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Emotion Monitoring Music Player Using Convolution Neural Network and Deep Learning

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Abstract:- Listening to different types of music of one's individual taste and mood is something that people desire for. On an average person spends most of his time on listening to music. Music has a high impact on an individual's brain activity. In the recent events there are plenty of music in different language and style that people are getting confused to select the exact music that suit's that person's particular emotion at time. In the existing system, the algorithms in use are relatively slow, less accurate and sometimes require use of additional hardware like EEG or sensors. Emotions of a person are easy to identify using the facial expressions. My model is based on identifying the person's emotion or mood to play the relevant songs for the emotion. In this project we use Haar Cascade algorithm to identify the facial expressions, we are also using the real time data set to identify the emotion of the user. My project will be voice activated, easy to access and make sure that it doesn't affect the individual's daily life. It also monitors the emotional status of the person at the end of every song's starting and ending to have a medical dataset of the individual's emotions status.

***Keywords*:-** *Emotion and Face Detection, Machine Learning, Music, Python, Tensorflow.*

I. INTRODUCTION

Listening to music is a form of entertainment that relaxes the mind of music lovers and music listener. In the current generation people love to hear different kinds of music like jazz, rock, melody, etc., and also love to hear music in different languages even though the person is not aware of that particular language certain music make them want to hear the song. As there are different music which is evolved, the music player also got revolutionized with features like fast forward, reverse, variable playback speed, genre classification, streaming playback with multicast streams and including volume modulation etc., Emotions are caused by many reasons which involve both physical and mental state of a person. Certain emotions are hard to contain and certain are easily suppressed, suppression of emotions sometimes may lead to total breakdown of a person's mental status. In the Darwin's book "The Study of Emotions", he had discovered by sending letters and a list of questions worldwide in different societies emotions were expressed in almost the same way. So, the facial expressions we make must be inherited. In anatomy we know that the muscles and nerves of the face were the same or similar in all humans. Darwin expressed the emotions with a series of photographs. Ekman did a long-term effort to test and extend Darwin's emotion identification by visiting a village where he asked the villagers to identify the emotions shown in the photographs. These features might help the people to identify emotions but still choosing a song with millions of options manually for the current emotional state is bit difficult. The emotional dataset used in this project includes Happy, Sad, Angry and Neutral that are taken from Kaggle. There are many emotions out of which some of the basic emotions are Anger, Fear, Sadness, Happiness, Disgust, Surprise, Aggression, Apathy, Anxiety, Boredom, Contempt, Depression, Doubt, Empathy, Envy, Embarrassment, Hostility, Euphoria, Frustration, Gratitude, Grief, Guilt, Hatred, Hope, Horror, Hunger, Hysteria, Loneliness, Love, Paranoia, Pity, Pleasure, Pride, Rage, Regret, Remorse, Shame, Shock, Suffering, Sympathy. There are also many variety of music, such as popular music, art music or religious music and secular music. Subgenres are also known as fusion genres some examples include jazz fusion and country rock fusion. Tensor flow a Deep learning Machine is trained and this model is created to compared the sample images with the current person's face. The Principle used here is Convolution Neural Network. The programming language used is Python pip3. Here the Python Eel is used as the user interface between the system and the user by using the OpenCV (Computer Vision) and Numpy.

The system camera captures the user image and convert it into grayscale, then the grayscale is then cropped into 480*581 pixels or cells by using Mat plot Library (virtualization tool). The created gray scale image is compared with the sample emotions images from Kaggle, that was trained before using Deep learning. The emotion of the user is been detected using Haar cascade facial vectors. The music player is created along with the voice based interaction and particular user monitoring system. Once the emotion of the particular user is detected then the song from the playlist is played.

II. PROPOSED SYSTEM

The emotional music player is automation for the interaction between the music player and the particular user. The emotions are recognized using deep learning mechanism. We use Olivetti faces which contain 400 faces and its desired values or parameters as training dataset. The webcam / laptop camera captures the image of the user then extract the facial features of the user from the captured image.

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The process involved in training the machine is by initializing some random values for smiling and not smiling. It predicts the output with the values which are closest to the model's prediction and adjust the values so that they match the predictions that was made previously.

We use this evaluation process to allow the testing of the model against any random data that the model has never seen, it is a representative of how the model might perform in the real world. With respect to the emotion detected the music is played from the selected playlist.

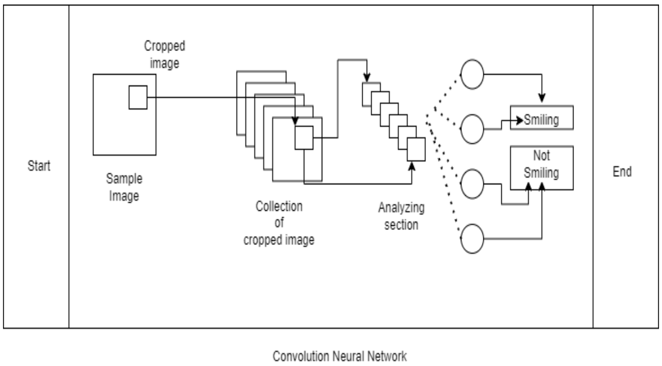

Fig.1: Convolution Neural Network Workflow

Convolution neural network is a procedure to crop the particular part of the actual sample image and is compared with the cropped testing set of images. After comparing with the sets of test images the algorithm calculates the value of the sample image and predicts the closest match of the emotion of the user.

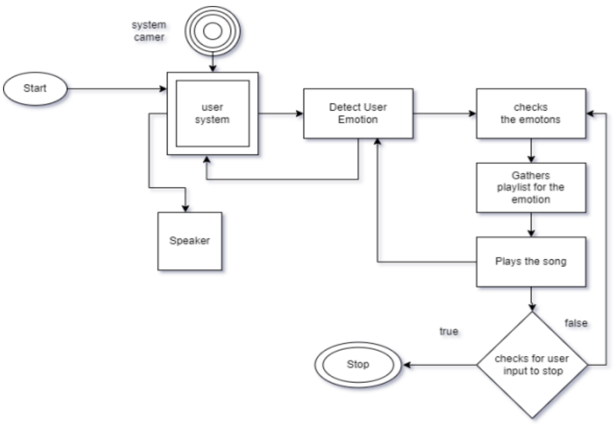

Fig.2: Flow chart of the Emotion based Music player using convolution neural network.

Fig.2 represents the pre-processing of the model that is detecting the image of the user, converting the image to gray scale and then noise is reduced from the image. Once the image is ready to be compared with the testing dataset, the emotions of the image are determined by convolution neural network. After determining the emotion of the image the playlist for that particular emotion is gathered and then the songs are played in accordance with the emotion. If the user wishes to stop the emotion detection, there is a small gap for the emotion detection loop to begin where the user response is required. If the user response is false then the emotion detection continues and if it is true then emotion detection stops. The noise reduction is done using gaussian filtering method.

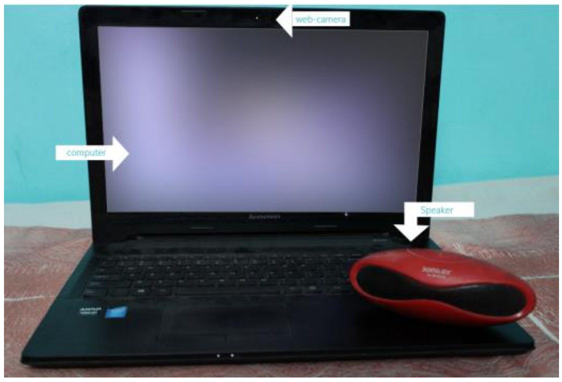

Fig.3: hardware's required for the model

From Fig.3 the hardware required for the model are Laptop with functional webcam and either inbuilt speakers or external speakers. As for the implementation of the model python programming language is used.

III. ACCURACY AND RESULT

Accuracy results of our model	
Image used of the model	439
Overall accuracy of the model	86%
Highest individual emotion accuracy	97%
Lowest individual emotion accuracy	76%

Table.1: Accuracy results of our model

From the accuracy table, The total number of images I used for training set are 439, the overall accuracy of our model is 86%, the highest individual accuracy of our model is Happy emotion and it has the accuracy of 97%, the lowest individual accuracy of our model is Sad emotion and it has the accuracy of 76%.

The results of the emotion detection is shown in the below screen shots.

Result from anaconda promt:

1. Neutral

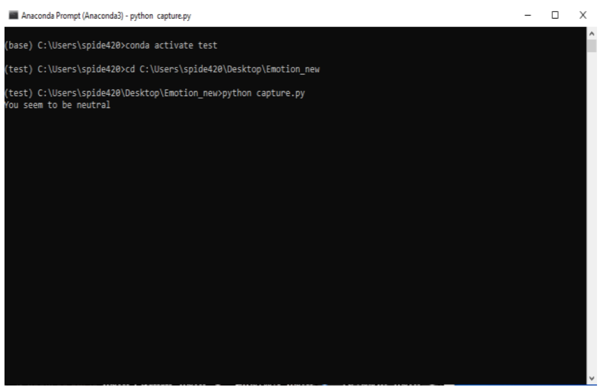

Fig.4: Anaconda prompt status neutral

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2. Sad

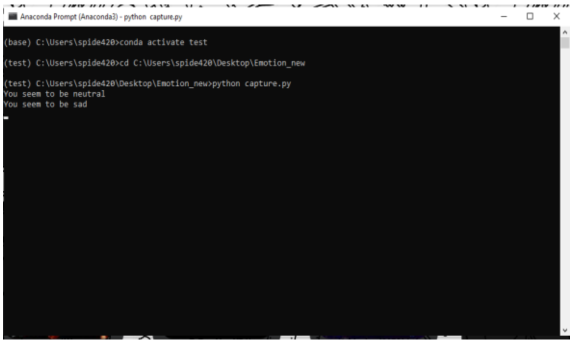

Fig.5: Anaconda prompt status sad

3. Happy

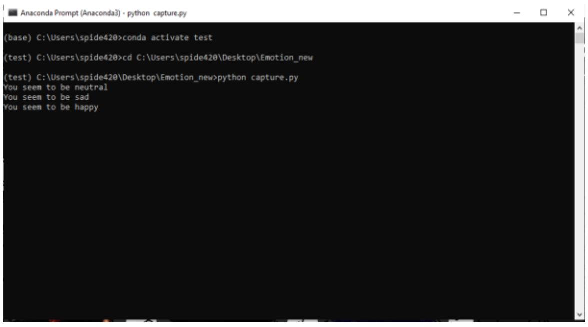

Fig.6: Anaconda prompt status happy

4. Angry

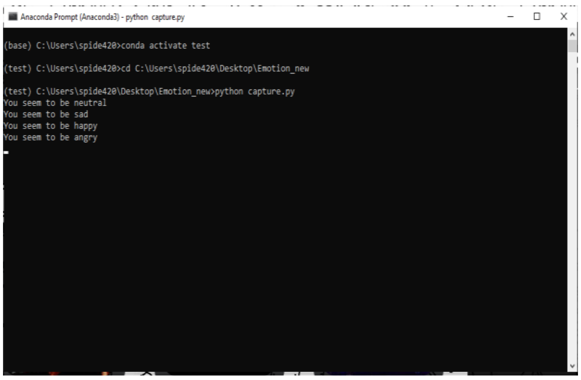

Fig.7: Anaconda prompt status angry

➢ *Results of the image*

1. Neutral

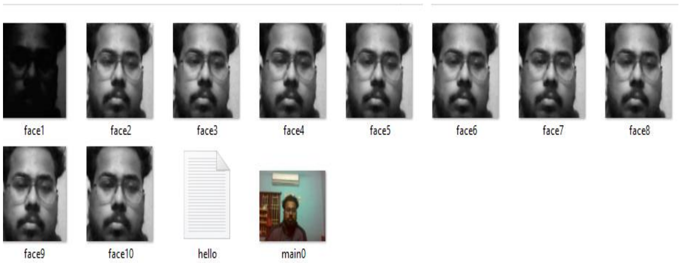

Fig.8: Neutral CNN image collection

2. Sad

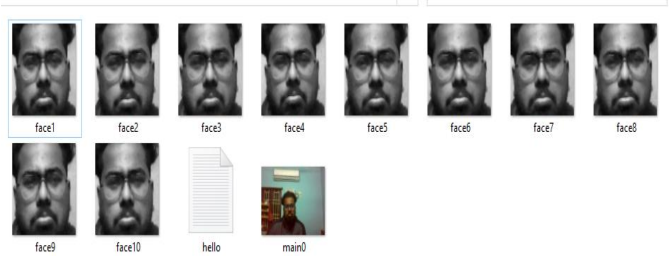

Fig.9: Sad CNN image collection

3. Happy

Fig.10: Happy CNN image collection

4. Angry

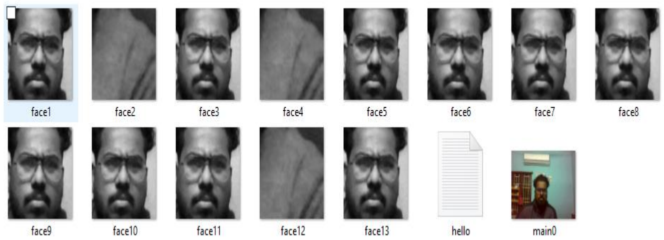

Fig.11: Angry CNN image collection

IV. CONCLUSION

Hence the model for the emotion based music player has been successfully designed and implemented which is capable of identifying the emotion of the user and playing the songs from the playlist of songs. It is supported with the voice input from the user to play, pause, next song and process termination. The player created is also user friendly. Since the model concentrates on one particular user it also captures the emotional status of the user at the beginning and at the end of every song. Usually the emotional status of one person is to be monitored by the respective handler or doctors and this model will help monitoring and improve one's emotional status through music.

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