



Facial Expression Detector using a Five-Layered Convolutional Neural Networks

Queenie Das, GeetikaGopi, Janani Suresh, Swarnalatha P

Abstract: A face is a very important aspect in communication. Often, it is through face expressions that people understand what another person is trying to convey or in what mood he/she is saying it in. It also helps in realising what a person's mental or emotional state is at a particular moment of time. Thus, recognising a facial expression is essential in day to day communication. Our proposed model implements a facial expression recogniser that categorises a face expression into one of the seven expressions: Happy, Sad, Angry, Surprised, Fearful, Neutral and Disgusted. The model uses Convolutional Neural Network (CNN) having five layers. The model gives an immediate representation of the predicted expression by displaying an emoji associated with. Not just that, our model will also show the percentage of each of the seven expressions so that the understanding of the expression is better. A face expression recogniser can be used in areas face biometrics, forensics and security system. Not only that, it can be used in a commercial or financial aspect by judging customer interests. Also, rarely used application of such an application is to aid Autistic people in communication.

Keywords: Convolution neural network, Emoticons, Facial Expression, Machine Learning

I. INTRODUCTION

A lot of research is being done in the field of Artificial Intelligence and the applications that can be made using its concepts. It can be applied to a large number of domains such as healthcare by disease detection or monitoring systems; marketing by predicting a customer's interest in a product; and chat bots and robotic systems that are emotionally intelligent. As there mentioned earlier, facial expressions are a key aspect for a well understood communication as hence, plenty of research has been carried out in this field. Ekman and Friesen [1] reported that Neutral, Happy, Angry, Sad, Surprised and Fearful are six main expressions that are most commonly used and recognized in various cultures. Apart from this, Disgust is also an expression that is commonly expressed while speaking about a particular topic. Our main motive behind implementing a Face Expression Recognizer is was to aid people suffering from Autism [2]. Autism makes

it difficult for the person to interact socially, especially through verbal communication. Children suffering from autism can have problems recognizing and processing the feelings that others have. An autistic kid can use this software to replace the facial expression of the person on screen in-front of the child to an emoji which will be familiar to the kid making him/her feel more secure in new surroundings [3]. Our model implements Convolutional Neural Network as the base of the architecture. CNNs can imitate the working of a human brain when analysis of any visuals is done. For implementation, we have used Keras and Tensorflow in Python along with OpenCV for the processing of the images [5]. The architecture of our CNN has five layers that are linearly stacked after the input layer. The input will be taken from a Web Cam in a computer or laptop. The five layers of neural networks pass on data that is finally fed to a softmax classifier which results in the output from the given set of classifications the data is trained on. Adam optimizer has been used for batch gradient descent.

II. LITERATURE SURVEY

Without understanding the facial expression of a person, the communication between two people is incomplete. Ekman and Friesen [1] reported that Neutral, Happy, Angry, Sad, Surprised and Fearful are main expressions that come up in a conversation most commonly. Using face expressions with ideograms and smileys is the emoji. Before emojis, there existed emoticons as "symbolic representations for facial expressions based on punctuation marks that could be covered using a standard keyboard" [6]. Nowadays, emojis as well as emoticons are widely used in the common means of communication such as instant messaging, and social media platforms like in Facebook and Instagram posts, Tweets and Youtube comments. Emojis were brought into view by mobile phone companies of Japan such as Docomo and Vodafone. Facial expression recognizers [7] have been developed for a long time now but to achieve accuracy in them is still a task that hasn't been completely successful. Systems such as these have existed from 2000s but with very less accuracy, often being able to differentiate just between happy and sad as stated in the survey done by Fasel, Beat, and Juergen Luetttin in 2003 [8].

III. METHODOLOGY

To train the model, we used a dataset provided by a Kaggle Facial Expression Recognition Challenge in 2013 [9]. The dataset is accessible by public and consists of 35,887 cropped greyscale images in total with one of the seven labels: Happy, Sad, Angry, Surprised, Fearful, Neutral and Disgusted.

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Fig. 1. Some of the images included in the Kaggle dataset [9]

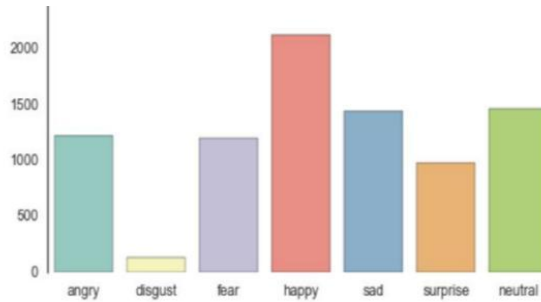


Fig. 2. The number of images for each category of expression in the dataset [9]

A CNN has four main layers—input, convolutional, dense (or fully-connected) and output [10]. We used Keras and Tensorflow in Python for implementing this model. The input layer takes pre-processed images that are provided by the dataset as it has fixed dimensions. We used OpenCV library also has Adaboost to locate and crop a face in an image [11]. The CNN that we have implemented consists of five layers in the convolutional layer of the neural network. We used Python as the language to code our implementation importing libraries such as NumPy, Keras and Tensorflow [5]. The output layer implemented by us uses a softmax function instead of the commonly used sigmoid function as the activation function [14]. This is so that the output gives the probability of each emotion and not just the one with the maximum value.

IV. RESULTS

The seven labels of expressions are as shown in Figure 3:

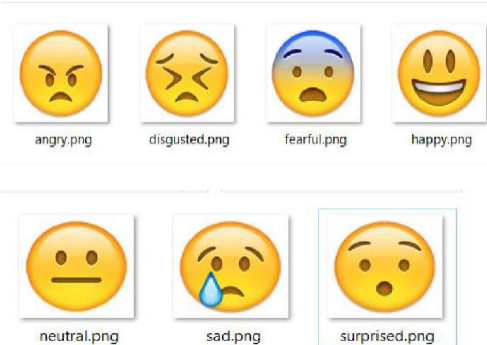


Fig. 3. The different expressions recognised by our model

The following are some sample outputs of the different expressions detected by the model. The output not only shows the expression that it recognised but it also shows the probability of each of the labels.

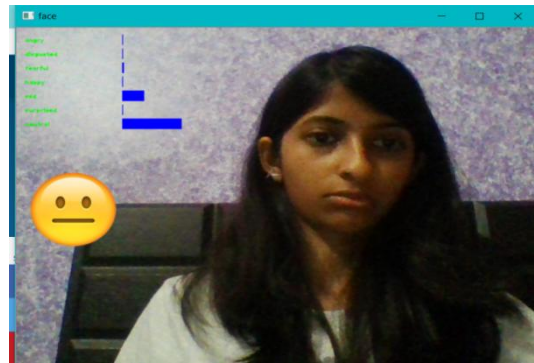


Fig 4. Neutral Expression



Fig 5. Happy Expression

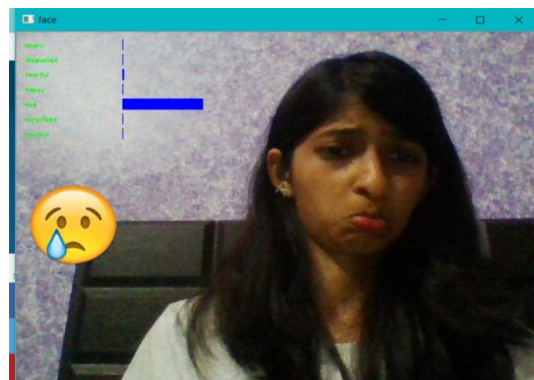


Fig 6. Sad Expression



Fig 7. Surprised Expression

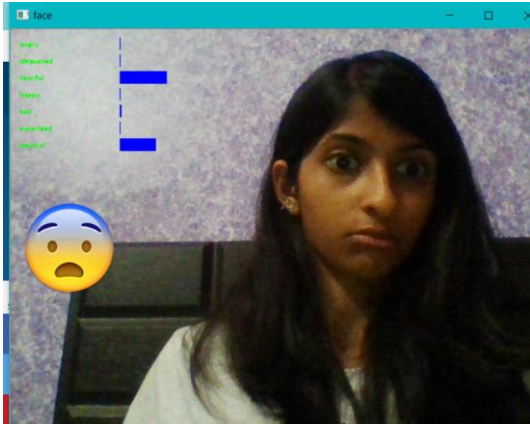


Fig 8. Fearful Expression

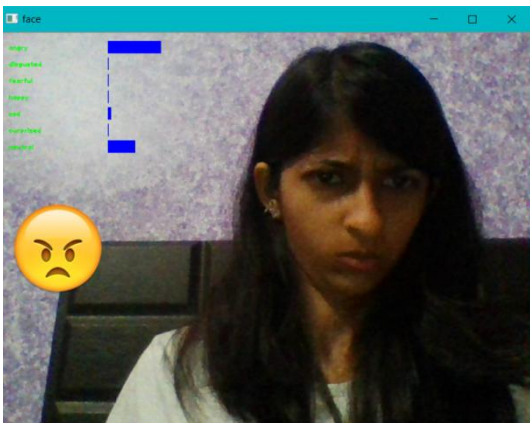


Fig 9. Angry Expression

V. FEASIBILITY

A. Technical Feasibility

- Software used to code the algorithms is Python based on Spyder.
- The format of the picture captured and used for in the project: SVG, PNG, JPG.
- Estimating the overall speed of the system by running simulations over the databases of images.

B. Economic Feasibility

- As the project is algorithm based, the only hardware requirement is an equipment to capture the facial expression of a person in real time (eg: webcam) and a computer to run the program.
- The language used for coding is Python, which is an open source programming language. Hence, no licence is required for working with it.

VI. EVALUATION

For Prototype testing a group of users were randomly selected to test the HCI component in specific. Two of the users were a student, other two were normal adults. For testing, a consultant was used to provide a brief on how to use the software. The critical incidents observed during the prototype testing was the user not being able to differentiate between changing expressions and moving on to the next. Some of them found it difficult to return back to the

homescreen. This problem was later overcome by redesigning the user interface and offering prompt messages.

VII. SURVEYING

First, the usability of the software was tested by using the following formula in various aspects.

$$S = \frac{PC}{T} \dots(1.1)$$

where:

S = performance score of the user, T = time spent by the user on the specified task, P = percentage of task completed and C = arbitrary constant based on the fastest possible task solution by a practised system expert.

Fig 10: Performance Score of the User

VIII. RESULT

The performance score was later graphed to compare the results of the various tasks.

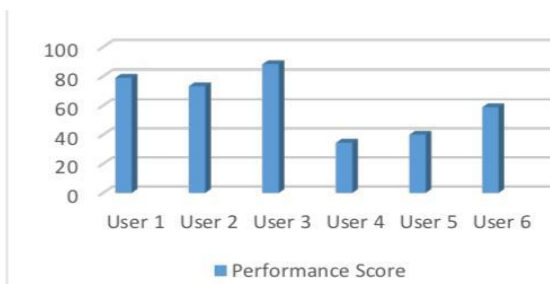


Fig 11. Task1 - Operating and walkthrough of software

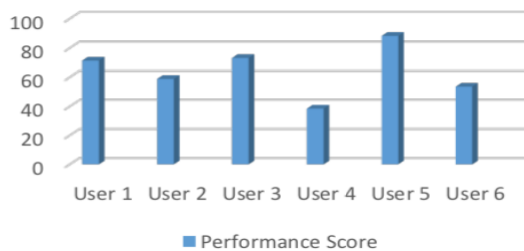


Fig 11. Task 2- Overall aesthetics and feel for the user

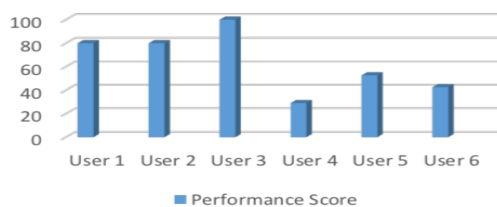
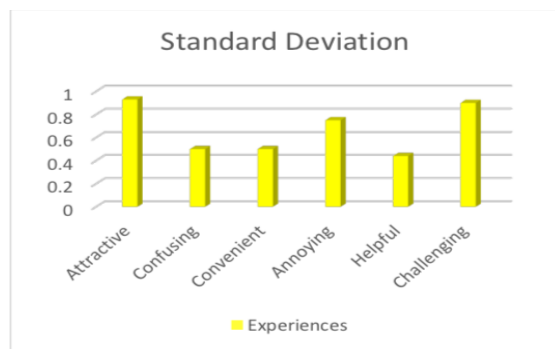
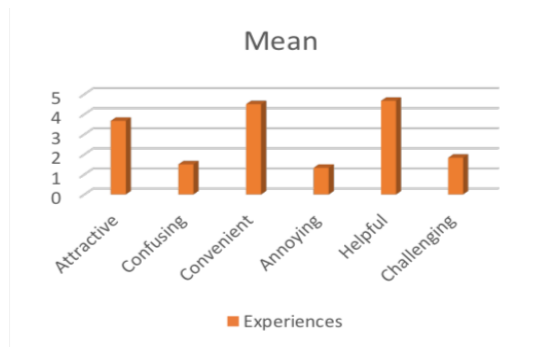


Fig 12. Task 3- Accuracy of the emotion recognition results

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IX. PERFORMANCE SCORE

A matrix was computed for multiple factors and we had calculated subjective measurement that included mean and sd for every user. A questionnaire was circulated to collect this data.



	Attr active	Conf using	Conv enient	Ann oyin g	Hel pfu l	Chall engin g
U se r 1	4	1	4	1	4	1
U se r 2	4	2	5	1	5	1
U se r 3	5	1	4	1	5	3
U se r 4	4	2	5	1	5	3
U se r 5	3	1	4	1	4	2
U se r 6	2	2	5	3	5	1
T ot al	22	9	27	8	28	11

X. FUTURE RESEARCH

We can research on making our CNN model more accurate by creating a larger dataset for expression other than Happy or Sad. As seen in Figure 2, the number of samples for expressions such as Disgust is very less and hence, the accuracy with which it will be recognized is less.

To aid as a solution to the above mentioned problem, we can make our model self-learning by constantly adding outputs to the dataset. Also, the model will be more useful and efficient if it works in real-time constantly. This means that instead of capturing the image of the expression by a key press, we can add a face detection algorithm so that the model won't require a key press.

XI. CONCLUSION

Applications -

1. Emotion Recognition Using Emoticons for Autistic Children. Autism makes it difficult for the person to interact socially, especially through verbal communication. Children suffering from autism can have problems recognizing and processing the feelings that others have. An autistic kid can use this software to replace the facial expression of the person on screen in-front of the child to an emoji which will be familiar to the kid making him/her feel more secure in new surroundings [3].
2. Security Cameras. Imagine a passport office/airport where security camera could analyze and determine if the person seemed nervous about having their picture taken. This could be used to possibly identify persons who may be potential security risks.
3. Advertisement. As the potential customer or consumer looks at the product or display, a camera could look at their face and figure out their emotion. Based upon the analysis of the person's emotional disposition, the machine learning algorithm could record whether a person was interested in the product or display.

Other Applications -

1. It can be used widely to trace highly threatening terrorist organizations and personnel.
2. It can be used in medicine, e-learning, monitoring, entertainment, law and marketing.
3. It can be used in home automation systems. For example, face recognition for door locks.
4. It can be used in schools to observe the behavior of students and in hospitals to detect various expressions of patients and take actions based on that.
5. This device can also be used to provide security in other areas provided face recognition capabilities are added to this project.

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Queenie Das, belongs to School Of Computer Science and Engineering from Vellore Institute Of Technology, Vellore, Tamil Nadu, India. Her research interests are Neural Networks, Image Processing and Cyber Security. She has undertaken many research projects under the Web Development domain. She worked as a Web Developer in IEEE Computer Society, VIT Student Chapter. She has worked as a Summer Intern at Cisco Systems, Inc. at Bangalore in 2019 and Technosys Services Pvt Ltd at Lucknow in 2018. She is very enthusiastic about emerging computing technologies and works passionately towards the betterment of her skills in every possible technical domain.



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