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Fast Facial Emotion Recognition using Convolutional Neural Network and Gabor Filter

A.Aravind, G.S.B.N.S.R.Sasank, G.V.Srinivasa Reddy, T. Sundhar Kumar

B.Tech Student, Dept. of ECE, Pragati Engineering College, Surampalem, Andhra Pradesh, India

B.Tech Student, Dept. of ECE, Pragati Engineering College, Surampalem, Andhra Pradesh, India

B.Tech Student, Dept. of ECE, Pragati Engineering College, Surampalem, Andhra Pradesh, India

B.Tech Student, Dept. of ECE, Pragati Engineering College, Surampalem, Andhra Pradesh, India

ABSTRACT: The emotions that evolved in the human face have a great influence on decisions and arguments about various subjects. The emotional states of a person can be classified into six main categories: surprise, fear, disgust, anger, happiness, and sadness. Unsheathe of these emotions from the face images can help in human-computer interaction as well as many other applications. A deep-learning-based framework is proposed in this paper for human emotion recognition. The framework proposed in this paper uses the Gabor filters for feature extraction and then a convolutional neural network (CNN) for classification. The experimental results show that the proposed methodology increases both the speed training process of CNN and the recognition accuracy.

KEYWORDS: CNN, Gabor filter, Deep-learning-based framework, facial emotion.

I. INTRODUCTION

Emotions have an important role in our everyday lives, and directly affect decisions, reasoning, attention, prosperity, and quality of life of the human. Initiating communication between people is through emotions and facial expressions. These days, with the influence of computers on human lives and the mechanization of the lives of individuals, the establishment of human and computer interaction (HCI) has played a crucial and very important role.Recently, deep neural networks achieved significantly good results in modeling complex patterns. A deep-learning-based framework is proposed in this paper for human emotion recognition. The proposed framework uses the Gabor filters for feature extraction and then the deep convolutional neural network.

S. L. Happy and A. Rout ray[1], Extraction of discriminative features from salient facial patches plays a vital role in effective facial expression recognition. His method is found to perform well consistently in different resolutions, hence, providing a solution for expression recognition in low resolution images.A. Nicolai and A. Choi [2] In his method, subject's face and facial features (eyes, mouth, etc.) are extracted. Next, the relevant identifying points are extracted from each facial feature. In the emotion recognition stage, the identifying points are used to fuzzify and determine the strength of different facial actions. These strengths are then used to determine the subject's displayed emotion.

II.EXISTING METHOD

The convolutional neural network is one of the most popular ways of analyzing images. This method is based on a two-level CNN framework. The first level is background removal which is used to extract emotions from an image. Here, the CNN network module is used to extract the primary expressional vector (EV). The EV is acquired using a perceptron unit applied on a background-removed face image. Each of the convolutional layers receives the input data, transforms it, and then gives it to the next layer. All the convolutional layers were capable of pattern detection. Each convolutional layer has four filters. The input image fed to the first-part CNN generally consists of shapes, edges, textures, and objects. The circle detector, edge detector, and corner detector filters are used at the start of the convolutional layer 1. Once the face has been detected, the second part CNN filter extracts facial features, such as ears, eyes, lips, nose, and cheeks. The second part CNN

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has layers with 3×3 kernel matrix, e.g., [0.25, 0.17, 0.9; 0.89, 0.36, 0.63; 0.7, 0.24, 0.82]. These values are selected between 0 and 1 initially. Here, we used minimum error decoding to optimize the filter values. Once the filter is adjusted by supervisory learning, it is then applied to the background-removed face (i.e., on the output image of the first-part CNN), for detection of different facial parts (e.g., eye, lips. nose, ears, etc.)

III.PROPOSED METHOD

The facial emotion recognition can be done using CNN only, but the accuracy is very low. So, in order to increase the accuracy, we have come with this method in which additional Gabor filters are used. In the proposed method, the input image can be resized to our requirement and is applied to Gabor filters and then convey the output results as inputs to the neural network. The output of the Gabor filter is given to the convolutional neural network.

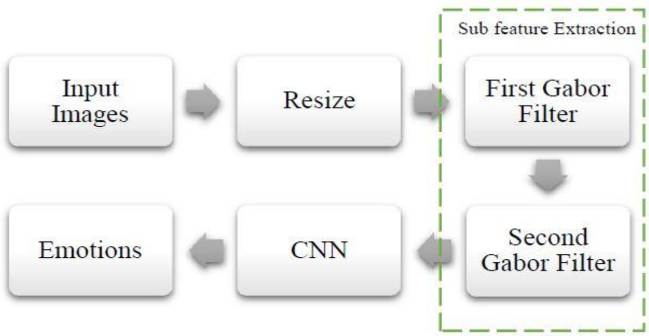

Fig: 1 proposed method

The first used Gabor filter extracts texture information in numerous scales and directions while the second extracts more sub-features from the previous Gabor feature map.

Equation of Gabor filter:

$g(x, y; \lambda, \theta, \varphi, \sigma, \lambda) = \exp(-(\llbracket x^{\prime} \rrbracket^{2}+\gamma/2\ y'/2)/(2\sigma^{2}))\ \exp(i(2\Pi x'/\lambda + j))$

in which the important part is:

$g(x, y; \lambda, \theta, \varphi, \sigma, \lambda) = \exp(-(\llbracket x^{\prime} \rrbracket^{2}+\gamma/2\ y'/2)/(2\sigma^{2}))\ \cos(2\Pi x'/\lambda + j)$

and the pure imaginary number is:

$g(x, y; \lambda, \theta, \varphi, \sigma, \lambda) = \exp(-(\llbracket x^{\prime} \rrbracket^{2}+\gamma/2\ y'/2)/(2\sigma^{2}))\ \sin(2\Pi x'/\lambda + j)$

Where:

$x' = x \cos\theta + y \sin\theta$ and

$y' = -x \sin\theta + y \cos\theta$

Here, λ — It represents the wavelength of the sinusoidal component.

ϴ — It represents the orientation of the traditional to the parallel stripes of Gabor function.

Ψ — It represents the phase offset of the sinusoidal function.

σ — It represents the sigma/standard deviation of the Gaussian envelope.

ɣ — It represents the spatial ratio.

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Fig-2: Original images

Following are the images shown after applying the first& second Gabor filters on original images with the following parameters:

(x, y)=(18,18), $\theta = \frac{\pi}{4}$, $\sigma = 1.5, \varphi = 0$, λ=5 -------------First Gabor filter

(x, y)=(18,18), $\theta = \frac{3\pi}{4}$, $\sigma = 1.5, \varphi = 0$, λ=5 -------------Second Gabor filter

Fig-3:Output of first Gabor filter

Fig-4:Output of secondGabor filter

IV.RESULTS

We have tested the proposed method on a variety of images which gives the output with much more accuracy than the existing CNN method.The below table shows the comparison of accuracy of proposed method and simple CNN.The proposed approach needs less time than the CNN approach to achieve the same accuracy. However, increase of running time is expected.

Epoch	CNN Method Accuracy	2Gabor +CNNMethod
1	0.1050	0.1326
10	0.5138	0.8619
15	0.7348	0.9227
20	0.8343	0.9558
25	0.9006	0.9779
30	0.9116	0.9716

Table -1 :Comparison of accuracy

Following are the graphs of accuracy of simple CNN method and proposed method

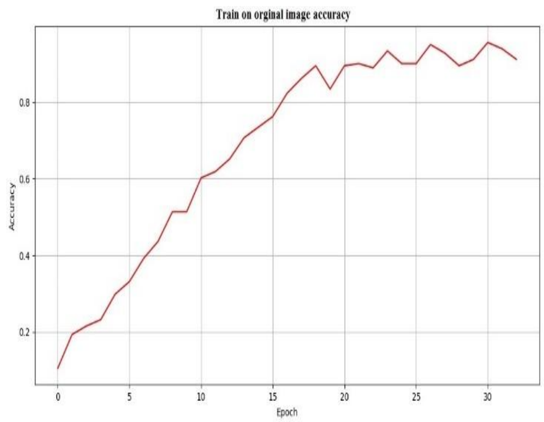

Fig-5:Graph of Simple CNN method

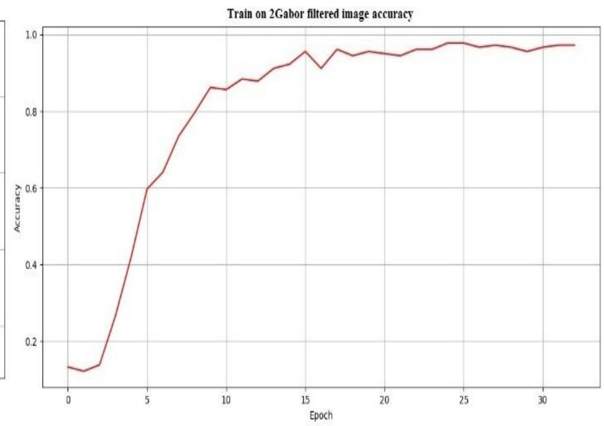

Fig-6: Graph of Proposed method

Theseare the output images:

Fig-7: output images

V.CONCLUSION

The experimental results show that with the help of Gabor filter, the system learning became faster and the accuracy has improved profoundly. This is because the Gabor filter actually extracts the image sub-feature and gives it to the neural network. By doing this, the convolutional neural network receives a number of sub-feature and takes one step further in extracting the emotions from the faces.

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