

Face Emotion Recognition with Image Processing and Neural Network (June 2022)

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ABSTRACT People use facial expressions to show emotional states. However, facial expression recognition remained a challenging and interesting problem in computer vision. This project proposes a new facial emotional recognition model using a convolutional neural network. Therefore a convolutional neural network based solution combined with image processing is used in classification of universal emotions: Anger, Sadness, Happiness, Disgust, Fear and Surprise. Frontal face images are given as input to the system. To complete the training of the CNN network model, I use the CK+ (Extended Cohn-Kanade dataset) CNN consists of three layers of convolution together with fully connected layers. The features extracted by the HOG(Histogram of Oriented Gradients), Convolutional Neural network (CNN) from facial expressions images were fused to develop the classification model through training by our proposed CNN model. And then I use more advanced CNN network model with FER2013 dataset.

INDEX TERMS Emotion Recognition, Deep learning, Neural Network Convolutional Neural Network (CNN), HOG , Object Detection, CK+ Dataset, FER2013 Dataset

I. INTRODUCTION

An emotion is a mental and physiological state that is subjective and private; includes many behaviors, actions, thoughts and feelings.

Research on emotions can be traced back to the book ‘The Expression of the Emotions in Man and Animals’ by Charles Darwin[1]. He believed that emotions to be species-specific rather than culture-specific, but in 1969 after realizing the universality of emotions despite cultural differences, Ekman and Friesen classified expression of emotion as universal: happiness, sadness, anger, disgust, surprise and fear. [2-3- 4- 5]

The ability to recognize emotions can be valuable in face recognition applications. Suspect detection systems and intelligence improvement systems are some other benefits. [6].

Haar wavelet transform[7], Gabor wavelet transform[8], Local Binary Pattern (LBP), and Active Presence Models (AAM)[9] are feature extraction methods based on static images. Whereas dynamic-based approaches assume the temporal association in the sequence of input facial expression within clinging frames. Hidden Markov Model, Support Vector Machine (SVM), AdaBoost, and Artificial Neural Networks are commonly used schemes for facial expression recognition. An important advancement in the field of deep

learning and implementation of CNN[10-11-12] has quite promising. However, a big issue with the using deep learning is that a large amounts of data are need to learn successful model.

While some improvement were made in the identification of facial expression with the CNN algorithm, some breaks are still exist, including too long training times and low recognizing rates in the complex environment.

In databases, two difficulties were observed in deep learning achievements in FER methods: (1) a low number of images, and (2) images from heavily structured conditions. These concern led to the the creation of FER techniques focused on the set of Web images.[13-14-15]

II. Background Review

Recent work on the study can be broadly divided into three categories: Face detection, Facial feature extraction and Emotion classification. The number of studies carried out in each of these categories is quite large and remarkable.

A. Face Detection

Given an image, detecting the presence of a human face due to possible variations of the face is a complex task. The different sizes, angles and poses a human face might have within the image can cause this variation. The emotions which are understandable from human face and different imaging conditions such as illumination also affect facial appearances. In addition, the presence of glasses, hair, beard and makeup have a considerable effect in the facial appearance.[17]

There are many different methods for face detection, such as color space method, Haar Cascade classifiers method, using dlib libraries.[16]

B. Face Feature Extraction

The next step after face detection is removal of facial features. The permanent features of face such as eyes, nose, mouth and facial lines are detected. Feature descriptors are used to extract face features.

The features descriptor is a representation of an image created by receiving useful information and eliminating unnecessary information, thus it simplifies the image.

Typically, feature descriptor converts an image of size height, width and 3 (channels) into a feature vector or array of length n.

Histogram of Oriented Gradient (HOG), focuses on the structure or shape of an object. When it comes to edge properties, only determines whether the pixel is an edge. And this is done by subtracting gradient and direction of the edges.[16]

C. Emotion Classification

Extracted feature points are process to obtain inputs for neural network. Neural network has being trained so that the emotions happiness, sadness, anger, disgust, surprise and fear are recognized. In this project, I used the Convolutional Neural Networks (CNN) method.[18]

In deep learning, a convolutional neural network (CNN) is a class of deep neural networks most widely applied to analyze visual images. It has applications in image and video recognition, image classification, medical image analysis, financial time series, and natural language processing.

Convolution Layer extracts the features of an input image from the training dataset where the core is a small part of an input image for feature classification. The design begins with starting CNN model by taking an input image (static or dynamic) created by adding a convolution layer,

flattening layer, merge layers, and dense layers. Convolution layers are added for better accuracy in large data sets.[16]

III. Emotion Recognition with Convolutional Neural Network

A simple CNN template with several building blocks that we can easily understand and associate with the proposed CNN model. Three types of layers make up a basic CNN, input, hidden, and output. The data enters the CNN via the input layer and then travels through many hidden levels before reaching the output layer. The network's prediction is reflected via the output layer. In terms of loss or error, the network's output is compared to the actual labels.

Hidden layers in the network act as a basic building element for data transformation. The four sub-functions: layer function, Pooling, Normalization and Activation can be dissected from each layer. Convolutional neural network architecture consists of the following layers. [16]

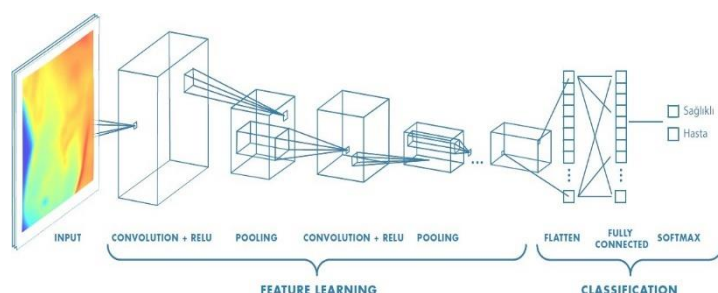


FIGURE 1.1. Understanding of Convolutional Neural Network (CNN)

- Convolutional Layer – Used to detect features
- Non-Linearity Layer – Introducing non-linearity to the system
- Pooling (Downsampling) Layer – Reduces the number of weights and controls overfitting
- Convolutional Layer – Used to detect features
- Fully-Connected Layer – Standard Neural Network used for classification[20]

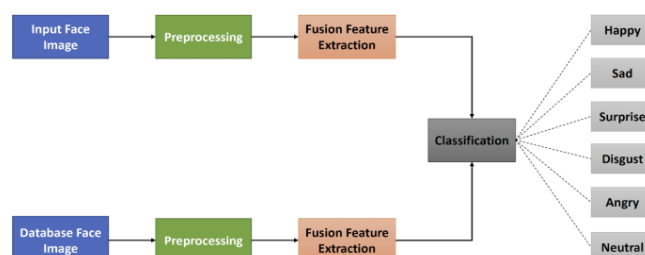


FIGURE 1.2. Facial Emotion Recognition (FER)

A. CK+ Dataset with HOG

CK + image set consisting of 981 facial images was used to recognize emotions from facial expression. First, the data set was created using the data set obtained from the CK + picture set. And this dataset has been trained through the model which we created by convolutional neural networks (CNN). The success rate of the model was calculated by entering test data into the trained model. Since the data in the complexity matrix is 20% test data, it will be $981 * 0.2 = 197$, so 197 data labels were obtained.

With the python programs I use, HOG, as depicted in Fig. 2.1 of each picture in the original CK+ picture set were found.

```
def Create_Hog_features(data):
    Feature_data = np.zeros((len(data),48,48))

    for i in range(len(data)):
        img = data[i]
        resized_img = resize(img, (128, 64))
        fd, hog_image = hog(
            resized_img,
            orientations=9,
            pixels_per_cell=(8, 8),
            cells_per_block=(2, 2),
            visualize=True,
            multichannel=True
        )
        Feature_data[i] = resize(hog_image, (48, 48))
    return Feature_data
```

FIGURE 2.1. Creating Hog Feature with Python

The data set created from the pictures obtained was applied to our CNN model is shown in figure 2.2.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 48, 48, 6)	156
max_pooling2d (MaxPooling2D)	(None, 24, 24, 6)	0
conv2d_1 (Conv2D)	(None, 24, 24, 16)	2416
max_pooling2d_1 (MaxPooling2D)	(None, 12, 12, 16)	0
conv2d_2 (Conv2D)	(None, 10, 10, 64)	9280
max_pooling2d_2 (MaxPooling2D)	(None, 5, 5, 64)	0
conv2d_3 (Conv2D)	(None, 3, 3, 128)	73856
max_pooling2d_3 (MaxPooling2D)	(None, 1, 1, 128)	0
flatten (Flatten)	(None, 128)	0
dense (Dense)	(None, 256)	33024
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 7)	1799

=====
Total params: 120,531
Trainable params: 120,531
Non-trainable params: 0

FIGURE 2.3. Cnn Model for CK+ dataset

The success rates of the facial expression recognition models created by using HOG and Original picture by CNN model and the results are given in Fig. 2.3

CNN model with different Features	Training accuracy score	Test accuracy score	Training Time(second)
Hog images features	%100	%98.98	122.935
Original images features	%100	%98.48	80.242

FIGURE 2.3. Accuracy Score comparison chart

Then, to test the accuracy of the model, I tested it with the pictures which is uploaded from the outside. I used the Cascade Classifier to find the frontal faces of the uploaded images. When the face detected is show in figure 2.4

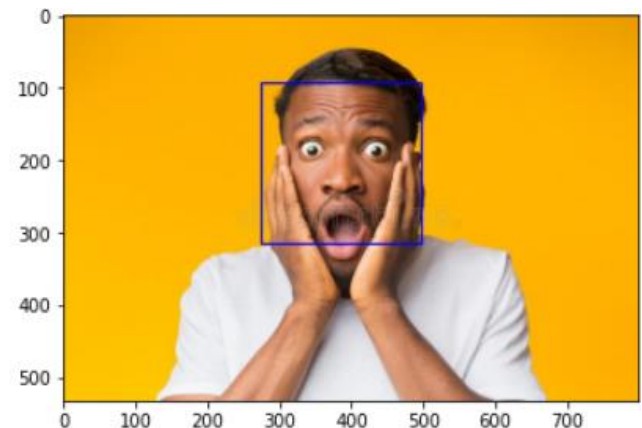


FIGURE 2.4. Detected Face from image

I cropped the frontal face images for the model to use and I converted to Hog image is show in figure 2.5

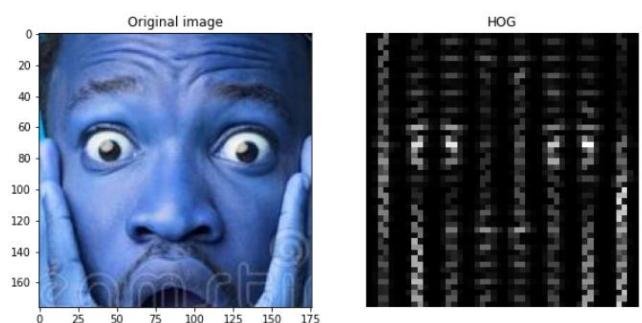


FIGURE 2.5. Cropped original image and Hog

I prepared the shape of the image for the prediction of the Cnn model is given is Figure 2.6.

```
Original Image : (176, 176, 3)
after gray: (176, 176)
(1, 48, 48)
-----
Hog_image : (128, 64)
after gray: (176, 176)
(1, 48, 48)
```

FIGURE 2.6. Shape of Images

And finally when I sent the prepared pictures to model to predict, I got different results from both.

Cnn trained with Hog image gave “Happy” result, Cnn trained with Normal cropped image gave “Suprise” result is shown in figure 2.7.

```
Prediction_Hog = HOG_model.predict(final_image_hog_image)
Prediction_Normal = normal_model.predict(final_image_face_roi)

print(Prediction_Hog[0])
print(Prediction_Normal[0])

[0. 0. 0. 1. 0. 0. 0.]
[0. 0. 0. 0. 0. 0. 1.]

print("Hog image = ",emotion(np.argmax(Prediction_Hog)))

Hog image = Happy

print("Normal image = ",emotion(np.argmax(Prediction_Normal)))

Normal image = Suprise
```

FIGURE 2.7. Predicted Emotion from Hog and Cropped Original images

B. FER2013 Dataset with different CNN

To complete the training of the CNN network model, I use the FER2013 databases and I create more advanced CNN.

Fer2013 contains approximately 30,000 facial RGB images of different expressions with size restricted to 48×48, and the main labels of it can be divided into 7 types: 0=Angry, 1=Disgust, 2=Fear, 3=Happy, 4=Sad, 5=Surprise, 6=Neutral. The Disgust expression has the minimal number of images – 600, while other labels have nearly 5,000 samples each.[21]

Unlike the Cnn we used in the CK+ dataset, I used a more advanced Cnn in the Fer2013 dataset is shown in figure 3.1.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 48, 48, 64)	640
conv2d_1 (Conv2D)	(None, 48, 48, 64)	36928
dropout (Dropout)	(None, 48, 48, 64)	0
conv2d_2 (Conv2D)	(None, 48, 48, 128)	73856
conv2d_3 (Conv2D)	(None, 48, 48, 128)	147584
max_pooling2d (MaxPooling2D)	(None, 24, 24, 128)	0
dropout_1 (Dropout)	(None, 24, 24, 128)	0
conv2d_4 (Conv2D)	(None, 24, 24, 256)	295168
conv2d_5 (Conv2D)	(None, 24, 24, 256)	590080
max_pooling2d_1 (MaxPooling2D)	(None, 12, 12, 256)	0
dropout_2 (Dropout)	(None, 12, 12, 256)	0
conv2d_6 (Conv2D)	(None, 12, 12, 512)	1180160
conv2d_7 (Conv2D)	(None, 12, 12, 512)	2359808
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 512)	0
dropout_3 (Dropout)	(None, 6, 6, 512)	0
flatten (Flatten)	(None, 18432)	0
dense (Dense)	(None, 1024)	18875392
dropout_4 (Dropout)	(None, 1024)	0
dense_1 (Dense)	(None, 7)	7175
=====		
Total params: 23,566,791		
Trainable params: 23,566,791		
Non-trainable params: 0		

FIGURE 3.1. Cnn Model for Fer2013 Dataset

The success rates of the facial expression recognition models created by using FER2013 dataset and Original picture by CNN model and the results are given in Fig. 3.2

Cnn Model	Training Accuracy Score	Testing Accuracy Score	Training Time(Second)
Original Cropped Images	0.8175	0.6914	3569.25

FIGURE 3.2. Accuracy Score for Cnn Model

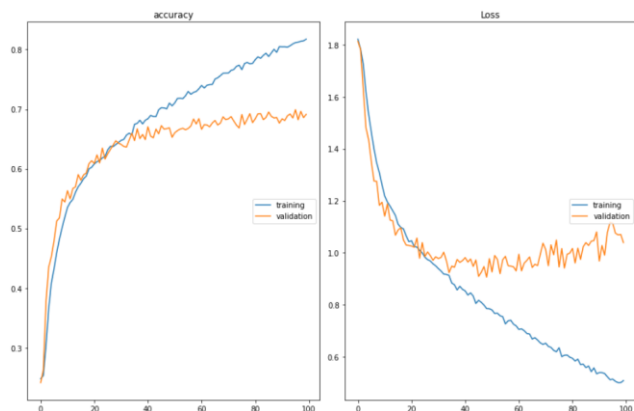


FIGURE 3.3. Plotloss with PlotLossesKeras

When we created a CNN model original pictures, it was found by using the confusion matrix how accurately 7 facial emotion expressions were predicted from training pictures and test pictures and the results are given in Fig. 3.4 and Fig.3.5 comparatively.

Confusion Matrix						
[[550 62 555 1049 684 637 458]						
[55 8 65 113 72 80 43]						
[537 67 562 1042 695 719 475]						
[929 111 966 1939 1323 1172 775]						
[669 78 658 1247 905 859 549]						
[670 55 669 1194 898 823 521]						
[406 45 424 839 559 555 343]]						
Classification Report						
	precision	recall	f1-score	support		
angry	0.14	0.14	0.14	3995		
disgust	0.02	0.02	0.02	436		
fear	0.14	0.14	0.14	4097		
happy	0.26	0.27	0.26	7215		
neutral	0.18	0.18	0.18	4965		
sad	0.17	0.17	0.17	4830		
surprise	0.11	0.11	0.11	3171		
accuracy			0.18	28709		
macro avg	0.15	0.15	0.15	28709		
weighted avg	0.18	0.18	0.18	28709		

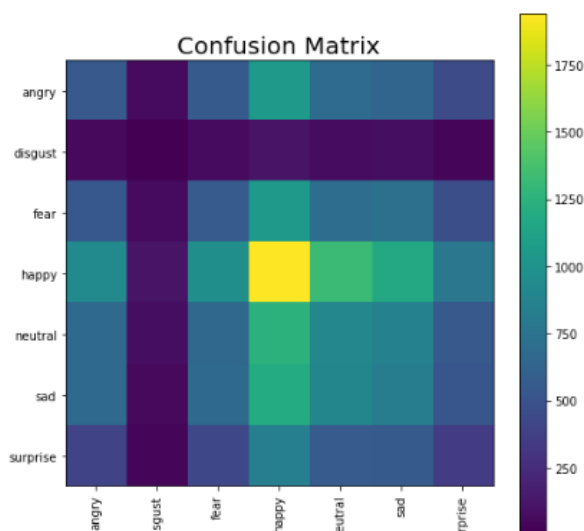


FIGURE 3.4. Confusion Matrix and Classification on training set

Confusion Matrix				
[[114 14 114 224 207 184 101]				
[12 1 12 31 21 20 14]				
[150 11 160 233 189 154 127]				
[232 25 236 448 328 285 220]				
[176 11 145 325 243 199 134]				
[151 13 175 327 238 207 136]				
[96 10 104 229 158 125 109]]				
Classification Report				
	precision	recall	f1-score	support
angry	0.12	0.12	0.12	958
disgust	0.01	0.01	0.01	111
fear	0.17	0.16	0.16	1024
happy	0.25	0.25	0.25	1774
neutral	0.18	0.20	0.19	1233
sad	0.18	0.17	0.17	1247
surprise	0.13	0.13	0.13	831
accuracy			0.18	7178
macro avg	0.15	0.15	0.15	7178
weighted avg	0.18	0.18	0.18	7178

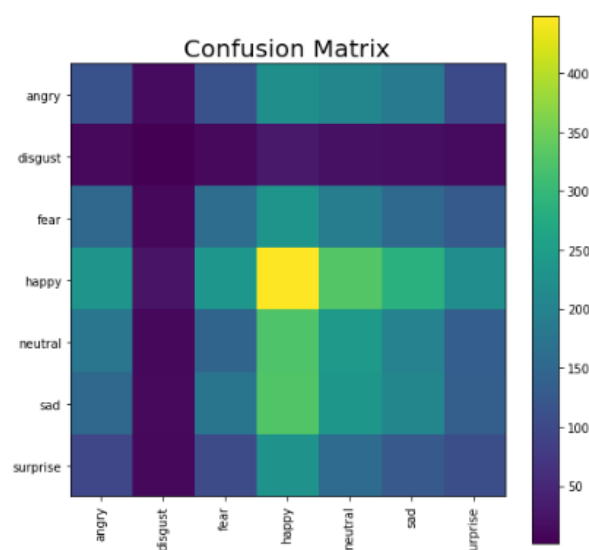


FIGURE 3.5. Confusion Matrix and Classification on test set

Then, I uploaded pictures from the outside and Cascade classifier detected frontal faces of the cropped images and I prepared the shape of the cropped images for the prediction of the Cnn model like I did on the Ck+dataset.



FIGURE 3.4. Original Image



FIGURE 3.5. Cropped Image with HaarCascade

And finally I sent the prepared pictures to model, Cnn trained with Normal cropped images gave “Happy” result is shown in figure 3.6.

```
Prediction_Fer2013 = saved_model.predict(final_image)
```

```
Prediction_Fer2013[0]
```

```
array([0., 0., 1., 0., 0., 0., 0.], dtype=float32)
```

```
emotion(np.argmax(Prediction_Fer2013))
```

```
'Fear'
```

FIGURE 3.6. Predicted Emotion with advanced CNN

IV. Conclusion

HOG and CNN features based on the CK+ dataset, HOG technique was train accuracy (100%), just original image I mean without Hog technique found same train accuracy (100%).

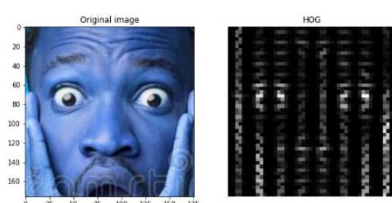


FIGURE 4.1. Test Image (Must be fear or surprise)

Despite this high accuracy, when I predicted images from the outside, I found different results in the two techniques is shown in figure 4.2.

```
print("Hog image = ",emotion(np.argmax(Prediction_Hog)))
```

```
Hog image = Sad
```

```
print("Normal image = ",emotion(np.argmax(Prediction_Normal)))
```

```
Normal image = Happy
```

FIGURE 4.2. Different Results HOG and Original image

Then I used a more advanced CNN model and replaced the dataset with FER2013, which contains about 35 thousand photos.

The model took a very long time to fit, but it correctly predicted a images that had never seen before is shown in figure 4.3.

```
emotion(np.argmax(Prediction_Fer2013))
```

```
'Fear'
```

FIGURE 4.3. Predicted Emotion with advanced CNN

V. References

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Online : <https://paperswithcode.com/dataset/fer2013>
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- 27) Realtime Face Emotion Recognition | Tensorflow | Transfer Learning | Python | Train your own Images (Youtube)
Online: https://www.youtube.com/watch?v=avv9GQ3b6Qg&ab_channel=DeepLearning_by_PhDScholar
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Online:
https://github.com/Baticute/Facial_Expression_Recognition_FER2013

VI. Project Source Code and Dataset

Dataset:

Ck+

<https://www.kaggle.com/datasets/shawon10/ckplus>

FER2013

<https://www.kaggle.com/datasets/msambare/fer2013>

Project Source Code:

Google Colab

<https://colab.research.google.com/drive/1xPbjMoQF7SHtY8Khsimr-xzcOQH9Sb0z?usp=sharing>

Github Repo

[https://github.com/mrtlckn/WorkAndStudy/blob/main/Deep%20Learning/Neural%20Network%20Project/EmotionPrediction_with_ImageProcessing_and_Neural_Network_\(CNN\).ipynb](https://github.com/mrtlckn/WorkAndStudy/blob/main/Deep%20Learning/Neural%20Network%20Project/EmotionPrediction_with_ImageProcessing_and_Neural_Network_(CNN).ipynb)