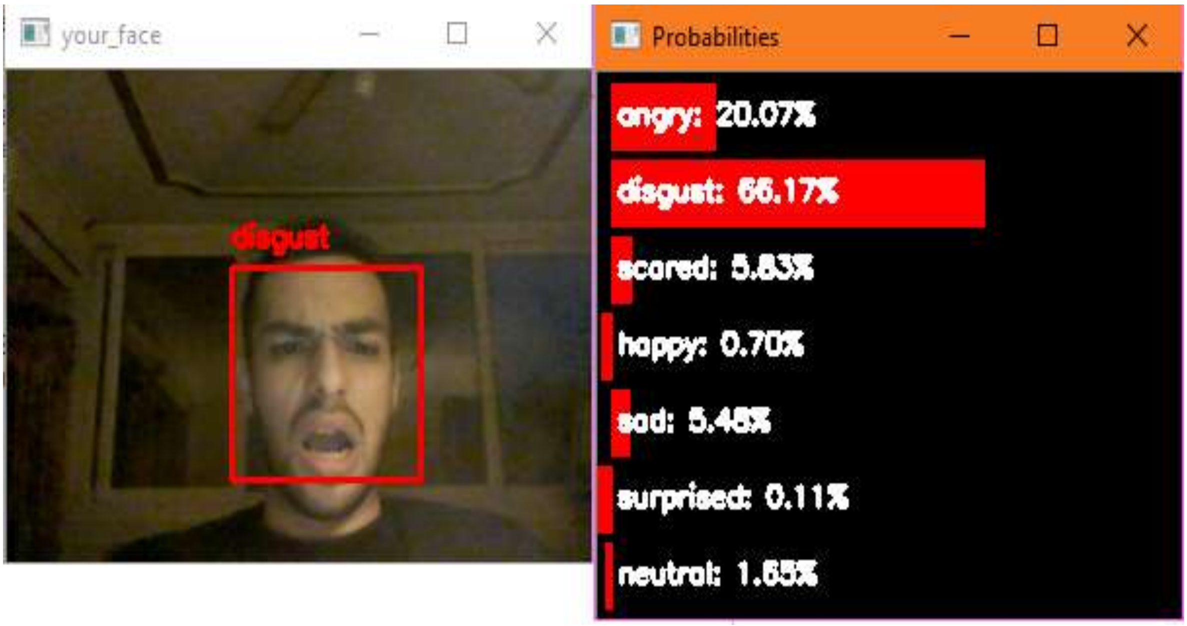
```
angry: 2.93%
disgust: 4.13%
scared: 63.46%
happy: 4.15%
sad: 9.58%
surprised: 7.45%
neutral: 8.29%
```

Figure 15: Sentiment analysis of Scared face



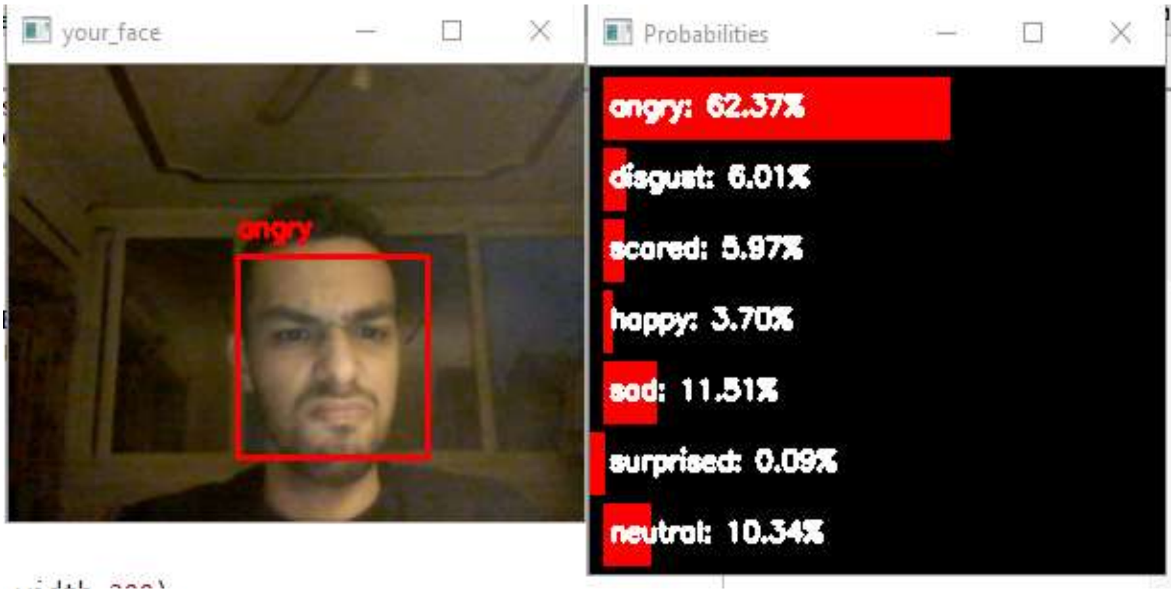
```
angry: 0.10%
disgust: 0.00%
scared: 0.08%
happy: 94.38%
sad: 0.24%
surprised: 0.02%
neutral: 5.17%
```

Figure 16: Sentiment analysis of Happy face



```
angry: 20.07%
disgust: 66.17%
scared: 5.83%
happy: 0.70%
sad: 5.48%
surprised: 0.11%
neutral: 1.65%
```

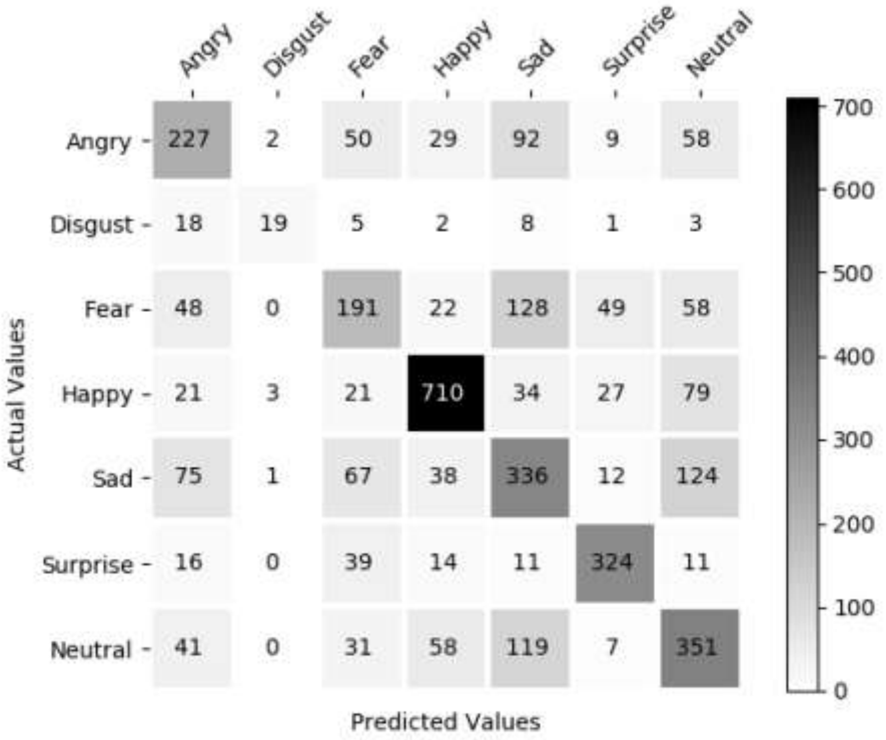
Figure 17: Sentiment analysis of Disgust face



```
angry: 62.37%
disgust: 6.01%
scared: 5.97%
happy: 3.70%
sad: 11.51%
surprised: 0.09%
neutral: 10.34%
```

Figure 18: Sentiment Analysis of Angry face

The confusion matrix generated over the test data is shown in figure 7. The dark blocks along the diagonal show that the test data has been classified well. It can be observed that the number of correct classifications is low for disgust, followed by fear. The numbers on either side of the diagonal represent the number of wrongly classified images. As these numbers are lower compared to the numbers on the diagonal, it can be concluded that the algorithm has worked correctly and achieved state of the art results.



Actual Values \ Predicted Values	Angry	Disgust	Fear	Happy	Sad	Surprise	Neutral
Angry	227	2	50	29	92	9	58
Disgust	18	19	5	2	8	1	3
Fear	48	0	191	22	128	49	58
Happy	21	3	21	710	34	27	79
Sad	75	1	67	38	336	12	124
Surprise	16	0	39	14	11	324	11
Neutral	41	0	31	58	119	7	351

Figure 19: Confusion matrix represented as a heatmap

V. FUTURE ENHANCEMENTS

This project has a lot of scope for enhancement and further development. The main concept of this project can be integrated in an artificial intelligence based chatbot which will, based on the emotional state of the user, speak/interact with the user. This will help the user in case of an emotional distress or a medical emergency. This project can be further improved to detect the emotions of multiple faces in a single frame/photo. Detecting the emotions of multiple faces in a large crowd will help with security measures and also in events it provides a scope of improvement based on the audience reactions. The current computational capacity of the system can be enhanced by using a faster processor and a system with bigger RAM capacity. This will help reduce the time taken to detect the emotion. The number of emotions that this project can detect is limited to only seven namely, sadness, happy, surprise, disgust, neutral, anger and fear. But the number of emotions can be increased by making changes in the algorithm making it efficient enough to detect other important emotions like confusion, boredom, pain and satisfaction. It can be further enhanced to accurately detect the emotions in fast moving vehicles, despite the moving objects.

V. CONCLUSION

In this project, a face is detected with the location of face in any input image or frame within bounding box coordinates using the module OpenCv2. This human face will have to display one of the following emotions happy, sad, fear, disgust, anger, surprise Hence, this input is then given to the model for feature extraction and classification. We designed an efficient CNN model for facial feature extraction and performed softmax classification technique for face emotion detection. Adam optimizer is used for adaptive training of deep neural networks. The experimental results on FER2013 dataset was demonstrated 0.6012 and a validation accuracy of 0.8978, indicating it has out-performed other basic classification models used for visual sentiment analysis. Here, categorical cross entropy is chosen as the loss function with evaluation metrics as ‘accuracy’.

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