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ENHANCED EMOTION RECOGNITION IN LIVE SETTINGS USING CNN MODELS

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ABSTRACT

A person's facial expressions serve as a communication tool in interpersonal relationships and are the outward representation of their affective state, cognitive activity, intention, personality, and psychopathology. In addition to being utilised in behavioural science and therapeutic settings, automatic facial expression detection can play a significant role in natural human-machine interactions. Facial feature extraction, facial expression categorisation, and face identification and localisation in a crowded scene are all tasks that an autonomous facial expression recognition system must do. Convolutional neural networks (CNNs) are used in the implementation of facial expression recognition systems.

The project's CNN model is built on a collection of facial expressions, and it uses labels for happy, sad, surprised, angry, and neutral face expressions.

I. INTRODUCTION

Facial expressions are important attributes in human communication that helps us to know the intentions of other people. In common, people are inferred to know the emotional states of others, such as happiness, sadness, disguist, anger, using facial expressions and vocal behavior. According to different number of surveys, actionable components will convey one third of the human communication, and non actionable components convey two thirds of the same. Among various non actionable components, by carrying emotional synonym, facial emotions are one of the main data channels in the one to one communication. Hence, it is quite common that research of facial emotion detection has been winning lot of attention over the past years with applications in wide range and not only permitting to perceptual and cognitive sciences, but also in Machine computing and computer graphics..

1.1OBJECTIVE:

To detect the emotions of the faces in live webcam video with high accuracy using convolutional neural networks and OPENCV library of computer vision. To use state-of-the-art machine learning capabilities to furnish efficient working of the model.

II. LITERATURE SURVEY

P. Abhang, S. Rao, B. W. Gawali, and P. Rokade, "Article: Emotion recognition using speech and eeg signal a review

In recent years the research interest is improving in the field of human computer interaction. This paper focus on one of the aspect of human computer interaction in concern with, the recognition of emotion in a person with the help of Electroencephalogram (EEG) signals and speech. EEG uses an electrical activity of the neurons inside the brain. EEG machine is used for acquisition of the electrical potential generated by the neurons when they are active. The Brain cells

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communicate with each other by sending electrical impulses. Emotions allow people to express themselves beyond the verbal domain. Speech is the most natural form of communication. A much of work is been done in speech recognition in various languages. It is one of the components that closely related to emotions. Very less work has been carried out using combine aspects of speech, emotion and EEG. Thus this paper attempts to review the combine efforts of EEG brain signal and Speech to recognize the emotions in humans.

P. Ekman, Universals and cultural differences in facial expressions of emotion. Nebraska

We present here new evidence of cross-cultural agreement in the judgement of facial expression. Subjects in 10 cultures performed a more complex judgment task than has been used in previous cross-cultural studies. Instead of limiting the subjects to selecting only one emotion term for each expression, this task allowed them to indicate that multiple emotions were evident and the intensity of each emotion. Agreement was very high across cultures about which emotion was the most intense. The 10 cultures also agreed about the second most intense emotion signaled by an expression and about the relative intensity among expressions of the same emotion. However, cultural differences were found in judgments of the absolute level of emotional intensity.

A. Kołakowska, A. Landowska, M. Szwoch, W. Szwoch, and M. R. Wrobel,´ Human-Computer Systems Interaction: Backgrounds and Applications 3, ch. Emotion Recognition and Its Applications

This paper aims at illustrating diversity of possible emotion recognition applications. It provides concise review of affect recognition methods based on different inputs such as biometrics, video channel or behavioral data. It proposes a set of research scenarios of emotion recognition applications in the following domains: software engineering, website customization, education, and gaming. The scenarios show complexity and problems of applying affective computing in different domains. Analysis of the scenarios allows drawing some conclusions on challenges of automatic recognition that have to be addressed by further research.

A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the

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ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

III. SYSTEM ANALYSIS AND DESIGN

EXISTING SYSTEM:

This model already existed in an image net classification based emotion detection system and it fails to detect more emotions from the video frame. In facial features were detected based on latent relations. In the another reference the authors proposed a intelligent facial emotion detection system to effectively detect the emotions from the live video feed using Recurrent neural networks and it takes lot of time to train the model and thus reduces the efficiency.

DISADVANTAGES:

- In the existing system, emotions in the faces were detected only from the static images (only from photos) and fail to detect facial expressions from live video frames.
- Emotions were detected from images accuracy is less.
- Facial expressions are limited only too few emotions like happiness and neutral.

PROPOSED SYSTEM:

We have developed a convolution neural network based model for classifying human facial emotions from dynamic facial expressions through live video frame in real time. We use transfer learning on the fully connected layers of an existing convolution neural network which was pre-trained for human emotion classification. Finally, a live video stream connected to a face detector system give feeding of images to the neural network. The results facilitate the easiness of implementing convolution neural networks in real time to detect human facial expression. The results demonstrate the feasibility of implementing neural networks in real time to detect human emotion

ADVANTAGES:

- The accuracy of the model is high compared with the existing model.
- Our model is very efficient in getting the emotions by training CNN.
- Our model detected facial expressions from live video frames.

IV. SYSTEM ARCHITECTURE:

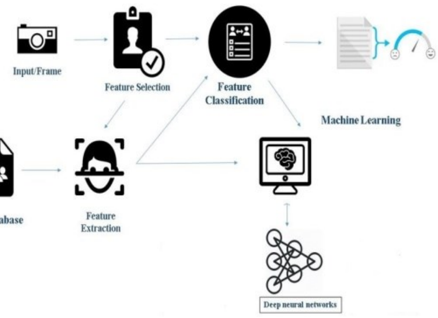

FIG:1.1 SYSTEM ARCHITECTURE

V. SYSTEM IMPLEMENTATION

Modules

Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Train & Test Data Sets, View Trained and Tested Datasets Accuracy in Bar Chart, View Trained and Tested Datasets Accuracy Results, View Prediction Of Cyber Attack Status, View Cyber Attack Prediction Status Ratio, Download Predicted Data Sets, View Cyber Attack Prediction Status Ratio Results, View All Remote Users..

View and Authorize Users

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In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

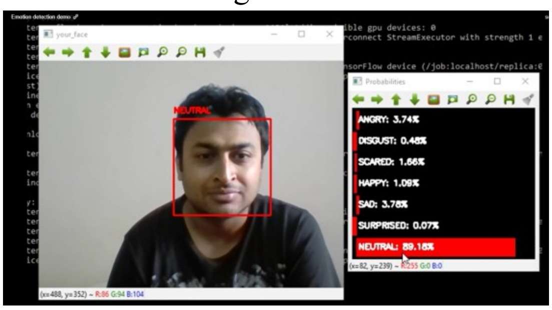
Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT CYBER ATTACK STATUS, VIEW YOUR PROFILE.

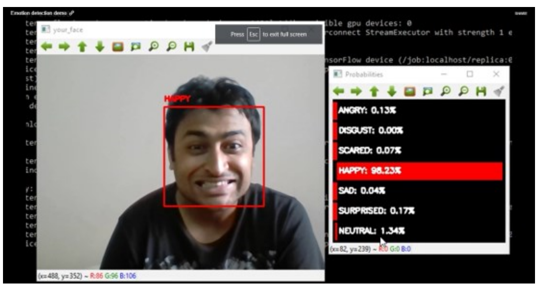
VI. SCREEN SHOTS

RESULT AND OUTPUT

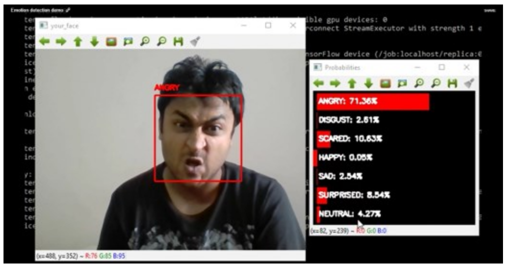
In this model the result can be said that the output will be shown in screenshots. This model which can detect multiple faces simultaneously .this will be accuracy that shows the emotion exactly of high accuracy. This can detect various emotions at a time by detecting multiple frames with their emotion recognition**.**



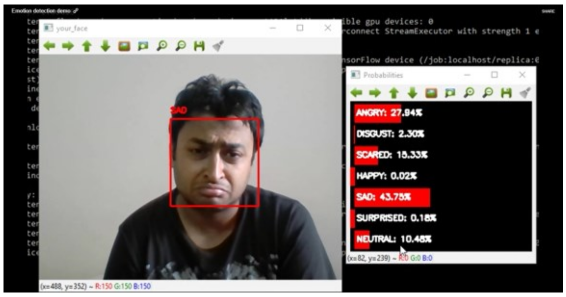
NEUTRAL



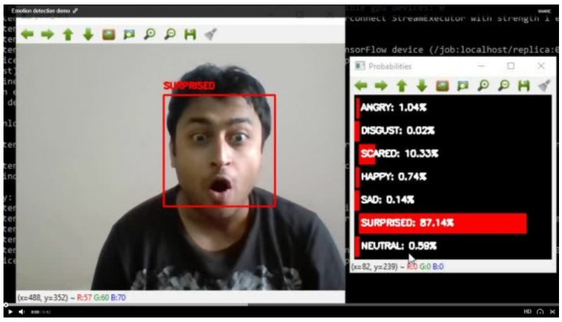
HAPPY



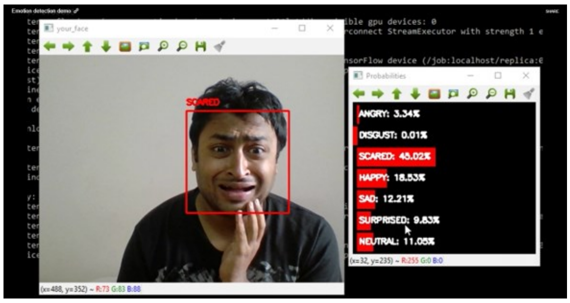
ANGRY



SAD



SURPRISE



SCARED

VII. CONCLUSION

Research on emotion detection is never-ending since there is no ideal solution in terms of accuracy. We have attempted the ideal method to identify Although it is not entirely accurate, it outperforms all other models currently in use. Numerous applications, including military and

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humanoid robots, can make use of our approach.

FUTURE ENHANCEMENTS:

In the future, we want to improve our model's usability by including emoticons or emojis into the emotions that are recognised. This may be accomplished by training recurrent neural networks with several emojis that correspond to the identified facial emotion. A happy face emoji is applied to the person's face if the identified emotion is, say, happiness.

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