Customer Feedback System Based On Facial Expressions

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Abstract - **Customer feedback is the information from the customer about the experience of services offered by the retailer. It helps the store owner to improve the customer service. The changes in the customer feedback collection systems aim to reduce the time and complexity of submission. One such straightforward approach to a customer feedback system is the facial expression based emotion feedback collection system. The facial expression based emotion feedback system is the magnified thought of Emotional Artificial Intelligence (EAI) and can have applications, including telerehabilitation and Advanced Driver Assistance Systems (ADAS). This paper focuses on enhancing the performance of the customer feedback system. The authors used the FER-2013 dataset to train the algorithm. VGG16 is a CNN-based architecture designed explicitly for classification and localization, and the model is trained with 7 class classifications of emotions, including Happy, Neutral, Sad, Disgusted, Surprised, Fearful, and Angry. The real-time image is captured using the Caffe Model face detector and validated using the trained emotion detection model. The web interface displays the emotion detected with corresponding ratings. The collected feedback is stored as a log file with the date, time, rating, and emotion detected once the customer presses the submit button. This convenient consumer feedback system reduces the customer's response time and helps retailers improve their services.**

Keywords – EAI, VGG16, customer feedback, emotion detection, facial expression, Machine learning.

I. INTRODUCTION

Emotion recognition is an emerging research area that focuses on collecting parameters related to the affective and cognitive domains. EEG (electroencephalogram)signals, ECG (Electrocardiogram) signals, eye-gaze information, Galvanic skin detection, and facial expressions are the various signals that researchers have focused on.

These emotion-detecting models are being efficiently used and applied in many applications, including Employee status tracking in MNCs [1], Tele-rehabilitation [2], and Police interrogation systems [3]. Facial Emotion Recognition (FER) is significant in many Internet of Things (IoT) applications and Human-Computer Interaction (HCI).

The customer feedback system is one such application that is constantly modified to make it a more convenient way of collection. The customer feedback system needs to be easy, short, and simple, reduce time, and trigger the customers to give feedback. Through the following solution, the paper aims to address all the attributes of the feedback systems.

A simplified customer feedback system helps the retailer grab the customers' attention and make them give feedback without interrupting them personally. The extracted features like date and time of submission, emotion detected, and corresponding rating specified for that emotion stored help the retailer make changes in the services provided and meet customer satisfaction. Customer satisfaction plays a significant role in the business growth and betterment of the company. This feedback system reduces complexity and simplifies the feedback process.

Our paper gives a detailed description and observation of the state-of-the-art paper in section II, the complete process of creating a facial emotion recognition model and its application in the customer feedback system described in section III and results in Section IV followed by future scope

II. LITERATURE SURVEY

A. Related work

This section discusses the state of art towards emotion detection with various approaches, along with the advantages, accuracies and their limitations.

Facial emotion recognition system is a most explored area with different types of machine learning and deep learning algorithms being used to reach the maximum accuracy. The authors in [4] compare the accuracies of CNN, KNN and random forest algorithms. Haar-Cascade Algorithm is employed for face detection and cropping. The paper reports the accuracy of each classifier, with CNN achieving the highest score of 67%, Random Forest and KNN achieving accuracies of 25.444% and 16.88% respectively. The CNN model's accuracy is got over 135 epochs.

Authors in [5] also give a wide range of algorithms comparison in facial emotion detection and suggest that CNN is the best approach and the second best being DBN (Deep Belief Network). Author describes the advantages of CNN as it is a simple network and has a unique architecture from the constituent layer also flexible to arrange/decide the layers.

The authors in [6] discuss the various applications of FER technology and mentions that VGG16 performs well on image recognition and processing. They also emphasise on the great ability of machines to detect the emotion of humans and mentions that the human-machine interaction will be much smoother and faster. Furthermore, applications of FER are discussed in [7] where they have used Viola Jones algorithm for face detection along with AlexNET for feature extraction.

The authors of [8] approach the facial emotion recognition using deep learning techniques, including VGG16, Xception, InceptionV3 along with CNN. They used datasets like Cohn-Kanade Dataset (CK+) and Japanese female facial emotion (JAFFE) for performance evaluation. They have also discussed studies involving real-time emotion detection using CNN and keras, which is open source and suitable for real time implementation. They used algorithms like CNN, KNN and Naïve Bayes as a probabilistic algorithm based on conditional probability. The CNN model achieved accuracy and specificity of over 80%, making it suitable for real-time facial emotion recognition.

The authors of [9] discuss the need for a system that can detect emotions directly from a webcam feed, eliminating the need to upload images. They used OpenCV, TensorFlow, and other libraries to train a model to detect emotions in real-time and also stress on the importance of creating their own dataset. They preprocess the images by converting them to grayscale and then use a pretrained model to predict the emotions. The model achieved an accuracy of 93% after training on a dataset comprising the FER-2013 dataset, additional images, and free GitHub images. The paper discusses potential applications of emotion detection technology, including its use in interviews, clinical settings, gaming, and fraud detection.

The authors in [10] discuss the importance of facial expression recognition in various applications, including customer satisfaction analysis in retail and restaurant settings, as well as in virtual classrooms and interactive media. It mentions that ADAGRAD optimizer outperforms other optimizers in achieving high accuracy in emotion detection. The CNN model is trained with an accuracy of 89.66% using ADAGRAD as the optimizer.

In paper [11], authors used Haar-cascade for facial detection, normalised the images and then it is passed through CNN. Their proposed Model uses four convolutional layers, four max pooling and two fully connected layers for which the obtained accuracy was 70%.

Similarly, authors in paper [12] proposed pipeline uses Haar-cascade and HOG Features to extract the face, but later SVM was used to detect facial expression and achieves the F1 score of 0.8759.

The authors in [13] and [14] uses CNN to build facial emotion detection models using different datasets. The proposed model in [13] is implemented using SVM classifier with the specialisation of three stage hybrid feature extraction technique. Deep learning algorithm and SIFT in combination are used to detect emotions and Whale optimiser for optimising the performance. The accuracy of 98.79% is achieved.

The accuracies achieved with the proposed model in [14] are 70.14% for FERC-2013 dataset and 98.65% for JAFFE dataset.

The authors in [15] had a different approach of using Attentional Convolution Network to build the model. Through their experiment they conclude that distinct regions of the face are associated with different emotions.

The authors in paper [16] experiment retraining the existing pretrained models of CNN namely VGG16, RESNET50 and SENET50 with different optimisation functions and different learning rates. Finally, they conclude the highest accuracy of 97% is attained through VGG16 with ADAM optimization function and learning rate of 0.001.

In paper [17] a total of 72 models are generated through 12 possible combinations of Saliency Mapping, LBP (Local Binary Pattern), HOG (Histogram of Oriented Gradient) and Key Facial Detection with 6 machine learning classification algorithms. Comparing all the models and investigating, the RSVM HOG+LBP is the best model with an accuracy of 94% tried on combination of CK+ dataset and locally collected dataset.

Papers [18],[19] and [20] focus on emotion detection in real-time scenarios. Model proposed in paper [18] is able to detect emotion with the accuracy of 70.65% in real time. Paper [19] shows the accuracy of 68% for emotion detection through Ensemble CNN implementation. The model detects facial emotion and gender of the person in real time. Authors in paper [20] achieving 78.1% accuracy aim to design the application for the proposed model with a graphical user interface that classifies emotions in real-time.

Facial expressions which appear for a very small time due to sudden strong pressure are called micro-expressions. Those expressions are involuntary and are brief expressions. Authors of paper [22] and [23] mainly focus on detecting those micro-expressions using different methods. Paper [22] uses a detection method of recognizing a local and temporal pattern (LTP) of facial movement. The two datasets which they used were CASME I [22] and CASME II [23]. They also mention these micro-expression detections also have applications in different domains such as national security, medical case, study of political psychology and educational psychology. Paper [23] works on two methods of recognizing Local Temporal Pattern (LTP) and Local Binary Pattern (LBP) to detect micro-expressions using SAMM and CAS(ME)2 datasets.

The paper [24] explores facial emotion recognition using Convolutional Neural Networks (CNNs) based on the iCV MEFED dataset. It discusses about the challenges in data preprocessing, emphasizes the importance of large datasets, and presents a CNN model with experiments on data augmentation. Results indicate varying accuracy for different emotions, with the algorithm performing best in detecting happiness and worst in detecting contempt.

In paper [25], the authors design a lightweight convolutional neural network for recognizing facial expressions. They have worked on 'FER-2013' and 'Wider face' dataset. They have eliminated the fully connected layer, added the L2-norm regularization term and combined the residual depth-wise separable convolution to reduce the number of parameters in convolution layer.

Authors in [26] carryout a survey on various algorithms to detect facial emotion detection, they have compared 15 papers along with their algorithms and accuracies on 7 major datasets.

The paper [27] proposes a deep learning-based facial emotion detection system using convolutional neural networks (CNNs). The system involves three main steps: face detection, feature extraction, and emotion classification. They evaluated the proposed CNN architecture using two datasets namely JAFFE (Japanese Female Facial Emotion) and FERC-2013 (Facial Emotion Recognition Challenge). The achieved accuracies are 70.14% for FERC-2013 and 98.65% for JAFFE. The proposed model outperforms a previous model (Model B) in terms of accuracy and computational time.

TABLE 1. COMPARISION BETWEEN ACCURACIES OF DIFFERENT MACHINE LEARNING ALGORITHMS

Algorithms	References	Accuracy achieved
CNN	[4]	67%
	[8]	80%
	[10]	89.66
	[11]	70%
	[13]	98.79%
	[14]	70.14% [FERC – 2013] 98.65% [JAFEE]
	[20]	78.1%
Random Forest	[4]	25.4%
KNN	[4]	16.88%
SVM	[12]	87.59%
	[18]	70.65%
RSVM	[17]	94%
Open-cv and TensorFlow	[9]	93%
Ensembled CNN	[19]	68%
VGG 16	[3]	62.2%
	[19]	68%

Facial emotion recognition models having application in different domains are illustrated in [1], [2] and [3] which emphasise the importance of EAI in every day-to-day application.

The primary goal of authors of [1] the Real-time Employee Emotion Detection System (RtEED) is to help employers monitor the well-being of employees by detecting their emotions in real time. This information is then relayed to the respective employees through messages. The system utilises the CMU Multi-PIE Face Data to train machine learning models. The RtEED system captures images of employees using webcams, detects faces, preprocesses the images, finds the best match positions in the images using Active Shape Model (ASM), identifies emotions using AdaBoost.

The authors of [2] present a medical application of FER in Tele-rehabilitation. The focus is to keep a look on the cognitive rehabilitation of patients by evaluating their emotions through facial expressions during motor rehabilitation exercises. The potential application of it is in neurodegenerative disorders, such as Parkinson's disease.

The paper [3] focuses on applying FER into police interrogation system simulation. The authors highlight the point on current method of depending on an official stenographer for transcription increase the risk of wrong detection of emotions. Their models achieve an accuracy of 62.2% using FER2013 dataset. Authors use web interface called "Through You" to illustrate their functionality. They also discuss about the system limitation such as brightness, occlusion and pose problem during image capture and propose the future scopes like improving face capture to 3D and well suitable environment for testing.

Authors of paper [21] aim to relieve the stress of an individual by automatically detecting the stress level and switching on the musical therapy session.

TABLE 2. APPLICATIONS OBSERVED IN LITRATURE SURVEY

Applications	References
Real-time Employee Emotion Detection System	[1]
Tele-rehabilitation	[2]
Police interrogation system	[3]
Music therapy	[21]

B. Objectives

Our work focuses on applying EAI to customer feedback system to simplify the feedback process and help retailers to bring out more feedback responses from the customers. The three objectives of the study are as follows.

1. Build a seven-class emotion detection model to classify the emotion from the video feed.
2. Create a user interface to capture the real-time emotions expressed by the customers in a feedback collection system.
3. Extract the emotion detected from the facial features and record the feedback as a rating, emoji along with date, time of submission and store it in a text file.

C. Dataset

Literature presents many freely available datasets like CK+ and FER-2013.We have used FER-2013[12] dataset over CK+ due to its extensive collection of images. This dataset comprises 48x48 pixel grayscale images categorised into seven emotions. The training set includes

28,709 examples [angry (3995), disgusted (436), fearful (4097), happy (7215), neutral (4965), sad (4830), and surprised (3171)]. Additionally, the test set comprises 3,589 examples [angry (958), disgusted (111), fearful (1024), happy (1774), neutral (1233), sad (1247), and surprised (831)]

Fig. 1. Expression of seven classes of emotion

III. METHODOLOGY

The proposed customer feedback system consists of a model trained using customised VGG16 and FER2013 dataset. The VGG-16 architecture is designed to process RGB images with a size of 224 x 224 pixels. It comprises a total of 16 layers, consisting of 13 convolutional layers and 3 fully connected layers. The initial convolutional layer takes the input image of size 224 x 224 and applies 64 filters. Subsequently, a max pooling layer is employed, reducing the image dimensions to 112 x 112. This pattern is repeated with the next convolutional layer using 128 filters and another max pooling layer, further reducing the size to 56 x 56. The process continues with subsequent convolutional layers employing 256 and 512 filters, along with max pooling layer, resulting in image size of 28 x 28, 14 x 14, and finally 7 x 7.

Max Pooling layers play a vital role in the architecture by reducing the dimensionality and parameters of the feature maps generated in the convolutional steps. The architecture concludes with three fully connected layers. The first two layers consist of 4096 channels each, and the third layer has 1000 channels, corresponding to the number of classes.

The activation function used in all layers, except the final fully connected layer, is Rectified Linear Unit (ReLU). It is a linear function that gives output zero for negative input and matching output for positive input. VGG16 consists of a total set convolution stride of 1 pixel to maintain the spatial resolution after the process of convolution. The final fully connected output layer uses the SoftMax activation function for multi-class classification.

A. Pre-processing

To ensure best performance of the system all the images should be of the same size and colour. VGG16 accepts RGB images as its input, so the grey scale images should be fed in RGB format. The images of the FER-2013 dataset are already pre-processed so only rescaling pixel values to a range between 0 and 1 was done.

B. Model Training

The input layer of VGG16 is designed for 224 x 224 image size, but in our case, we have images of 48 x 48 dimensions. Instead of rescaling our images to 224 x 224, which is not ideal due to loss of information and increased noise, we modify the input layer of VGG16 model. This allows us to input images of our desired size i.e 48 x 48. The change of input image size is shown in model summary in Fig 3. Furthermore, the output layer of VGG16 originally has 1000 channels for a thousand classes, whereas we only require 7 classes. Therefore, the output layer was modified to better suit the classification needs.

C. Optimizer

ADAM optimizer which is an extension of Stochastic Gradient Descent (SGD). SGD maintains a constant learning rate, whereas the Adam optimizer (adaptive moment estimation) has an ability to adaptively adjusts learning rate of network weights individually. It computes individual learning rates based on the past gradients and their second moments.

D. Testing Model

To execute this, we need a face detector which detects our face and then the detected face should be cropped and sent to the trained model to detect emotion. There are many face detectors like haar-cascade and caffe models. Out of which the caffe model achieves much accuracy in detecting faces.

E. Web Page

We integrated our trained model into a Python Flask web application, complemented by HTML and CSS. This HTML file facilitates user interaction by allowing us to assign ratings to each of the seven emotions, and these ratings can be adjusted according to our preferences. As emotions are detected, the corresponding ratings are displayed on the webpage. Upon clicking the submit button, the assigned ratings, the current emotion detected, along with the date and time of submission, are recorded in a text file. This process continues iteratively. Retailers can utilise the generated text file to access the record of all the customer feedback.

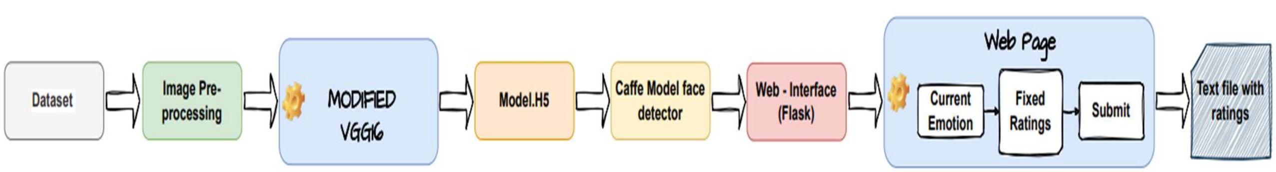

Fig. 2. Proposed pipeline

F. Evaluating results

The evaluation of model is done using performance metrices like confusion matrix and classification report.
The confusion matrix we constructed consists of seven classes which gives us the brief pictorial representation of the classification of classes. The matrix shown in Fig 7 conveys the information of expected and actual values which gives a better idea of how well our model classifies and what type of errors it makes.

```
Layer (type)                Output Shape              Param #
=================================================================
input_2 (InputLayer)        [(None, 48, 48, 3)]       0

block1_conv1 (Conv2D)       (None, 48, 48, 64)        1792

block1_conv2 (Conv2D)       (None, 48, 48, 64)        36928

block1_pool (MaxPooling2D)  (None, 24, 24, 64)        0

block2_conv1 (Conv2D)       (None, 24, 24, 128)       73856

block2_conv2 (Conv2D)       (None, 24, 24, 128)       147584

block2_pool (MaxPooling2D)  (None, 12, 12, 128)       0

block3_conv1 (Conv2D)       (None, 12, 12, 256)       295168

block3_conv2 (Conv2D)       (None, 12, 12, 256)       590080

block3_conv3 (Conv2D)       (None, 12, 12, 256)       590080

block3_pool (MaxPooling2D)  (None, 6, 6, 256)         0

block4_conv1 (Conv2D)       (None, 6, 6, 512)         1180160

block4_conv2 (Conv2D)       (None, 6, 6, 512)         2359808

block4_conv3 (Conv2D)       (None, 6, 6, 512)         2359808

block4_pool (MaxPooling2D)  (None, 3, 3, 512)         0

block5_conv1 (Conv2D)       (None, 3, 3, 512)         2359808
block5_conv2 (Conv2D)       (None, 3, 3, 512)         2359808

block5_conv3 (Conv2D)       (None, 3, 3, 512)         2359808

block5_pool (MaxPooling2D)  (None, 1, 1, 512)         0

global_average_pooling2d_1   (None, 512)              0
(GlobalAveragePooling2D)

dense_2 (Dense)             (None, 512)               262656

dropout_1 (Dropout)         (None, 512)               0

dense_3 (Dense)             (None, 7)                 3591

=================================================================
Total params: 14,980,935
Trainable params: 14,980,935
Non-trainable params: 0
```

Fig. 3. Model summary

IV. RESULTS

This work mainly aimed at applying the EAI into customer feedback systems and help retailers in betterment of their business. This is achieved through a well-trained emotion detection model with 62% accuracy and a web interface which gives the detailed output of the feedback submitted by the customer. The parametric analysis in training and testing phases are mentioned below:

A. Training phase

During training, initially the model started with a validation loss of 2.37 and accuracy of 23%. Over 80 epochs it achieved 62% accuracy.
The loss and accuracy graphs are shown in Fig 4 and Fig 5 respectively.

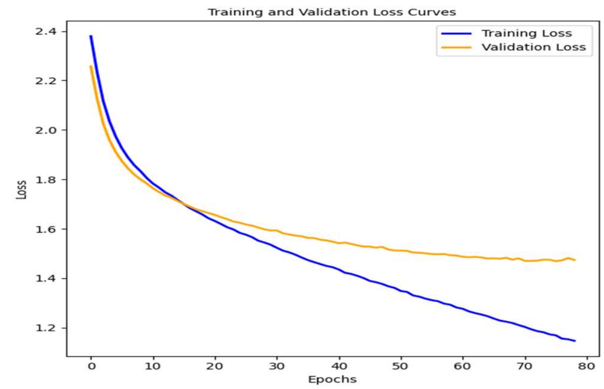

Fig. 4. Epochs vs loss

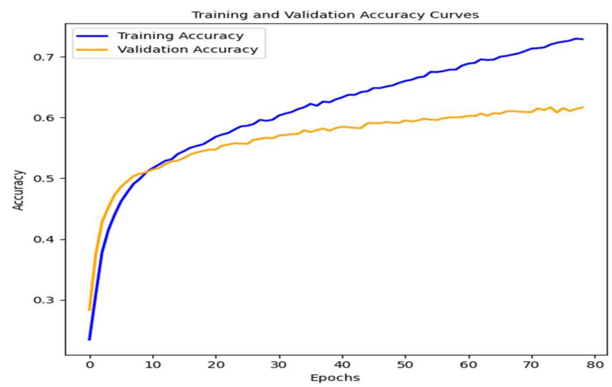

Fig. 5. Epochs vs accuracy

B. Classification report

Going through the constructed Classification report of our model following interferences can be drawn

1. The lowest precision achieved with fear emotion standing at 47% .
2. The highest precision achieved with disgust standing at 82% .

Performance of other emotions we achieved are represented in Fig 6.

	precision	recall	f1-score	support
angry	0.53	0.53	0.53	958
disgust	0.82	0.21	0.33	111
fear	0.47	0.39	0.43	1024
happy	0.80	0.85	0.82	1774
neutral	0.55	0.61	0.58	1233
sad	0.49	0.50	0.49	1247
surprise	0.76	0.72	0.74	831
accuracy			0.62	7178
macro avg	0.63	0.55	0.56	7178
weighted avg	0.61	0.62	0.61	7178

Fig. 6. Classification report

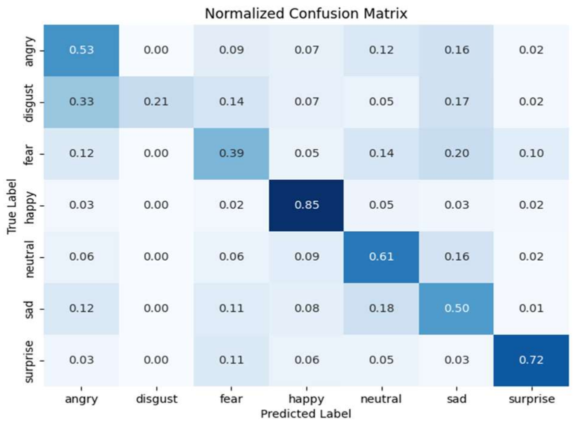

Fig. 7. Confusion matrix

Here is a comparison table of precision we achieved vs the authors of paper [7].

TABLE 3. COMPARISION TABLE

		Proposed Model	**[7]**
Accuracy	Training	72%	65%
	Validation	62%	62.2%
Precision	Fear	47%	33%
	Happy	80%	74%

C. Testing

We used our trained model to check how good is the performance in real - world scenario. With this being tested we went on to test our web interface. This webpage hosts locally at address 127.0.0.0.1.5000 and displays a video feed which shows customers current emotion and rating. Web page showing emotions are shown in Fig 8.

It also has a submit button when pressed, it extracts customers current emotion , corresponding rating , date, time of submission and stores it in the form of text file as shown in Fig 9.

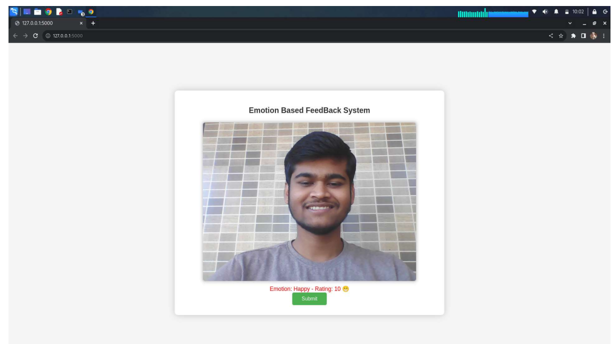

Fig. 8. Web page

```
Emotion: Happy -  Rating: 10 😁, Time: 12/2/2023, 9:33:41 AM
Emotion: Neutral -  Rating: 7 😐, Time: 12/2/2023, 9:59:35 AM
Emotion: Happy -  Rating: 10 😁, Time: 12/2/2023, 10:02:58 AM
Emotion: Sad -  Rating: 4 😔, Time: 12/2/2023, 10:04:14 AM
Emotion: Surprised -  Rating: 0 😱, Time: 12/2/2023, 10:05:27 AM
```

Fig. 9. Text file

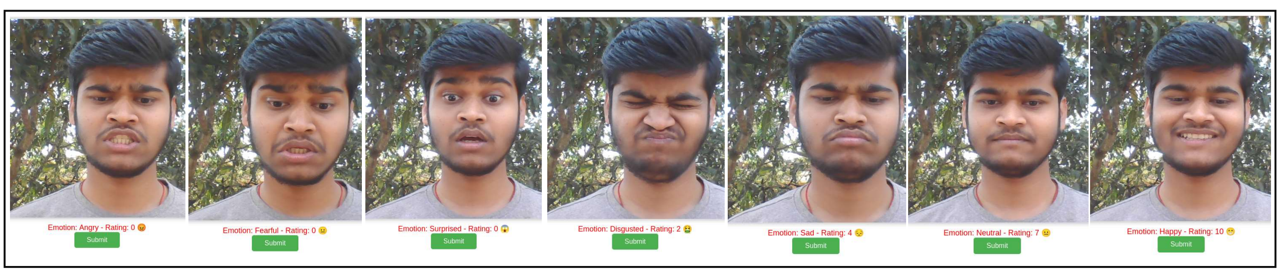

Fig. 10. Person 1 with background 1

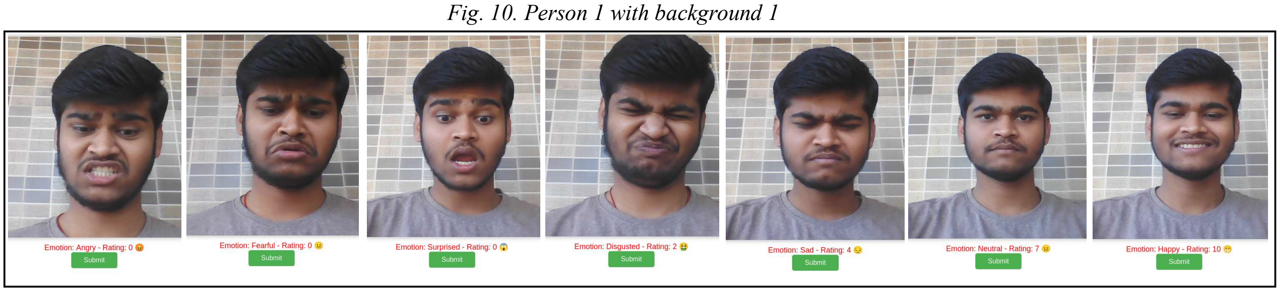

Fig. 11. Person 1 with background 2

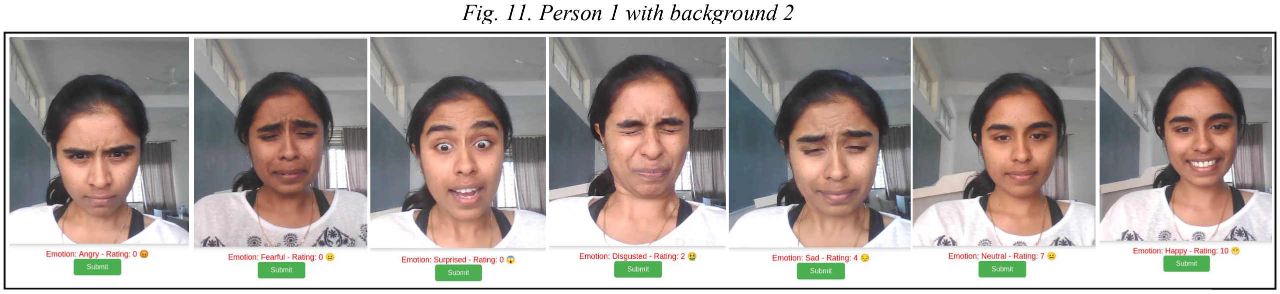

Fig. 12. Person 2

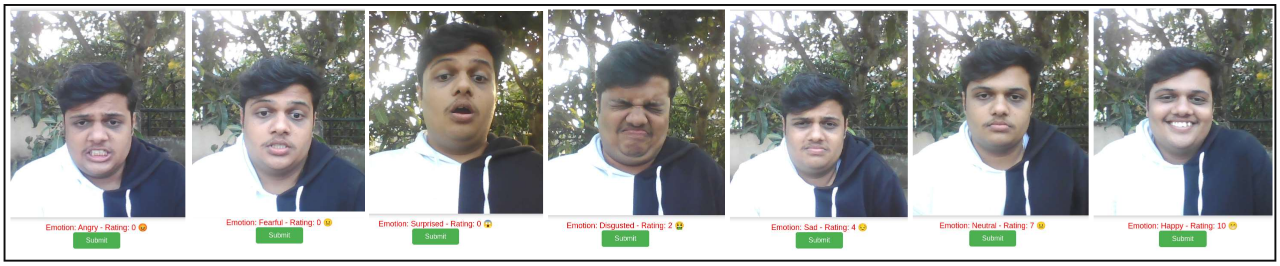

Fig. 13. Person 3

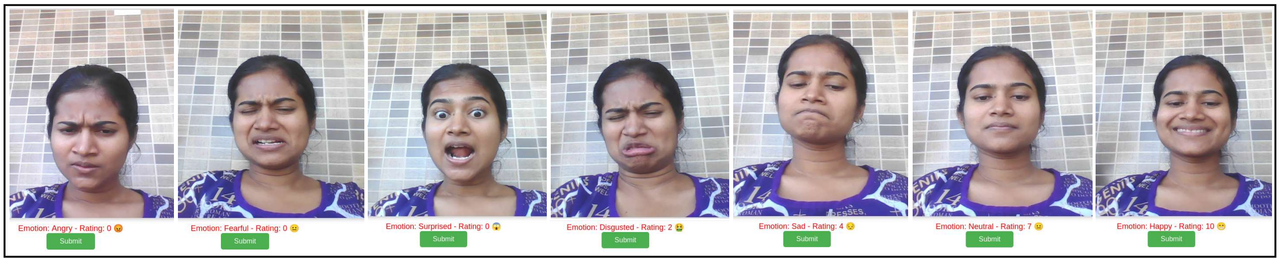

Fig. 14. Person 4

V. CONCLUSION

Customer feedback and rating helps shopkeeper to improve his services provided to the customer. But sometimes this feedback process could be time-consuming. In this paper, the proposed framework is an innovative and time-saving approach to record a person's feedback on a website.

The above-mentioned objectives are met with the emotion detection model being validated with 62% accuracy and a real-time web-interface which submits the corresponding ratings along with date, time and emotion detected. Accuracy can be further improved by training the model using different dataset. State of paper using FER-2013 dataset have achieved maximum accuracy of 65%. Our results are evident that the proposed model is not biased towards any gender or background.

This application has high scope in future shopping automatic customer feedback system. This model can be further improvised to capture facial emotion of group of people at a time and by increasing the accuracy. Our project explores the different application area of EAI and gives idea of vast area of EAI application to be explored.

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