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Facial Emoji Recognition

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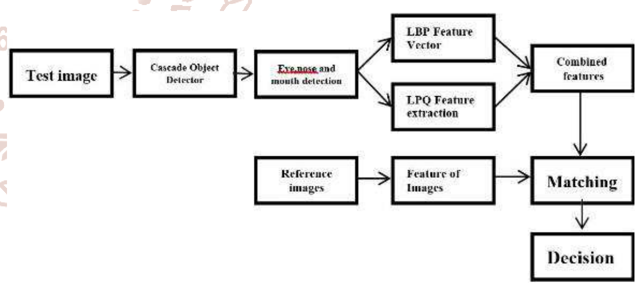
ABSTRACT

Facial emoji recognition is a human-computer interaction system. In recent times, automatic face recognition or facial expression recognition has attracted increasing attention from researchers in psychology, computer science, linguistics, neuroscience, and similar fields. Facial emoji recognizer is an end user application which detects the expression of the person in the video being captured by the camera. The smiley relevant to the expression of the person in the video is shown on the screen which changes with the change in the expressions. Facial expressions are important in human communication and interactions. Also, they are used as an important tool in studies about behavior and in medical fields. Facial emoji recognizer provides a fast and practical approach for non-meddlesome emotion detection. The purpose was to develop an intelligent system for facial based expression classification using CNN algorithm. Haar classifier is used for face detection and CNN algorithm is utilized for the expression detection and giving the emoticon relevant to the expression as the output.

1. INTRODUCTION

Facial emotion recognition and analysis has been gaining a great attention in the advancement of human machine interface as it provides a natural and efficient way to communicate between humans. Some application are as related to face and its expressions include person identification and access control, video call and teleconferencing, forensic applications, human-computer interaction, automated surveillance, cosmetology, and so on. But the performance of the face expression detection certainly affects the performance of all the applications.

Many methods have been suggested to detect human face in pictures and videos, they can be divided into four types: knowledge-based methods, feature-based methods, template based methods and appearance-based methods. When these methods are used separately, they cannot solve all the problems of face detection like pose, expression, orientation. Hence it is recommended to operate with several successive or parallel methods. Most of the existing facial expression recognition methods which are popularly used till today are focused on recognition of five primary expression categories such as: happiness, sadness, fear, anger and disgust. We implement HAAR classifier for face detection, CNN algorithm for expression detection and two functions are used: relu and soft max(these are activity functions).



Facial expressions play a major role in enhancing communication and interactions between people. Also, they are used as an important tool tool in psychological studies and in medical rehabilitation.

Face based emotion detection techniques may give a rapid and feasible approach for non-invasive emotion detection, to investigate emotional recognition using facial expression by emoji in real time.

The purpose is to develop an feasible system for facial image or video based expression detector. The objective of this project is to understand the facial emotion recognition in real time and develop Automatic Facial Expression Recognition System which can take video as input and recognize and classify it into five different expression.

2. RELATED WORK

Darwin was the first to imply that some of these facial expressions of emotion have their origins in the evolution of the human species.

These face expressions helped the living things live because it looked necessary to social animals like humans or chimpanzees to express these forthcoming behaviors given by the emotions so they could avoid fights, conflict, disagreement, danger, or allow comfort, approach, and so forth. However, these emotion expressions are not capable of modification by social learning.

Different cultures apply different display rules to direct their expressions of emotion. Although the current evidence supports Darwin's basic premise it is not without controversy. Future technological advances will allow facial expression research to expand to address many of the important issues that remain.

Ekman and Friesen observed the facial muscles which are important in expressing emotion and made their findings to a system of 46 action units (AUs). These action units, in which some are raising of the inner eyebrow and raising of the outer eyebrow, were extremely important in considering human expressions. Before this system was published, facial expression research relied heavily on human labelling of example expressions and many researchers were concerned about bias related to cultural context or the labeller's emotional state at the time. The advent of Ekman and Feisen's facial action coding system in 1977 put these concerns to rest and quickly became the golden standard.

In 2004, Paul Viola and Michael Jones developed an extremely efficient face detector with high performance by using an adaboost learning algorithm to classify features derived from Haar-like features. This method was applied by Wang et al for facial expressions he later was able to sort faces into one of 7 archetypal facial expression with 92.4% accuracy. An investigation by White hill and Omlin found that the use of Haar features in combination with the Ada boost boosting algorithm was at least two orders of magnitude faster than the more standard classification using SVMs and Gabor filters without a significant drop in performance.

More recently, work done by Happy et al in 2015 found that the viola-jones algorithm was valuable not in direct detection of emotions but as a pre-processing step to efficiently detect the most important face regions (IE lip corners and eyebrow edges) which where then further processed with local binary pattern histograms. Their solution performed similarly to other state-of- the-art methods but required far less computational time.

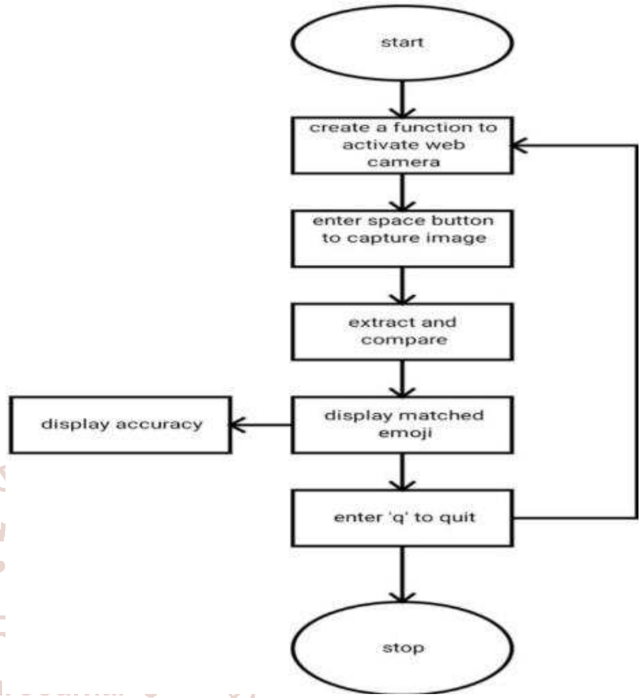
Eigen faces are computed for all the training images and classification of test image is done by the following steps: Generate vector of all the images and matrix of vector is created for each image type,

Mean of the training faces is created, Subtract the test image with each of the mean image, Co-variance matrix is calculated for each of the difference vectors created.

3. PROBLEM STATEMENT

Facial emoji recognizer is an end user application which detects the expression of the person in the video being captured by the camera. The smiley relevant to the expression of the person in the video is shown on the screen which changes with the change in the expressions. We implement HAAR classifier for face detection, CNN algorithm for expression detection and two functions are used: relu and soft max(these are activity functions)

4. METHODOLOGY



Facial expressions can be described as the arrangement of facial muscles to convey a certain emotional state to the observer in simple words. Emotions can be divided into six broad categories—Anger, Disgust, Fear, Happiness, Sadness, Surprise, and Neutral. In this, train a model to differentiate between these, train a convolutional neural network using the FER2013 dataset and will use various hyper-parameters to fine-tune the model.

1. Decomposing an image.

Images are composed of pixels and these pixels are nothing more than numbers. Often it is considered that the Coloured images can be divided into three colour channels, which are :red, green, and blue and each channel is represented by a grid (2-dimensional array). Each cell in the grid stores a number between 0 and 255 which denotes the intensity of that cell.

2. Importing Necessary Libraries

3. Define Data Loading Mechanism

Now, we will define the load_data() function which will efficiently parse the data file and extract necessary data and then convert it into a usable image format.

All the images in our dataset are 48x48 in dimensions. Since these images are gray-scale, there is only one channel. We will extract the image data and rearrange it into a 48x48 array. Then convert it into unsigned integers and divide it by 255 to normalize the data. 255 is the maximum possible value of a single cell and by dividing every element by 255, we ensure that all our values range between 0 and 1.

We will check the *Usage* column and store the data in separate lists, one for training the network and the other for testing it.

4. Defining the model.

We will use Keras to create a Sequential Convolutional Network. Which means that our neural network will be a linear stack of layers. This network will have the following components:

A. **Convolutional Layers:** These layers are the building blocks of our network and these compute dot product between their weights and the small regions to which they are linked to. This is considered as the method in which layers learn certain features from these images.

B. **Activation functions:** are those functions which are applied to the outputs of all layers in the network. In this project, we will resort to the use of two functions— R*elu* and *Soft max*.

C. **Pooling Layers:** These layers will down sample the operation along the dimensions. This helps reduce the spatial data and minimize the processing power that is required.

D. **Dense layers:** These layers are present at the end of a C.N.N. and these take in all the feature data generated by the convolution layers and does the decision making.

E. **Dropout Layers:** randomly turns off few neurons in the network to prevent over fitting.

5. Callback functions

Callback functions are those functions which are called after every epoch during the training process. We will be using the following callback functions:

1. Reduce LR On Plateau: Training a neural network can plateau at times and we stop seeing any progress during this stage. Therefore, this function monitors the validation loss for signs of a plateau and then alter the learning rate by the specified factor if a plateau is detected.

   lr_reducer = Reduce LR On Plateau(monitor='val_loss', factor=0.9, patience=3)

2. Early Stopping: At times, the progress stalls while training a neural network and we stop seeing any improvement in the validation accuracy (in this case). Majority of the time, this means that the network won't converge any further and there is no point in continuing the training process. This function waits for a specified number of epochs and terminates the training if no change in the parameter is found.

   early_stopper=
   EarlyStopping(monitor='val_acc',in_delta=0,
   patience=6, mode='auto')

Model Checkpoint: Training neural networks generally take a lot of time and anything can happen during this period that may result in loss of all the variables and weights.

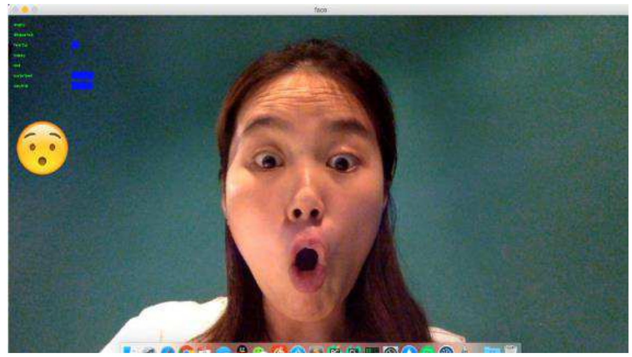
Creating checkpoints is a good habit as it saves your model after every epoch. In case your training stops you can load the checkpoint and resume the process.

6. Train

7. Test the model

The project is started off by defining a loading mechanism and loading the images. Then a training set and a testing set are created. After this a fine model and a few callback functions are defined. The basic components of a convolutional neural network are considered and then we training is done to the network.

5. OUTPUT



In the above figure, i.e., Sample output is the window where the user expressions are captured by the web cam and the respective emotions are detected.

On detecting the emotion, respective emoticon is shown on the left side of the screen. This emoticon changes with the change in the expression of the person in front of the web cam. Hence changes with the change in the expression of the person in front of the web cam. Hence this real time application is very beneficial in various fields like psychology, computer science ,linguistics ,neuroscience and related disciples.

6. APPLICATIONS

Robust spontaneous expression recognizers can be developed and deployed in real-time systems and used in building emotion sensitive HCI interfaces. The project can have an impact on our day to day life by enhancing the way we interact with computers or in general, our surrounding living and work spaces. High correct recognition rate , significant performance improvements in our system. Promising results are obtained under face registration errors, fast processing time.

System is fully automatic and has the capability to work with video feeds as well as images. It is able to recognize spontaneous expressions. Our system can be used in Digital Cameras where in the image is captured only when the person smiles, or if the person doesn't blink his eyes. In security systems which can identify a person, in any form of expression he presents himself. Rooms in homes can set the lights, television to a persons taste when they enter the room.

This can be used by the doctors in understanding the intensity of pain or illness of a deaf patient.

7. CONCLUSION

Proposed is a human emotion detector using emoticon using machine learning, python to predict emotions of the people and represent them using emoticon. . These include image acquisition, preprocessing of an image, face detection, feature extraction, classification and then when the emotions are classified the system assigns the user particular music according to his emotion. Our system focuses on live videos taken from the webcam.

The main aim of this project is to develop automatic facial emotion recognition system in which an emoticon is used for giving the output for individuals thus assigning them various therapies or solutions to relief them from stress. The emotions used for the experiments include happiness, Sadness, Surprise, Fear, Disgust, and Anger that are universally accepted.

8. REFERENCES

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