A Face Emotion Recognition Method Using Convolutional Neural Network and Image Edge Computing

03CS6902 Mini Project

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student, for the course work in **03CS6902 Mini Project**, under our guidance and supervision, in partial fulfillment of the requirements for the award of the degree, M. Tech. Computer Science & Engineering (Image Processing) of **APJ Abdul Kalam Technological University**.

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Vishnu Vinod

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Abstract

Facial emotion recognition is the process of detecting human emotions from facial expressions. The human brain recognizes emotions automatically and software has now been developed that can recognize emotions as well. This technology is becoming more accurate all the time, and will eventually be able to read emotions as well as our brains do. The facial expression recognition, as an important means of intelligent human-computer interaction, has a broad application background. It has been applied in the fields of assistant medicine, distance education, interactive games and public security. The facial emotion recognition extracts the information representing the facial expression features from the original input facial expression images through computer image processing technology, and classifies the facial expression features according to human emotional expression, such as happiness, surprise, aversion and neutrality. In the recent years, the development of facial expression recognition technologies has been rapid and many scholars have contributed to the development of facial expression recognition. Although the CNN algorithm has made some progress in the field of facial expression recognition, it still has some shortcomings, such as too long training time and low recognition rate in the complex background. To avoid the complex process of explicit feature extraction in traditional facial expression recognition, a facial expression recognition method based on CNN and image edge detection is proposed in this project.

Contents

Chapter 1

Introduction

Human emotions can be classified as fear, contempt, disgust, anger, surprise, sad, happy, and neutral. These emotions are very subtle. Facial muscle contortions are very minimal and detecting these differences can be very challenging as even a small difference results in different expressions. Also, expressions of different or even the same people might vary for the same emotion, as emotions are hugely context dependent. While we can focus on only those areas of the face which display a maximum of emotions like around the mouth and eyes, how we extract these gestures and categorize them is still an important question. Neural networks and machine learning have been used for these tasks and have obtained good results.

1.1 Proposed Project

1.1.1 Problem Statement

Computers and other electronic devices in our daily lives will become more user-friendly if they can adequately interpret a person's facial expressions, thereby improving human-machine interfaces. The goal of this project is to develop a framework which can predict, from the grayscale picture of a person's face, which emotion the facial expression conveys.

1.1.2 Proposed Solution

Here a face emotion recognition system based on image processing and convolutional neural network is proposed. The facial expression recognition extracts the information representing the facial expression features from the original input facial expression images through computer image processing technology, and classifies the facial emotion features according to human emotional expression, such as happiness, surprise, aversion and neutrality using a convolutional neural network. Two convolutional neural networks VGG-16 and RESNET-50 which are pre-trained with millions of images are going to be used to recognize emotion from the input image and to analyze the change in accuracy.

1.2 Relevance

Human emotion recognition plays an important role in the interpersonal relationship. The automatic recognition of emotions has been an active research topic from early eras. Therefore, there are several advances made in this field. Emotions are reflected from speech, hand and gestures of the body and through facial expressions. Hence extracting and understanding of emotion has a high importance of the interaction between human and machine communication.

Chapter 2

Report of Preparatory Work

2.1 Literature Survey Report

By studying the following works it is concluded that emotion recognition using convolutional neural network as classifier with a proper processing method for optimal feature selection from input face image can obtain better performance.

1. **Optimal feature selection and deep learning ensembles method for emotion recognition from human brain EEG sensors** [2], IEEE Access, vol. 5, pp. 14797–14806, 2017

   In this method, they proposed an EEG feature extraction and selection method for emotion (happy, calm, sad, and scared) recognition. They employed Hjorth parameters in the frequency domain. The Hjorth parameters are useful for differentiating the power spectra that are used as a feature vector. To select the optimal feature set, they analyzed the extracted feature set using a balanced one-way ANOVA (p-value ¡ 0.05) method. Furthermore, top ranked classifiers the were used for the emotion classification using the optimal feature sets for each subject separately. Comparatively, the proposed method performs better than existing emotion recognition methods. The proposed feature selection method OF obtained the best emotion recognition rates of 76.6Based on the results, the conclusion is optimal feature selection is a good choice for enhancing the performance of EEG-based emotion recognition.

2. **Facial expression recognition based on local region specific features and support vector machines** [7], Multimed. Tools Appl., vol. 76, no. 6, pp. 7803–7821, Mar. 2017

   They propose a new method for the recognition of facial expressions from single image frame that uses combination of appearance and geometric features with support vector machines classification. The proposed face representation in provides better face registration than mainstream face representation, i.e. holistic representation. Performance improvement as well as dimensionality reduction is obtained with searching local face regions carrying the most discriminating information for facial expression classification.

3. **Facial expression recognition with faster R-CNN** [6], Procedia Comput. Sci., vol. 107, pp. 135–140, Jan. 2017

   In order to avoid the complex explicit feature extraction process and the problem of low-level data operation involved in traditional facial expression recognition, they proposed a method of Faster R-CNN (Faster Regions with Convolutional Neural Network Features) for facial expression recognition in this paper. Firstly, the facial expression image is normalized and the implicit features are extracted by using the trainable convolution kernel. Then, the maximum pooling is used to reduce the dimensions of the extracted implicit features. After that, RPNs (Region Proposal Networks) is used to generate high-quality region proposals, which are used by Faster R-CNN for detection. Finally, the Softmax classifier and regression layer is used to classify the facial expressions and predict boundary box of the test sample, respectively. The dataset is provided by Chinese Linguistic Data Consortium (CLDC), which is composed of multimodal emotional audio and video data. Experimental results show the performance and the generalization ability of the Faster R-CNN for facial expression recognition. The value of the mAP is around 0.82.

4. **Contrast limited fuzzy adaptive histogram equalization for enhancement of brain images** [5], Int. J. Imag. Syst. Technol., vol. 27, no. 1, pp. 98–103, 2017

   Contrast limited fuzzy adaptive histogram equalization (CLFAHE) is proposed to improve the contrast of MRI Brain images. The proposed method consists of three stages. First, the gray level intensities are transformed into membership plane and membership plane is modified with Contrast intensification operator. In the second stage, the contrast limited adaptive histogram equalization is applied to the modified membership plane to prevent excessive enhancement in contrast by preserving the original brightness. Finally, membership plane is mapped back to the gray level intensities. The performance of proposed method is evaluated and compared with the existing methods in terms of qualitative measures such as entropy, PSNR, AMBE, and FSIM. The proposed method provides enhanced results by giving better contrast enhancement and preserving the local information of the original image.

5. **A recursive framework for expression recognition: From Web images to deep models to game dataset** [4], Mach. Vis. Appl., vol. 29, no. 3, pp. 489–502, 2018

   In this paper, they propose a recursive framework to recognize facial expressions from images in real scenes. Unlike traditional approaches that typically focus on developing and refining algorithms for improving recognition performance on an existing dataset, they integrate three important components in a recursive manner: facial dataset generation, facial expression recognition model building, and interactive interfaces for testing and new data collection. To start with, they first create a candid-images-for-facial-expression (CIFE) dataset. they then apply a convolutional neural network (CNN) to CIFE and build a CNN model for web image expression classification. In order to increase the expression recognition accuracy, they also fine-tune the CNN model and thus obtain a better CNN facial expression recognition model. Based on the fine-tuned CNN model, they design a facial expression game engine and collect a new and more balanced dataset, GaMo. The images of this dataset are collected from the different expressions our game users make when playing the game. Finally, they evaluate the GaMo and CIFE datasets and show that our recursive framework can help build a better facial expression model for dealing with real scene facial expression tasks.

6. **Semantic-emotion neural network for emotion recognition from text** [3], IEEE Access, vol. 7, pp. 111866–111878, 2019

   In this paper, they propose a recursive framework to recognize facial expressions from images in real scenes. Unlike traditional approaches that typically focus on developing and refining algorithms for improving recognition performance on an existing dataset, they integrate three important components in a recursive manner: facial dataset generation, facial expression recognition model building, and interactive interfaces for testing and new data collection. To start with, they first create a candid-images-for-facial-expression (CIFE) dataset. they then apply a convolutional neural network (CNN) to CIFE and build a CNN model for web image expression classification. In order to increase the expression recognition accuracy, they also fine-tune the CNN model and thus obtain a better CNN facial expression recognition model. Based on the fine-tuned CNN model, they design a facial expression game engine and collect a new and more balanced dataset, GaMo. The images of this dataset are collected from the different expressions our game users make when playing the game. Finally, they evaluate the GaMo and CIFE datasets and show that our recursive framework can help build a better facial expression model for dealing with real scene facial expression tasks.

2.2 System Study Report

When comparing different conventional methods for emotion recognition, convolutional neural network shows better performance. By considering different methods that are discussed early, emotion recognition from face image is using in most methods. When we consider a face image, there must be some noise in the image, we have to choose optimal features representing the emotion from the face image and to recognize emotion in the image the features must be in their enhanced form. As the results implicates the quality or features of the input face image affect the emotion recognition rate of the classifier.

Image classification is the process of labeling images according to predefined categories. The process of image classification is based on supervised learning. An image classification model is fed a set of images within a specific category. Based on this set, the algorithm learns which class the test images belong to, and can then predict the correct class of future image inputs, and can even measure how accurate the predictions are. Convolutional neural networks are composed of multiple layers of artificial neurons. Artificial neurons, a rough imitation of their biological counterparts, are mathematical functions that calculate the weighted sum of multiple inputs and outputs an activation value. The behavior of each neuron is defined by its weights. When fed with the pixel values, the artificial neurons of a CNN pick out various visual features. When we input an image into a convolutional neural network, each of its layers generates several activation maps. Activation maps highlight the relevant features of the image. Each of the neurons takes a patch of pixels as input, multiplies their color values by its weights, sums them up, and runs them through the activation function.

Chapter 3

Project Design

The proposed system has two stages, facial emotion data pre-processing and facial emotion recognition using convolutional neural network. In the first stage the input facial image will be processed by using some image processing techniques to extract emotion features and in the second stage the facial image will be classified to the specific emotion based on the features using convolutional neural network.

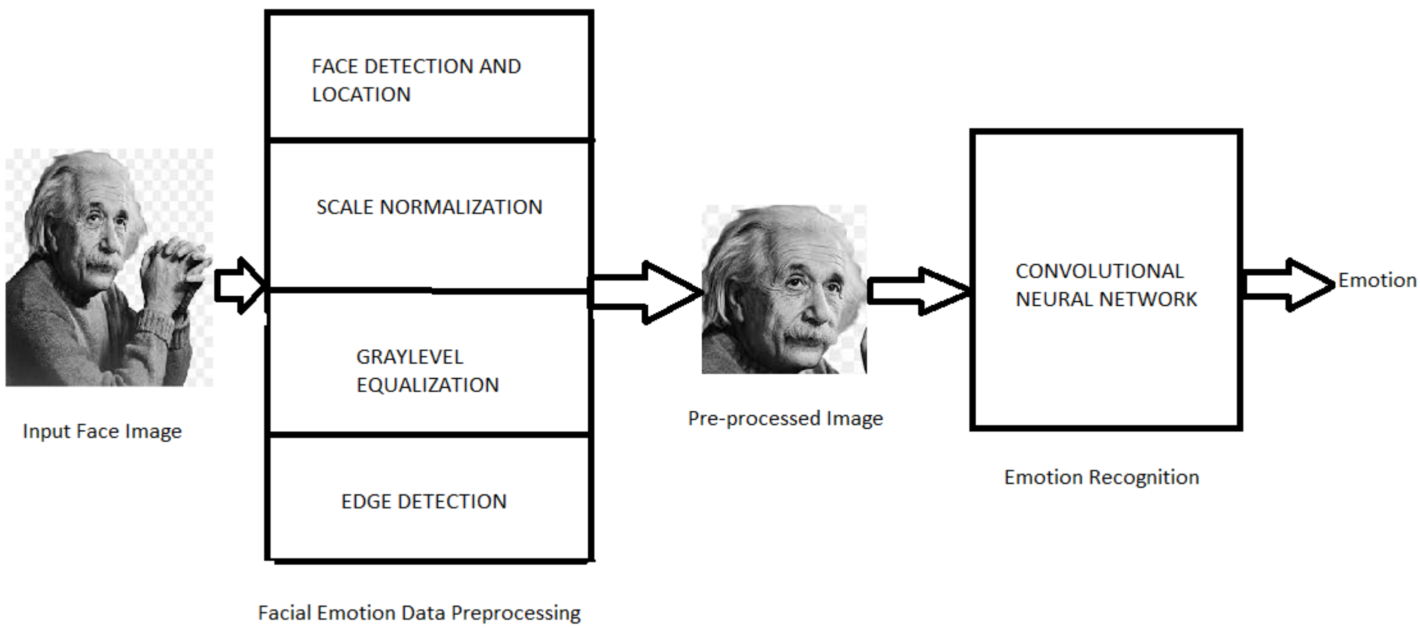

Figure 3.1: Work Flow

3.1 Facial Emotion Data Preprocessing

Because the original pictures of facial expressions have complex background, different sizes, different shades and other factors, a series of image pre-processing processes have to be completed before facial expressions are input into the network for training. Firstly, we locate the face in the image and cut out the face image. Then, we normalize the face image to a specific size. Next, we equalize the histogram of the image to reduce the influence of illumination and other factors. Finally, we extract the edge of each layer of the image in the convolution process. The extracted edge information is superimposed on each feature image to preserve the edge structure information of texture image.

3.1.1 Face Detection And Location

This method uses the Haar-like to extract facial features, and uses an integral graph to realize fast calculation of Haar-like features, and screens out important features from a large number of Haar-like features. Then, we use the Adaboost algorithm to train and integrate the weak classifier into a strong classifier

Haar-like feature

Haar-like features are digital image features used in object recognition. A Haar-like feature considers adjacent rectangular regions at a specific location in a detection window, sums up the pixel intensities in each region and calculates the difference between these sums.

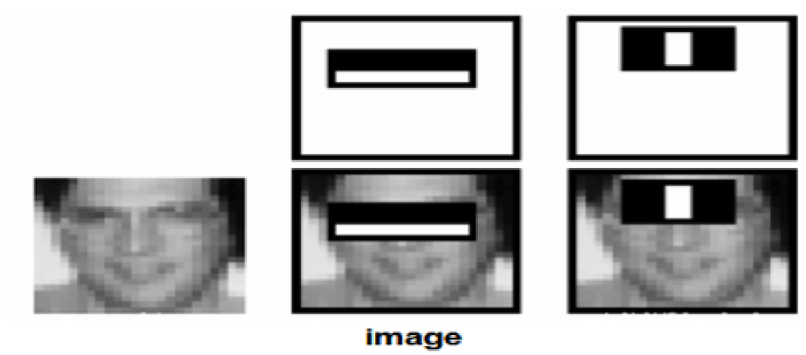

Figure 3.2: Haar Feature

Integral Images

An Integral Image is an intermediate representation of an image . Value for location (x, y) on the integral image equals the sum of the pixels above and to the left (inclusive) of the (x, y) location on the original image . This intermediate representation is essential because it allows for fast calculation of rectangular region.

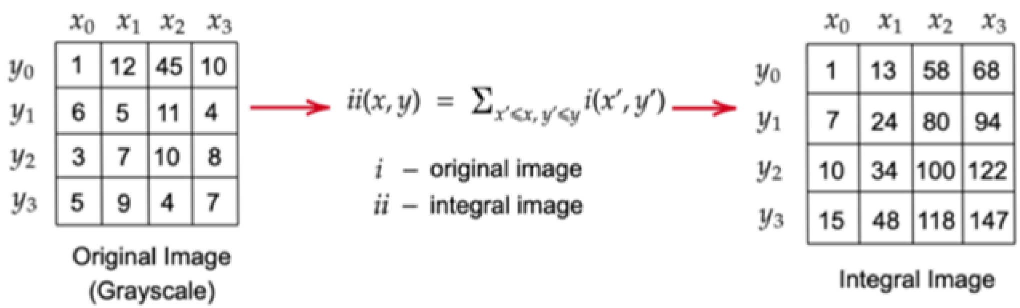

Figure 3.3: Integral Image

Haar Cascade Classifier

This is basically a machine learning based approach where a cascade function is trained from a lot of images both positive and negative. Based on the training it is then used to detect the objects in the other images. Based on the training it is then used to detect the face from the images. And using certain program codes(like OpenCV) we can extract the face from the input image as an image.

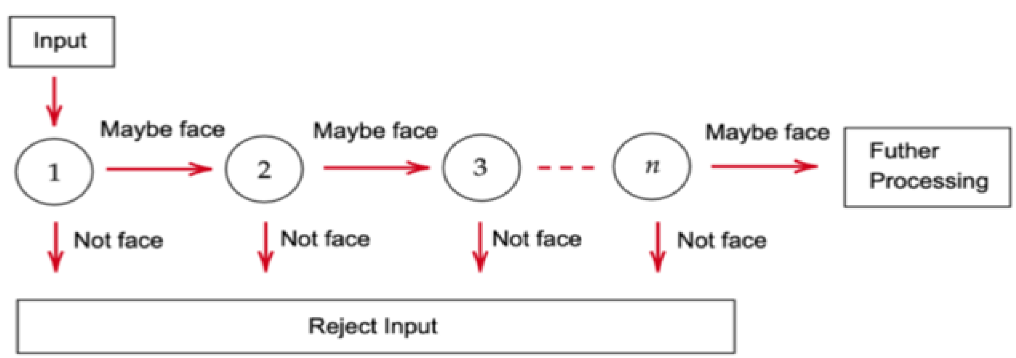

Figure 3.4: Haar Classifier

Adaboost Algorithm

AdaBoost algorithm, short for Adaptive Boosting, is a Boosting technique that is used as an Ensemble Method in Machine Learning. It is called Adaptive Boosting as the weights are re-assigned to each instance, with higher weights to incorrectly classified instances. Boosting is used to reduce bias as well as the variance for supervised learning. It works on the principle where learners are grown sequentially. Except for the first, each subsequent learner is grown from previously grown learners. In simple words, weak learners are converted into strong ones. Adaboost algorithm also works on the same principle as boosting, but there is a slight difference in working. Let's discuss the difference in detail.

3.1.2 Scale Normalization

Through normalization, the input image is scaled to 128*128 size. Let point (x, y) in the original picture be normalized and mapped to point x' , y' . The mapping is as follows

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Where sx represents the scaling ratio of the image in the direction of x axis and sy represents the scaling ratio of the image in the direction of y axis. In the process of image scaling, bilinear interpolation algorithm is also needed to fill the image.

Bilinear interpolation algorithm

Bilinear Interpolation is a resampling method that uses the distance weighted average of the four nearest pixel values to estimate a new pixel value. The four cell centers from the input raster are closest to the cell center for the output processing cell will be weighted and based on distance and then averaged.
A, B, C and D are the four points around the pixel (x, y). The corresponding gray values are g (A), g (B), g (C), g (D). To get the gray value of point (x, y) and calculate the gray value of points E and F, the formula is as follows:
g (E) = (x - xD) (g (C) - g (D)) + g (D)
g (F) = (x - xA) (g (B) - g (A)) + g (A)
xA and xD are the abscissa of point A and point D, respectively. The gray scale formula of (x, y) is as follows: g (x, y) = (y - yD) (g (F) - g (E)) + g(E) where yD represents the ordinates of CD points.

3.1.3 Gray Level Equalization

In the actual image acquisition process, it is easy to be affected by illumination, shadows and other factors. It is necessary to average the gray level of the image to enhance the contrast of the image. The Histogram Equalization (HE) method is used to process images. Histogram equalization is a technique for adjusting image intensities to enhance contrast.

Histogram Equalization

Histogram Equalization is a computer image processing technique used to improve contrast in images. It accomplishes this by effectively spreading out the most frequent intensity values, i.e. stretching out the intensity range of the image. This method usually increases the global contrast of images when its usable data is represented by close contrast values. This allows for areas of lower local contrast to gain a higher contrast.The basic idea is to transform the histogram of the original graph into a uniform distribution form. If the gray level of the gray image is Ł, the size

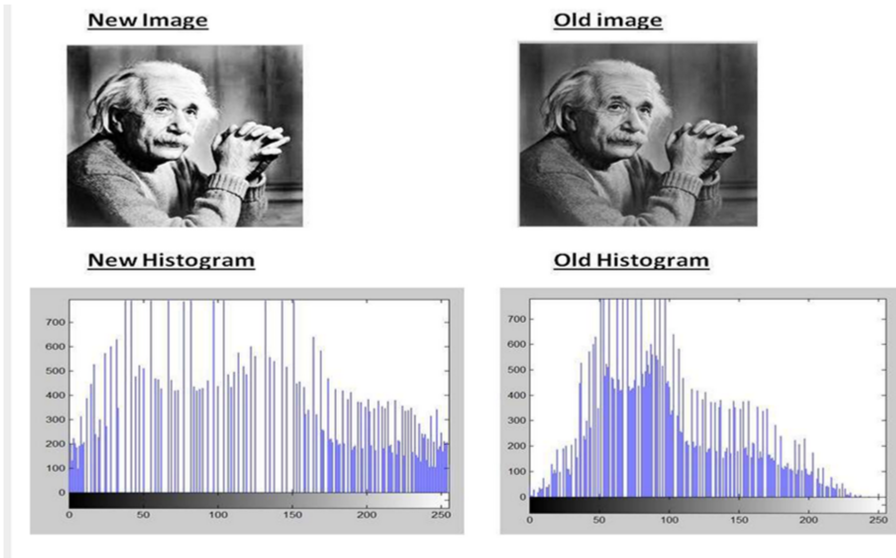

Figure 3.5: Histogram

is M×N, and the number of pixels in the r_i gray level is E, the corresponding probability of gray level occurrence is as follows:

$$P_r(r_i) = \frac{n_i}{M \times N}, \quad i = 0, 1..., L-1 \tag{3.1}$$

Subsequently the cumilative distribution function is calculates using the following equation.

$$T(r_i) = \sum P_r(r_j), \quad i = 0, 1..., L-1 \tag{3.2}$$

Finally the image histogram is averaged using the following mapping relations:

$$e_j = INT[(e_{max} - e_{min})T(r) + e_{min} + 0.5], \quad j = 0, 1..., L-1 \tag{3.3}$$

3.1.4 Image Edge Detection

Kirsch edge operator is used to extract image edge information. The Kirsch operator or Kirsch compass kernel is a non-linear edge detector that finds the maximum edge strength in a few predetermined directions. The operator takes a single kernel mask and rotates it in 45 degree increments through all 8 compass directions: N, NW, W, SW, S, SE, E, and NE. Each pixel in the image is operated with these 8 kernels (convolution) . The edge magnitude of the Kirsch operator is calculated as the maximum magnitude across all directions.

$$N=\begin{vmatrix}+5 & +5 & +5\\ -3 & 0 & -3\\ -3 & -3 & -3\end{vmatrix}\ \mathrm{NW}=\begin{vmatrix}+5 & +5 & -3\\ +5 & 0 & -3\\ -3 & -3 & -3\end{vmatrix}\ \mathrm{W}=\begin{vmatrix}+5 & -3 & -3\\ +5 & 0 & -3\\ +5 & -3 & -3\end{vmatrix}$$

$$\mathrm{SW}=\begin{vmatrix}-3 & -3 & -3\\ +5 & 0 & -3\\ +5 & +5 & -3\end{vmatrix}\ \mathrm{E}=\begin{vmatrix}-3 & -3 & +5\\ -3 & 0 & +5\\ -3 & -3 & +5\end{vmatrix}\ \mathrm{NE}=\begin{vmatrix}-3 & +5 & +5\\ -3 & 0 & +5\\ -3 & -3 & -3\end{vmatrix}$$

$$\mathrm{S}=\begin{vmatrix}-3 & -3 & -3\\ -3 & 0 & -3\\ +5 & +5 & +5\end{vmatrix}\ \mathrm{SE}=\begin{vmatrix}-3 & -3 & +5\\ -3 & 0 & +5\\ -3 & +5 & +5\end{vmatrix}$$

Figure 3.6: Kernels Used

Convolving mask over image

Place the center of the mask at each element of an image. Multiply the corresponding elements and then add them , and paste the result onto the element of the image on which you place the center of mask.

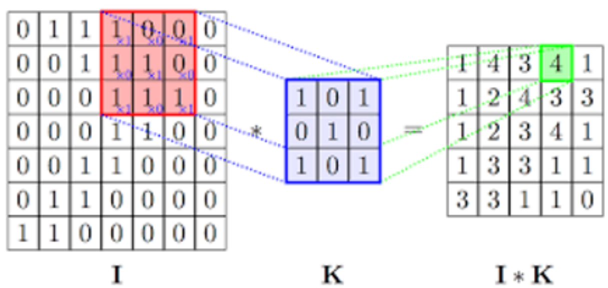

Figure 3.7: Convolution of Mask

3.2 Convolutional Neural Network For Emotion Recognition

Image classification is the process of labeling images according to predefined categories. The process of image classification is based on supervised learning. An image classification model is fed a set of images within a specific category. Based on this set, the algorithm learns which class the test images belong to, and can then predict the correct class of future image inputs, and can even measure how accurate the predictions are. Convolutional neural networks are composed of multiple layers of artificial neurons. Artificial neurons, a rough imitation of their biological counterparts, are mathematical functions that calculate the weighted sum of multiple inputs and outputs an activation value. The behavior of each neuron is defined by its weights. When fed with the pixel values, the artificial neurons of a CNN pick out various visual features. Training of CNN with facial emotion images is very important. FER-2013 dataset is going to use for training and testing the CNN. Here VGG-16 and RESNET-50 are used for emotion recognition.

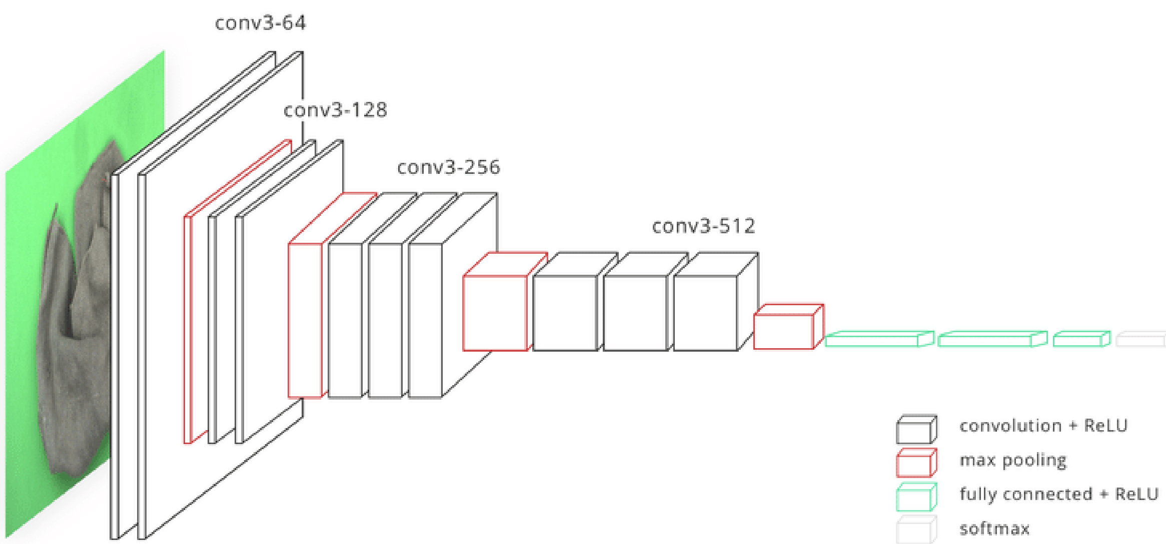

Figure 3.8: VGG-16 Convolutiuonal Neural Network

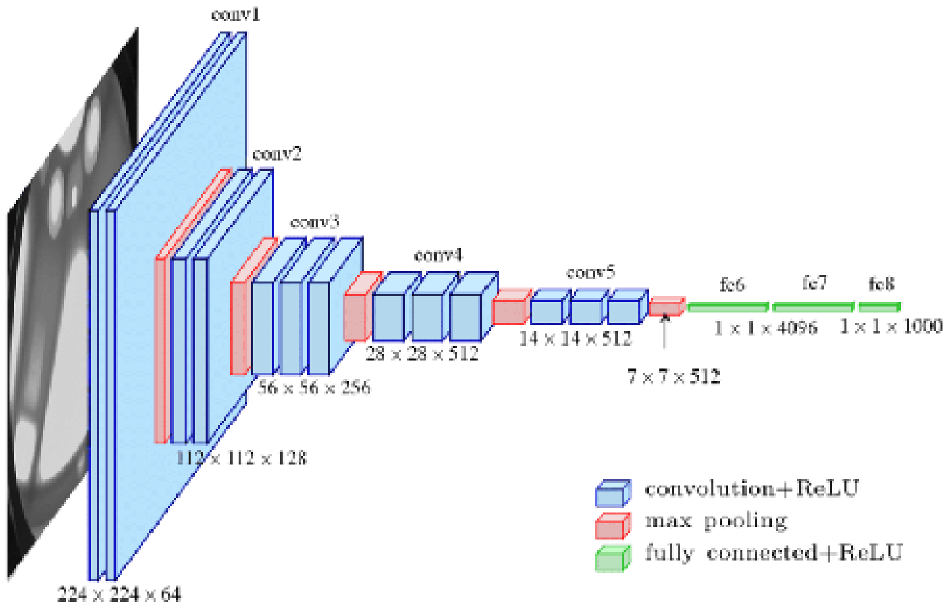

Figure 3.9: RESNET-50 Convolutiuonal Neural Network

3.3 Hardware & Software Requirements

Processor	: Intel Core i5 7th Gen 3.2GHz
Software and Libraries	: Python, Tensorflow, Keras, OpenCv
RAM	: 16GB
Graphics Card	: 6GB NVIDIA GeForce GTX 1060 GPU
Operating System	: Any Operating System
Supporting Environment	: Google Colab is usind for training and testing neural networks.

Chapter 4

Implementation

4.1 Facial Emotion Data Preprocessing

4.1.1 Face Detection And Location

Here the portion of the face from the input image is extracted. For that Haar Cascade Classifier is used. The python library opencv has a built in function CascadeClassifier() for implementing this method. So it is used here.

Figure 4.1: After extracting face

4.1.2 Scale Normalization

After extracting face from input image it has to be converted to a specific size. For that the inbuilt function resize() with the opencv library is used.

Figure 4.2: After Normalization

4.1.3 Gray Level Equalization

Here the normalized image get enhanced using histogram equalization method. The opencv library has the function equalizeHist() for performing histogram equalization on an image.

Figure 4.3: After Enhancing

4.1.4 Image Edge Detection

For enhancing edge features of the image Kirsh edge operator is used, which is implemented by developing filter by using numpy package and performing convolution of the filter with the image by using opencv functions.

Figure 4.4: After Edge Detection

4.2 Emotion Recognition

Here two pretrained neural networks VGG-16 and RESNET-50 are used. For training and testing the neural networks with the dataset of emotion images the python packages Tensorflow, Keras and opencv are used. These packages have built in functions for pre-processing dataset, training and testing the neural networks and for saving the training networks for future purposes.

Chapter 5

Results & Conclusions

The initial stage of this project was pre-processing of the input facial expression image. Mainly four operations are performed on the image to pre-process it. For the implementation of these operations the python package opencv is used and obtained a better image having enhanced features. For the dataset Fer-2013 used for training and tasting the neural networks the pre-processing operations are not needed. Because the dataset Fer 2013 was already processed.

Figure 5.1: Input Image

Figure 5.2: Pre-processed Image

After training the neural networks VGG16 and RESNET50 with the emotion image dataset, both of them are analysed based on their accuracy in emotion recognition. And it is found that both of them have an accuracy around 50%. VGG16 neural nertwork has 48% maximum accuracy over 48 epochs of testing and RESNE50 has 50% maximum accuracy over 48 epochs of testing.

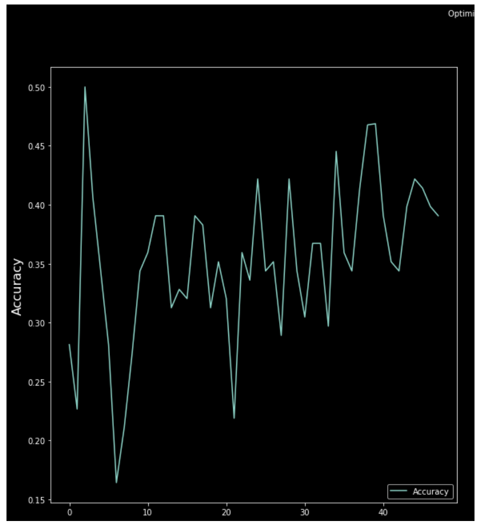

Figure 5.3: vgg16 accuracy plot

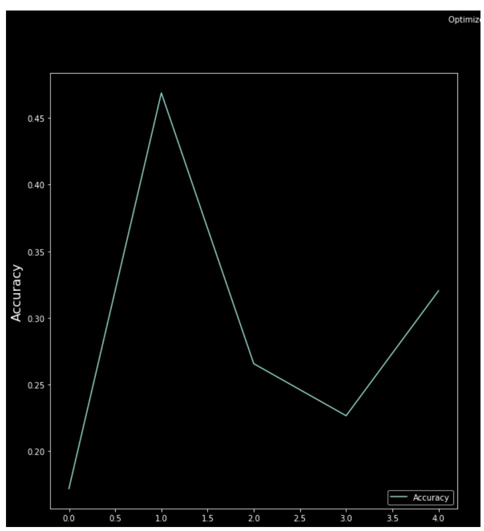

Figure 5.4: resnet50 accuracy plot

5.1 Conclusion

With the development of computers, facial expression recognition plays an important role in many applications, such as human-computer interaction and medical escort. However, facial expression recognition is a complex task for computers. Firstly, the facial expression image is normalized, and the edge of each layer of the image is extracted in the convolution process. The extracted edge information is superimposed on each feature image to preserve the edge structure information of the texture image. Finally, the expression of the test sample image is classified and recognized by using a Softmax classifier with neural networks. When compared to existing methods emotion recognition from facial image is more accurate and easy to implement. And the use of neural networks will increase the recognition rate but it depends upon the pre-processing methods and the architecture of convolutional neural network used.

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