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HUMAN EMOJIS USING PYTHON

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ABSTRACT

This project is a real time recognition system that traces every mood of the human. It can be a smiling face or it can be the face full of anger. This project consists of models made through various algorithms of machine as well as deep learning. It also uses some of the very powerful packages in python to create an application software that recognizes the expression of human in real time. Some of the libraries are: TensorFlow, Keras, OpenCV, Matplotlib. This project consists of two modules: (i)Processing and generating the model for the application using different algorithms and (ii) Application for using the model using OpenCV to recognize the human facial expression. an approach of Emoji Generation using Facial Expression Recognition(FER) using Convolutional Neural Networks(CNN) with Machine Learning and Deep learning. This model created using CNN can be used to detect facial expressions in real time. Facial Expression Recognition usually performed in four-stages consisting of the following of pre-processing, face detection, feature extraction, and expression classification. In this project we applied various methods to spot the key seven human emotions: anger, disgust, fear, happiness, sadness, surprise and neutrality

1.INTRODUCTION

This project uses dataset from Kaggle website which consists of 48x48-pixel grayscale images of face Emoji are ideograms and smileys used in electronic messages and webpages. Emoji exist in various genres, including facial expressions, common objects, places and types of weather, and animals. They are much like emoticons ,but emoji are pictures rather than typographic approximations; the term "emoji" in the strict sense refers to such pictures which can be represented as encoded characters, but it is sometimes applied to messaging stickers by extension

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Absolutely! Emojis have become a popular and powerful means of communication in our digital world.

They allow us to express ourselves, convey emotions, and add a touch of creativity to our conversations. With their wide range of symbols and expressions, emojis have become a universal language that transcends barriers and allows us to connect with others on a deeper level. In addition to enhancing conversations, emojis have also found their way into various datadriven research fields, such as data science and storytelling. Researchers are exploring the use of emojis to understand sentiment analysis, brand perception, and even user behavior. By analyzing the patterns and usage of emojis, valuable insights can be derived, leading to a better understanding o how people communicate and feel about certain topics. So, whether you're using emojis to express joy, sadness, excitement, or anything in between, they have certainly become an integral part of our online communication and continue to evolve as a fascinating area of study.

A facial expression is one or more motions or positions of the muscles beneath the skin of the face. According to one set of controversial theories, these movements convey the emotional state of an individual to observers. Facial expressions are a form of nonverbal communication. Facial expressions are vital to social communication between humans. Facial expression classifiers generalizes the learned features to recognize different expressions from unseen faces. With advancements in computer vision and deep learning, it is now possible to detect human emotions from images in an improved way. A Convolutional Neural Network (CNN) is a Deep Learning Algorithm which takes an image as the input, assigning importance to various objects in the image so that it can differentiate it from others. The preprocessing required in a CNN model is lower as compared toother classification models. We are using CNN because it has an ability which automatically detects the important features without any human supervision.

1.1 FACIAL EMOTION RECOGNITION

Facial emotion recognition is the process of detecting human emotions from facial expressions. In the fer2013 dataset, the "emotion" column represents the category or mood of the facial expressions found in the corresponding image. The emotions are categorized as follows: 0 represents Angry, 1 represents Disgust, 2 represents Fear, 3 represents Happy, 4 represents Sad,

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5 represents Surprise, and 6 represents Neutral .On the other hand, the "pixels" column contains the grayscale pixel values of the registered face images. These images are standardized to a size of 48x48 pixels, with the faces centered and occupying a consistent amount of space in each image. The grayscale values in the "pixels" column provide the necessary data to analyze and classify the facial expressions into the respective emotion categories .This dataset was used in a Kaggle competition back in 2013, where participants were challenged to develop models that accurately categorize the facial expressions based on the given emotions. The competition aimed to leverage data science techniques to gain insights into human emotions and improve our understanding of facial expression analysis.

2.LITERATURE SURVEY

Human facial expressions can be easily classified into 7 basic emotions: happy, sad, surprise, fear, anger, disgust, and neutral. Our facial emotions are expressed through activation of specific sets of facial muscles. These sometimes subtle, yet complex, signals in an expression often contain an abundant amount of information about our state of mind. Through facial emotion recognition, we are able to measure the effects that content and services have on the audience/users through an easy and low-cost procedure. For example, retailers may use the semetrics to evaluate customer interest. Healthcare providers can provide better service by using additional information about patients' emotional state during treatment. Entertainment producers can monitor audience engagement in events to consistently create desired content. Humans are well-trained in reading the emotions of others, in fact, at just 14 months old, babies can already tell the difference between happy and sad. But can computers do a better job than us in accessing emotional states? To answer the question, we designed a deep learning neural network that gives machines the ability to make inferences about our emotional states. In other words, we give them eyes to see what we can see In this deep learning project, we aim to classify human facial expressions in an effective manner to filter and map corresponding emoji or avatars. The application can be used in large corporations or firms for collecting feedback from the customers in real time.

The results generated from the application can be further used in research and development processes. Emoji are used more and more frequently in network communication, and the way they are used is becoming more and more diversified as well. They not only have unique

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semantic and emotional features, but are also closely related to marketing, law, health care and many other areas. The research on emoji has become a hot topic in the academic field, and more and more scholars from the fields of computing, communication ,marketing, behavioral science and so on are studying them.

3.SYSTEM DESIGN

3.1 DESCRIPTION OF DIAGRAM:

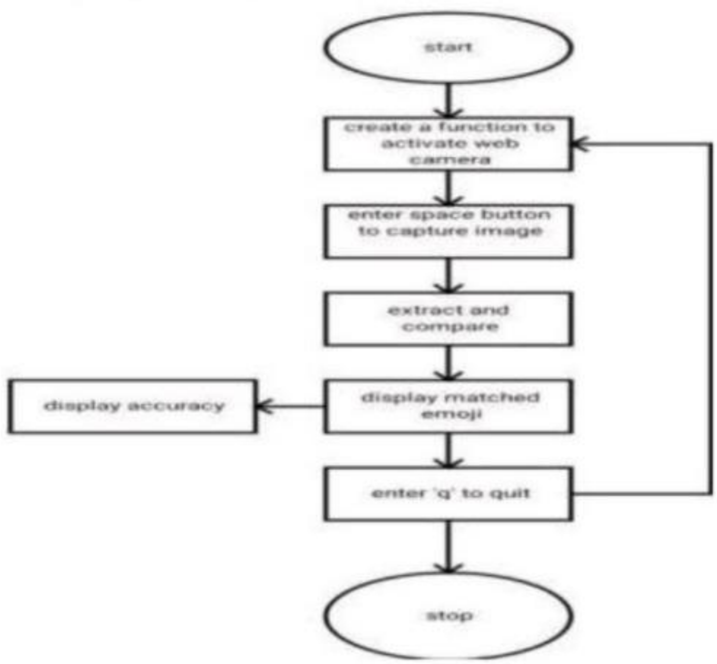

Fig 1: Description Of Diagrams

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, Happy ,Sad, 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 .The design starts with the initializing CNN model by taking an input image (static or dynamic) by adding a convolution layer, pooling layer, flatten layers, and dense layers. Convolution layers will be added for better accuracy for large datasets. The dataset is collected from a CSV file (in pixel format) and it's converted into images and then classify emotions with respective expressions.

3.2 ACTIVITY DIAGRAM:

Creating an activity diagram for generating emojis using human expressions involves illustrating the flow of activities within the system.

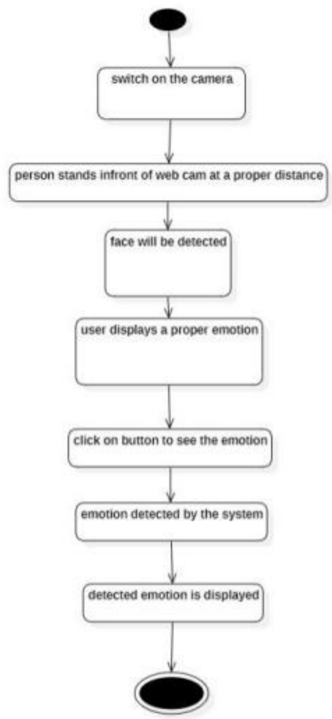

Fig 2: Activity Diagram

4.OUTPUT SCREENS

In the above figures, i.e., output is the window where the user expressions are captured by the webcam and the respective emotions are detected. On detecting the emotion, the 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 webcam. Hence changes with the change in the expression of the person in front of the webcam. Hence this real time application is very beneficial in various fields like psychology, computer science, linguistics, neuroscience and related disciplines.

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Fig 3:Surprised Emoji

Fig 4: Happy Emoji

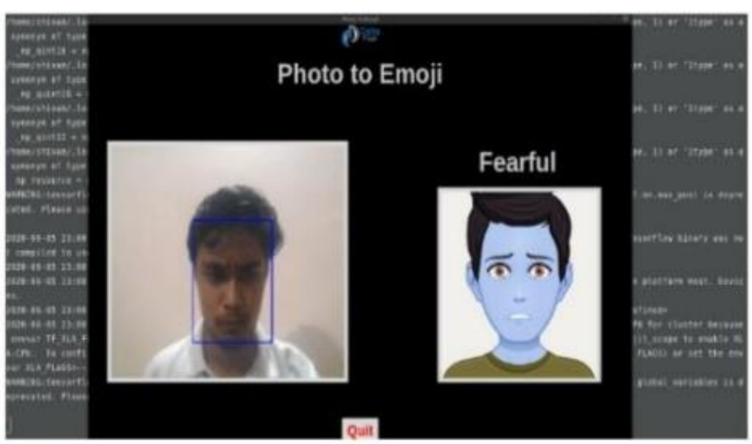

Fig 5: Fearful emoji

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Results were obtained by experimenting with the CNN algorithm. It was observed that the loss over training and test set decreased with each epoch. The batch size was 256,which was kept constant over all experiments. The following changes were made in the neural network architecture to achieve good results:

● Number of epochs: It was observed that the accuracy of the model increased with increasing number of epochs. However, a high number of epochs resulted in overfitting. It was concluded that eight epochs resulted in minimum over fitting and high accuracy.

● Number of layers: The neural network architecture consists of three hidden layers and a single fully connected layer. A total of six convolution layers were built, using 'relu' as the activation function.

● Accuracy: The final, state-of-the-art-model gave a training accuracy of 79.89%and a test accuracy 60.12% as shown in the table. The architecture used could correctly classify 22936 out of 28709 images from the train set and 2158 out of3589 images from the test set.

5. CONCLUSION

In this paper, an approach for FER using CNN has been discussed. A CNN model on the FER2013 dataset was created and experiments with the architecture were conducted to achieve a test accuracy of 0.6212 and a validation accuracy of 0.9508.This state-of-the-art model has been used for classifying emotions of users in real time using a webcam. The webcam captures a sequence of images and uses the model to classify emotions and generate the corresponding emoji. Proposed is a human emotion detector using emoticons using machine learning, python to predict emotions of the people and represent them using emoticons. 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. The main aim of this project is to develop an 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 relieve them from stress. The emotions used for the experiments include happiness, Sadness, Surprise, Fear, Disgust, and Anger that are universally accepted.

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6.FUTURE ENHANCEMENT

Face expression recognition systems have improved a lot over the past decade. The focus has definitely shifted from posed expression recognition to spontaneous expression recognition. Promising results can be obtained under face registration errors, fast processing time and significant performance improvements can be obtained in our system. System is fully automatic and has the capability to work with images feed. It is able to recognize spontaneous expressions. The system can be used in Digital Cameras wherein the image can be captured only when the person smiles. Insecurity systems which can identify a person, in any form of expression he presents himself. Doctors can use the system to understand the intensity of pain or illness of a deaf patient. Interactive and Animated Emojis: Explore the integration of interactive or animated emojis to add a dynamic and engaging element to expressions. This could involve emojis that respond to user interactions or change over time. Augmented Reality (AR) Emojis: Investigate the incorporation of AR technologies to bring emojis into the real world. Users could use AR to place emojis in physical spaces or interact with them in novel ways. Emoji Analytics and Insights: Provide users with insights into their emoji usage patterns, including frequently used emojis, preferred styles, and the correlation between emotions and communication. This could help users understand their expressive tendencies.

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