Improved Methods for Automatic Facial Expression Recognition

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Abstract—Facial expressions constitute one of the most effective and instinctive methods that allow people to communicate their emotions and intentions. In this context, the both Machine Learning (ML) and Convolutional Neural Networks (CNNs) have been used for emotion recognition. Efficient recognition systems are required for good human-computer interaction. However, facial expression recognition is related to several methods that impact the performance of facial recognition systems. In this paper, we demonstrate a state-of-the-art of 65% accuracy on the FER2013 dataset by leveraging numerous techniques from recent research and we also proposed some new methods for improving accuracy by combining CNN architectures such as VGG-16 and Resnet-50 with auxiliary datasets such as JAFFE and CK. To predict emotions, we used a second approach based on geometric features and facial landmarks to calculate and transmit the feature vector to the SVM model. The results show that the ResNet50 model outperforms all other emotion prediction models in real time by maximizing.

Keywords—Facial Expression, Machine Learning, Deep Learning, Facial Land- Marks, Convolution Neural Network [CNN].

1 Introduction

Facial expressions are nonverbal signals that take an important role in interpersonal relationships and are widely used in emotion interpretation, cognitive science, and social interaction. Facial expression recognition's primary function is to group expressions on photographs of human faces into several categories, such as happiness, fear, neutral, surprise, sad, and so on [1,2]. Extracting and validating emotional cues by analyzing user's facial expressions [3,4] is of great importance to improve the level of interaction in human-computer communication systems. To establish emotional interactions between humans and computers, a system that recognizes human emotions is of high priority. An automated system that can determine a person's emotions from their expressions gives the machine the ability to personalize its response. Facial expression recognition's primary function is to group expressions on photographs of human faces into several categories, such as happiness, fear, neutral, surprise, sad, and soon.

This is an important aspect of psychology since a person's facial expression determines how much of an impact their spoken words have on them. This system can be divided into three modules, namely face registration, feature extraction and classification. In this paper, we are interested in all modules of this system, so we decided to work on different approaches to benchmark the performance of the different models. The first method based on geometric features and facial landmarks, using this method we calculate a feature vector and feed it after to our SVM model for training and predict the emotions. The processing pipeline for this technique, which begins with picture preprocessing, feature extraction, and emotion classification, may be seen as follows:

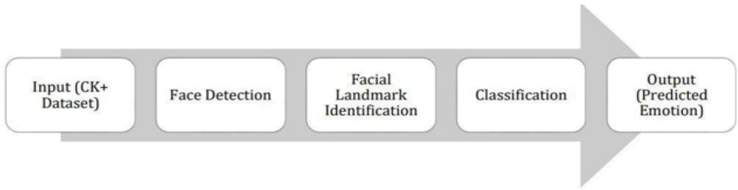

Fig. 1. System process

In deep learning [5], the features are automatically extracted by the neural network, in contrast to standard machine learning, where we manually extract face features from an input image to do emotion categorization. Convolutional neural networks are a type of neural network that are well recognized for extracting valuable characteristics from images and for collecting spatial information (CNN). Due to their strong generalization capabilities and invariance to geometric changes, CNNs are taken into consideration in this paper.

The next section talks about related research in this field. The proposed strategies are discussed in Section III. The analysis and outcomes of the experiment are highlighted in Section IV. Finally, Section V brings the article to a close.

2 Related Work

The analysis and automated detection of facial expressions have garnered a lot of interest from the computer vision research community during the past ten years. The scientific and computer vision research community has envisioned the creation of systems that can distinguish facial expressions in movies or photos, first inspired by the results of cognitive scientists. The majority of these systems make an effort to group expressions into a few major emotional subcategories, including surprise, fear, wrath, joy, and disgust.

Previous research has created many techniques with improving face emotion recognition ability. They trained a conventional neural network (CNN) to recognize face emotions in the study [6,7,8], this CNN is fed a 64*64 image as input. An input layer, five convolutional layers, three pooling layers, a fully connected layer, and an output layer make up the network. For validation, they used the JAFFE and CK+ databases. In the paper [9-10] they extract some spatial features by using the 68 facial landmarks, they calculated the horizontal and vertical distances between all landmark pairs, and they used SVM for classification.

Any facial emotion recognition approach, according to [11-13], entails three steps: feature extraction, dimensionality reduction, and classification, they claim that the main problems with FER are dimensionality and feature selection. They said that analyzing the entire image requires a significant amount of memory and computer power. They then suggested geometric features as a substitute and employed CNN Classifier and face landmark recognition for feature extraction. They evaluated the effectiveness of their system using the databases JAFEE, MUG, CK, and MMI.

The paper [14] presents the most recent developments in artificial intelligence related to automated emotion recognition (FER) using models of deep learning. The researchers demonstrated that deep learning-based FER models and various CNN architectures, including databases, can coexist to produce highly precise results. However, the techniques mentioned are limited in that they only address the six basic emotions and do not address the more complex emotions.

The authors of [15] proposed a framework that offers a mobile application tailored to the user's visual emotions. It processes the collected emotional data of a mobile user by wireless sensor [16] on the cloud and analyzes them immediately. The proposed method is based on detecting small groups of facial cue movements and choosing the emotional expression involved. According to the findings, the localization process has a positive impact on the negative emotion of the user and invites immediate feedback from the user to mitigate it.

Many datasets can be employed to train emotion recognition from facial expressions. The Facial Expression Recognition 2013 (FER2013) [17] and CK dataset (later extended into The Extended Cohn-Kanade Dataset (CK+)) [18] are the most commonly used datasets in this context.

3 Proposed Methodologies

In this section we will discuss the different methodologies that we propose based on machine learning and deep learning in order to compare their performance.

3.1 Emotion detection with Machine Learning

This section describes the whole proposed methodology based on geometric features and facial landmarks. As we discussed in the introduction, the process of this approach will be in this order starting by image pre-processing, feature extraction and emotion classification. The dataset used for this approach is Cohn-Kanade (CK), this dataset was made available to encourage study into the automated recognition of specific facial expressions. These 7 emotions, happiness, surprise, fear, sadness, neutral, disgust, and anger, were reported by 210 participants in this sample. Each picture is 48*48 pixels in size. Figure 2 shows a sample of images representing the seven emotions.

Fig. 2. Various emotions from the CK dataset

For Image pre-processing step, the dataset includes photos taken in a variety of lighting situations. Therefore, it is necessary to ensure that all images are equalized to similar lighting conditions, so we applied histogram equalization on all images in the dataset. We have also applied normalization; Image normalization is a common image processing technique that modifies the intensity range of the pixels. Its normal purpose is to convert an input image to a range of pixel values that are more familiar or normal to the senses, hence the term normalization. The size and color of the photos were standardized using normalization to make computations easier.

The first step of an automatic facial expression recognition system is to locate the face region, it is the face detection step. The main role of this step is to determine the presence or not of human face in an image.

To detect the faces in the images, it is necessary to crop them, to convert them into gray levels and to record them. This is done by OpenCV and its methods by utilizing the built-in Dlib [19] function, which returns an object detector capable of recognizing faces in the picture.The Dlib library also provides a face detection function called get_frontal_face_detector(). This function returns an array of rectangle objects. An image's rectangular region is represented as a rectangle object. Each rectangle object contains four values, which means that it also returns the coordinates of the ROI that contains the face. Figure 3 shows a sample of image from the database and face detected from the image.

Fig. 3. Face detected from the image

After the face detection, the next step is to predict the facial landmarks. Facial landmarks are a set of key points on images of human faces. The points are defined by their (x,y) coordinates on the image. These markers are used to identify and depict the significant facial features. They help us to classify the images.

The 68 (x, y) coordinates on the face are estimated using the pre-trained facial land-markdetector in the Dlib package. These coordinates relate to facial structures. After the facial landmark's prediction, the first thing to do is to find ways to transform these superimposed points on the face into features to pass them to the classifier, so after extracting the coordinates of the face interest points, we will calculate the feature vector that describes the emotion of a person for the purpose of knowing the positions of the face landmarks in relation to each other.

We can do this by averaging the two axes, which gives a central point, the location of all the points with regard to this center point may then be determined. Figure 4 shows the visualization of the face landmarks on an image of our dataset.

Fig. 4. visualization of the face points

From these points we calculated the distance and the angle of each point on the face andstore it in the vector list. This is the formula for calculating the distance and angle.

$$D = \sqrt{(y_i - u_y)^2 + (x_i - u_x)^2} \quad \alpha = \arctan\left(\frac{y_i - u_y}{x_i - u_x}\right)$$

3.2 Emotion detection with Deep learning

CNN Model. We have four stages in our CNN model. The size of the input image is decreased at the conclusion of each step. Each layer in the first three phases of the algorithm starts with a convolution and finishes with a dropout. An input layer for a 48 x 48-pixel picture serves as the model's first phase's input, and convolution is applied to this input. There are 64 kernels in the initial phase. The inputs for the fol-lowing layer are then obtained by doing a batch normalization. The subsequent layers repeat the convolution and the batch normalization.

The following layer employs max pooling with a pool size of 2 x 2, resulting in an output size of 24 x 24. Then dropout occurs at a rate of 0.25 percent. There are 128 kernels in the second phase, with a 0.4 dropout rate. The output size of the second phase's max pooling is 12 x 12. There are 256 kernels in the third phase, and the dropout rate is 0.25. In the third step, max pooling, the output size is decreased to 6 x 6. The 512 kernels in the following layer have a dropout rate of 0.25. The output size is reduced to 3 x 3 by max pooling in the third step.

The last step begins with a flattening layer (Flatten), followed by dense and output layers. The data has to be a one-dimensional array in order to categorize the seven emo-tions. The two-dimensional data are transformed into a one-dimensional array via the flattening layer (Flatten). The dense layer receives the output that has been flattened and applies the SoftMax function to it. After doing a batch normalization, the output layer displays the class probabilities. The model's structure is depicted in Figure 5.

Fig. 5. CNN structure

VGG16 model. VGG16 is a CNN (Convolutional Neural Network) that is widely regarded as one of the best computer vision models available today. Using an architecture with extremely tiny (3 x 3) convolution filters, the model's developers examined the networks and raised the depth, which demonstrated a notable improvement over earlier configurations. There are now 16–19 weight layers deep, or around 138 trainable parameters. The architecture of the model is seen in Figure 6.

Fig. 6. VGG16 architecture

To train the model on the dataset. It takes almost 2 hours and 34 minutes for the training process for 100 iterations and a batch size of 128. We first imported all the libraries I will need to implement VGG16. We used the sequential method because we are creating a sequential model. We applied data augmentation as a pre-processing method. For data augmentation, we utilized Keras' "ImageDataGenerator". By rotating, flipping, and using other predetermined processes, it creates 32 augmented pictures from a single photograph. If the validation accuracy does not improve every 10 epochs, the learning rate is changed using Keras' ReduceLROnPlateau callback. The model was trained with a batch size of 128 across a total of 100 epochs.

ResNet50 model. In order to obtain better results, we tried to apply transfer learning on the pre-trained ResNet50 model [19]. Our objective is to refine this pretrained model on the FER 2013 [20] dataset and the auxiliary database in this approach JAFFE and CK.

The Resnet-50 and Senet-50 models may be found in the VGGFace library, which is what we utilized. The VGGFace2 dataset, which consists of 3.3 million face pho-tos, was used to train these models earlier. Additionally, the VGG16 model is made available by the library. It was developed using the VGGFace dataset. With 2.6 mil-lion face photos, VGGFace [21] is huge. We have frozen the entire network except for the batch normalization layers. Next, we added two fully connected layers (FC) with 4096 and 1024 neurons. We added a 50% drop out after each of these fully connected layers, and before the first fully connected layer. We used the Stochastic Gradient Descent (SGD) optimizer with a learning rate of 0.01. If the validation accuracy does not improve every 10 epochs, the learning rate is changed using KerasReduceL-ROnPlateau callback. The model was trained with a batch size of 128 across a total of 50 epochs. Figure 7 shows the architecture of the model.

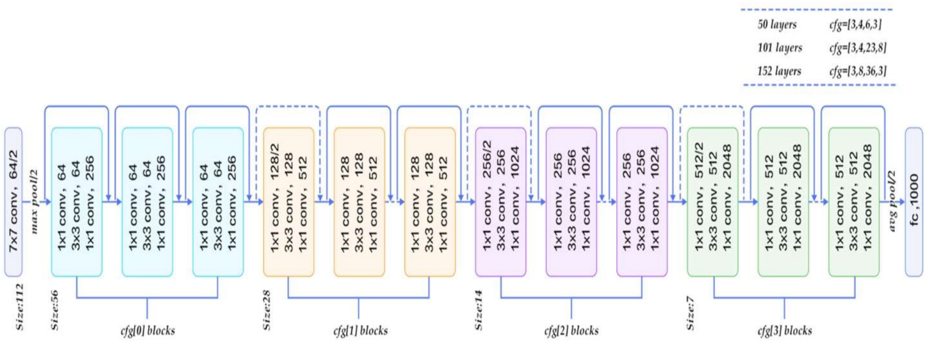

Fig. 7. ResNet50 architecture

4 Results and Analysis

Each model is trained separately, the training time varies depending on the size of the data, at least in our case, which takes at least 45 minutes for the ML approach and up to 3 hours for the different DL approaches with large data, and also depends on the number of epochs we want to use for training.

The metric used to measure the performance of the model is accuracy. This metric is defined below.

$$\text{Accuracy} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Confusion matrix: The confusion matrix provides values for the four combinations of true and predicted values, namely true positive (TP), true negative (TN), false positive(FP) and false negative (FN).

The model based on ML approach was able to classify the test images into one of the emotions (anger, contempt, disgust, fear, happiness, sadness, surprise) with 89% accuracy and an inference time of 0.7s. The following table shows the comparison between the proposed method and the method on the CK+ Dataset [22].

Table 1. Comparison between the proposed method and the GSDS method

	GSDS	PROPOSED
ANGER	0.78	0.85
CONTEMPT	0.64	0.93
DISGUST	0.93	0.89
FEAR	0.80	0.74
HAPPINESS	0.99	1
SADNESS	0.64	0.88
SURPRISE	1	0.96
TOTAL	0.887	0.893

For the VGG16 model the training process for 100 iterations and a batch size of 128 took almost 2 hours and 34 minutes, the results are shown in figure 8.

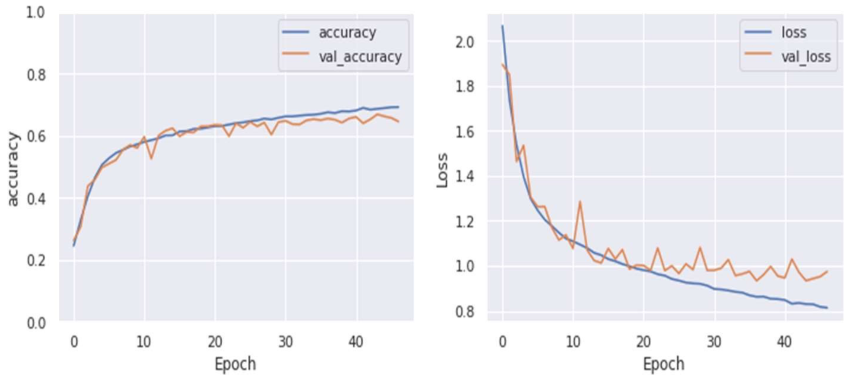

Fig. 8. Results of training, validation accuracy and loss VGG-16

Using a batch size of 128 and 50 training epochs, the transfer learning-based ResNet50 model was trained. The results are displayed in figure 9.

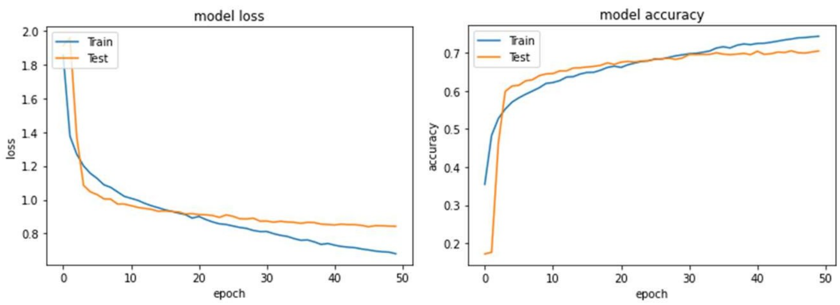

Fig. 9. Results of training, validation accuracy and loss ResNet50

We will now discuss these detailed training results for each architecture, the following table shows a comparison between the different models based on several criteria.

Table 2. Performance comparison of the models

Model	Dataset	Accuracy	Model size	Interface time
CNN	FER2013	65%	16.5 Mo	0s 413ms
VGG-16	FER2013	63%	15.3 Mo	0s 861ms
Res-Net50 Transfer Learning	FER2013, JAFFE, CK+	70.04%	186 Mo	1s 807ms

Another criterion that is very important in this comparison is the prediction in real time, since our system is supposed to be used in VR systems [23] for example, so we made a test with an external camera to see the performance of all the models in real time, and from this test we concluded that the ResNet50 model has a better performance in the prediction in real time of all the emotion classes. As indicated in the aforementioned literature [24–26], the method provided in this paper may be designed and implemented utilizing image segmentation techniques based on wavelet transformations.

5 Conclusion

This research investigates the possibility for identifying face expression based on Machine Learning and Deep Learning techniques. First, we demonstrate that 68 points, as opposed to the entire image's pixels, may be used to distinguish and fore-cast face expressions. Feature extraction was a key component of the experiment. The additional distance and angle features gave the CK+ database good accuracy (89%). And it is clear that the outcomes are similar to those of the alternative strategy. We demonstrate that the application of transfer learning and data augmentation improved the performance of the ResNet50 model when compared to the other proposed architectures using the FER, CK+, and JAFFE databases.

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