International Journal of Artificial Intelligence and Machine Learning
Volume 11 • Issue 2 • July-December 2021

Automatic Multiface Expression Recognition Using Convolutional Neural Network

Padmapriya K.C., Anna University, Chennai, India
Leelavathy V., Anna University, Chennai, India
Angelin Gladston, Anna University, Chennai, India

ABSTRACT

Human facial expressions convey a lot of information visually. Facial expression recognition plays a crucial role in the area of human-machine interaction. Automatic facial expression recognition system has many applications in human behavior understanding, detection of mental disorders, and synthetic human expressions. Recognition of facial expression by computer with high recognition rate is still a challenging task. Most of the methods utilized in the literature for the automatic facial expression recognition systems are based on geometry and appearance. Facial expression recognition is usually performed in four stages consisting of pre-processing, face detection, feature extraction, and expression classification. In this paper, the authors applied various deep learning methods to classify the seven key human emotions: anger, disgust, fear, happiness, sadness, surprise, and neutrality. The facial expression recognition system developed is experimentally evaluated with FER dataset and has resulted in good accuracy.

KEYWORDS

Convolution Neural Network, Facial Expression Recognition, Feature Extraction, FER Datasets, Haarcascade Classifier

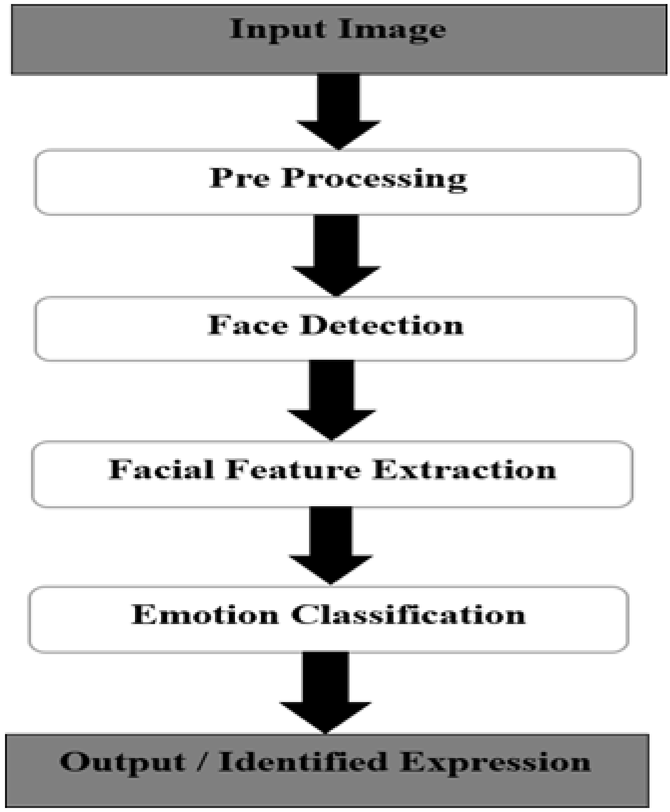
1. INTRODUCTION

"2018 is the year when machines learn to grasp human emotions" is a famous quote by Andrew Moore, dean of computer science at Carnegie Mellon. With the advent of modern technology, our desires went high and it binds no bounds. In the present decades enormous research works are taking place in the fields of digital image and image processing. Image Processing is a vast area of research in present day world and its applications are very widespread. One of the most important application of Image processing is Facial expression recognition. Our emotions are revealed by the expressions in our face. Facial Expressions plays an important role in interpersonal communication. Facial expression is a non-verbal scientific gesture which gets expressed in our face as per our emotions (Dai et. al., 2019).

Automatic recognition of facial expression plays an important role in artificial intelligence and robotics and thus it is a need of the generation. Some application related to this includes Personal identification and Access control, Videophone and Teleconferencing, Forensic application, Human-Computer Interaction, Automated Surveillance, Cosmetology and so on.

DOI: 10.4018/IJAIML.20210701.oa8

Figure 1. Steps in Facial Expression Recognition



The objective of this work is to enhance the automatic facial expression recognition which can take human facial images containing some expression as input and recognize and classify it into seven different expression classes such as neutral, angry, disgust, fear, happy, sadness and surprise with improved accuracy compared to the other available systems.

Human facial expressions can be easily classified into 7 basic emotions: happy, sad, surprise, fear, anger, disgust, and neutral (Dai et. al., 2019). 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 these metrics 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. To answer the question, in this work a deep learning neural network is devised that gives machines the ability to make inferences about our emotional states. As shown in Figure 1 such a facial expression recognition process involved the following steps: pre-processing of input images, detecting the face, extracting the facial features, and then finally classifying the emotions.

Thus facial expression recognition process comprises of:

1. Locating faces in the scene also named as face detection (Dai et. al., 2019);
2. Extracting facial features from the detected face region e.g., detecting the shape of facial components or describing the texture of the skin in a facial area; this step is referred to as facial feature extraction;
3. Analyzing the motion of facial features and/or the changes in the appearance of facial features and classifying this information into some facial-expression- interpretative categories such as facial muscle activations like smile or frown, emotion (affect) categories like happiness or anger, attitude categories like, liking, disliking and ambivalence. (Ismail et. al., 2019). This step is also referred to as facial expression interpretation.

Several works have already been done in this field and our goal is to model the Automatic Facial Expression Recognition with improved accuracy and the contribution in this paper is the recognition of emotions in multiple detected faces within a single frame captured from the live feed by the standard webcam. This is done by extending the openCV's Haar cascade classifier for finding the face co-ordinates of multiple faces in each frame. The contributions are tested with FER dataset images as well as with live feed by the standard webcam.

2. LITERATURE SURVEY

Jianzhu et. al., (2018) has mentioned emotion recognition has a key role in affective computing. Recently, fine-grained emotion analysis, such as compound facial expression of emotions, has attracted high interest of researchers working on affective computing. A compound facial emotion includes dominant and complementary emotions namely, happily-disgusted and sadly-fearful, which is more detailed than the seven classical facial emotions namely, happy, disgust, and so on. Current studies on compound emotions are limited to use data sets with limited number of categories and unbalanced data distributions, with labels obtained automatically by machine learning-based algorithms which could lead to inaccuracies.

To address these problems, they released the iCV-MEFED data set, which includes 50 classes of compound emotions and labels assessed by psychologists. The task is challenging due to high similarities of compound facial emotions from different categories. In addition, they have organized a challenge based on the proposed iCV-MEFED data set, held at FG workshop 2017. They have analyzed the top three winner methods and performed further detailed experiments on the proposed data set. Experiments indicated that pairs of compound emotion like, surprisingly-happy vs happily-surprised are more difficult to be recognized if compared with the seven basic emotions.

Tengfei et. al., (2019) to explore human emotions, in their work, designed and built a multi-modal physiological emotion database, which collects four modal physiological signals, i.e., electroencephalogram, galvanic skin response, respiration, and electrocardiogram. To alleviate the influence of culture dependent elicitation materials and evoke desired human emotions, they specifically collected an emotion elicitation material database selected from more than 1500 video clips. By the considerable amount of strict man-made labeling, they elaborately choose 28 videos as standardized elicitation samples, which are assessed by psychological methods. The physiological signals of participants were synchronously recorded when they watched these standardized video clips that described six discrete emotions and neutral emotion.

With three types of classification protocols, different feature extraction methods and classifiers, support vector machine and k-Nearest Neighbor were used to recognize the physiological responses of different emotions, which presented the baseline results. Simultaneously, they presented a novel attention-long short-term memory (A-LSTM), which strengthened the effectiveness of useful sequences to extract more discriminative features. In addition, correlations between the EEG signals and the participants' ratings are investigated.

Mustaqeem et. al., (2020) declared emotional state recognition of a speaker is a difficult task for machine learning algorithms which plays an important role in the field of speech emotion recognition (SER). SER plays a significant role in many real-time applications such as human behavior assessment, human-robot interaction, virtual reality, and emergency centers to analyze the emotional state of speakers. Previous research in this field is mostly focused on handcrafted features and traditional convolutional neural network (CNN) models used to extract high-level features from speech spectrograms to increase the recognition accuracy and overall model cost complexity. In contrast a novel framework for SER using a key sequence segment selection based on redial based function network (RBFN) similarity measurement in clusters was introduced. The selected sequence is converted into a spectrogram by applying the STFT algorithm and passed into the CNN model to extract the discriminative and salient features from the speech spectrogram.

Furthermore, they normalized the CNN features to ensure precise recognition performance and feed them to the deep bi-directional long short-term memory (BiLSTM) to learn the temporal information for recognizing the final state of emotion. They processed the key segments instead of the whole utterance to reduce the computational complexity of the overall model and normalize the CNN features before their actual processing, so that it can easily recognize the Spatio-temporal information. They evaluated over different standard dataset including IEMOCAP, EMO-DB, and RAVDESS to improve the recognition accuracy and reduced the processing time of the model, respectively.

Ismail et. al., (2019) recognized emotions for a text-independent and speaker-independent emotion recognition system based on a novel classifier, which is a hybrid of a cascaded Gaussian mixture model and deep neural network (GMM-DNN). This hybrid classifier has been assessed for emotion recognition on ''Emirati speech database (Arabic United Arab Emirates Database)'' with six different emotions. The sequential GMM-DNN classifier has been contrasted with support vector machines (SVMs) and multilayer perceptron (MLP) classifiers, and its performance accuracy is indexed at 83.97%, while the other two perform at 80.33% and 69.78% using SVMs and MLP, respectively. These results demonstrated that the hybrid classifier significantly gives higher emotion recognition accuracy than SVMs and MLP classifiers. Also, the performance of the classifier has been tested using two distinct emotional databases and in normal and noisy talking conditions. The dominant signal mask provided by the hybrid classifier offers better system performance in the presence of noisy signals. Dong et. al., (2020) said that recently, the performance of facial image-based emotion recognition has been improved with deep learning's power. Nonetheless, huge data and label information for training are burdensome. In particular, annotating emotion labels in the continuous domain is very costly. Thus, a novel semi-supervised learning that can not only reduce the annotation cost, but also improve emotion recognition performance by training with additional unlabeled data was introduced. The method employed deep metric learning to improve feature embedding performance. Also, pseudo labels of unlabeled data are produced by analyzing inter-data distance in the feature space. Since pseudo labeling makes unlabeled data trainable, it increases overall performance. The experimental results showed that the proposed method provides outstanding performance in the well-known MAHNOB-HCI dataset and the INHA dataset. Shan et. al., (2019) presented a novel facial expression database, Real-world Affective Face Database (RAF-DB), which contains approximately 30,000 facial images with uncontrolled poses and illumination from thousands of individuals of diverse ages and races. During the crowdsourcing annotation, each image is independently labeled by approximately 40 annotators. An expectation– maximization algorithm was used to reliably estimate the emotion labels, which reveals that real-world faces often express compound or even mixture emotions. A cross-database study between RAF-DB and CK+ database further indicates that the action units of real-world emotions are much more diverse than, or even deviate from, those of laboratory-controlled emotions.

To address the recognition of multi-modal expressions in the wild, a new deep locality-preserving convolutional neural network (DLP-CNN) method that aims to enhance the discriminative power of deep features by preserving the locality closeness while maximizing the inter-class scatter was introduced. Benchmark experiments on 7-class basic expressions and 11-class compound expressions, as well as additional experiments on CK+, MMI, and SFEW 2.0 databases, showed that their DLP-CNN outperformed the state-of-the-art handcrafted features and deep learning-based methods for expression recognition in the wild.

Shiqing et. al., (2018) motivated by the powerful feature learning ability of deep neural networks, proposed to bridge the emotional gap by using a hybrid deep model, which first produces audio–visual segment features with Convolutional Neural Networks (CNNs) and 3D-CNN, then fuses audio–visual segment features in a Deep Belief Networks (DBNs). Their method was trained in two stages. First, CNN and 3D-CNN models pre-trained on corresponding large-scale image and video classification tasks are fine-tuned on emotion recognition tasks to learn audio and visual segment features, respectively.

Second, the outputs of CNN and 3D-CNN models are combined into a fusion network built with a DBN model. The fusion network was trained to jointly learn a discriminative audio–visual segment feature representation. After average-pooling segment features learned by DBN to form a fixed length global video feature, a linear Support Vector Machine was used for video emotion classification. Experimental results on three public audio–visual emotional databases, including the acted RML database, the acted eNTERFACE05 database, and the spontaneous BAUM-1s database, demonstrated the promising performance of the proposed method.

Vaibhavkumar et. al., (2013) focused on various feature methods for recognizing human facial expression. A number of approaches have been developed for extracting features from face images are Principal Component Analysis (PCA), Linear Discriminate Analysis (LDA), Gabor Filter/Energy, Line Edge Mapping (LEM), Neural Network and Independent Component Analysis (ICA), Local Binary Pattern (LBP), Support Vector Machine, Active Appearance Model (AAM) and using SIFT descriptor.

Swati M and Avinash D (2013) used different methods of features extraction such as appearance based method, geometric based method, texture based method etc. were proposed. In the current research the mostly used methods are geometric based method and appearance based method. Geometric based feature extraction method, extract feature information using shape, distance and position of facial components and appearance based feature extraction method uses appearance information such as pixel intensity of face image. After getting the features, classification methods are applied to recognize facial expression.

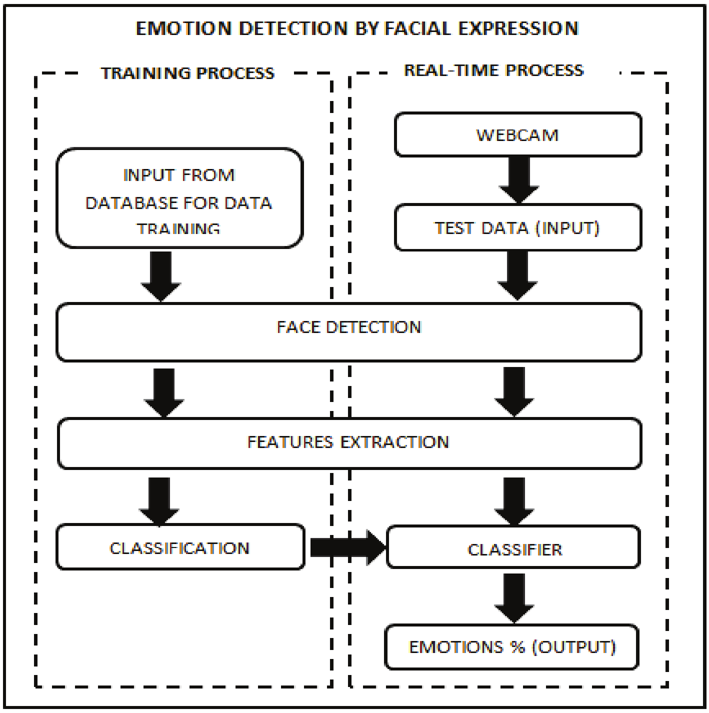
Alexandru S and James W (2017) worked on recognizing human emotion in the context of video footage or based on audiovisual data (mixing speech recognition and video techniques). Many papers seek to recognize and match faces, but most papers do not use convolutional neural networks to extract emotions from still images. An exception to this is a paper by Kahou et al. which actually trains a deep convolutional neural network on a set of static images, but then applies this to video data. Ekman, P. et. al., (1992) focused on issues relevant to the fact that voluntary facial action generated physiological changes. The key point of consideration is whether the voluntary facial muscular performances generate emotion of only the physiology of the emotion.

3. EXPERIMENTAL DESIGN

The overall design of the proposed multi-face emotion expression recognition is given in a detailed fashion in this section. The illustrative diagram as shown in Figure 2 shows the training process involved to develop the model and the testing involved. It includes the pre-processing, face detection, facial feature extraction and the emotion expression recognition.

Process flow involved, as per various literature surveys are the four basic steps which are required to be performed on a sequential basis: Preprocessing, Face registration, Facial feature extraction and Emotion classification.

Figure 2. Overall Block Diagram



3.1 Preprocessing

Preprocessing is a common name for operations with images at the lowest level of abstraction both input and output are intensity images. The preprocessing steps that are applied are reducing the noise, converting the image to binary/grayscale, pixel brightness transformation and geometric transformation.

3.2 Face Registration

Face Registration is a computer technology being used in a variety of applications that identifies human faces in digital images. In this face registration step, faces are first located in the image using some set of landmark points called "face localization" or "face detection" (Alexandru et. al., 2017). These detected faces are then geometrically normalized to match some template image in a process called "face registration".

3.3 Facial Feature Extraction

Facial Features extraction is an important step in face recognition and is defined as the process of locating specific regions, points, landmarks, or curves/contours in a given 2-D image or a 3D range image. In this feature extraction step, a numerical feature vector is generated from the resulting registered image (Vaibhavkumar et. al., 2013). Common features that can be extracted are lips, eyes, eyebrows and nose tip and in expression classification, the third step of classification, the classifier constructed and employed attempts to classify the given faces portraying one of the seven basic emotions.

4. EXPERIMENTAL RESULTS

This section presents the detailed implementation details of the proposed multi-face emotion expression recognition approach. The dataset used in the experimental study and the experimental details are given in detail. The various library packages used are OpenCV, Numpy, Numpy array, Scipy, Keras, Tensorflow, SYS, Sigmoid function and Softmax function.

4.1 Dataset

The dataset used for training the model is from a Kaggle Facial Expression Recognition Challenge a few years back (FER2013). The data consists of 48x48 pixel gray scale images of faces. The faces have been automatically registered so that the face is more or less centered and occupies about the same amount of space in each image. The task is to categorize each face based on the emotion shown in the facial expression in to one of seven categories, 0=Angry, 1=Disgust, 2=Fear, 3=Happy, 4=Sad, 5=Surprise and 6=Neutral (Swati et. al., 2013).

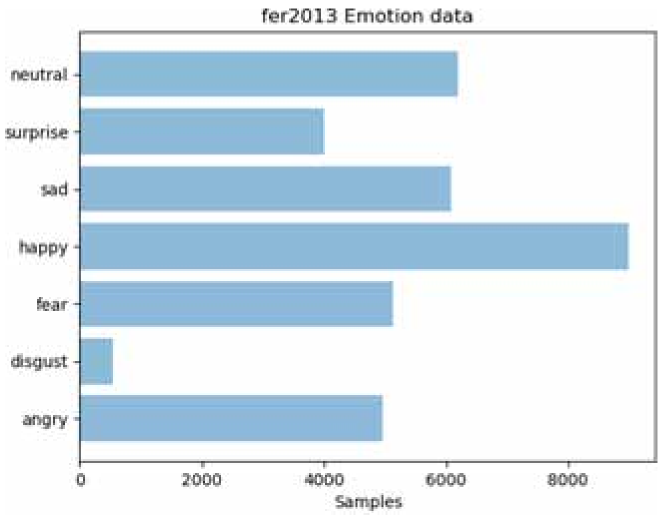
The training set as shown in Figure 3 consists of 28,709 examples. The public test set used for the leaderboard consists of 3,589 examples. The final test set, which was used to determine the winner of the competition, consists of another 3,589 examples. The images are labeled as 0 for the angry emotion and there are 4593 such images. For disgust the images are labeled as 1 and they are 547 in number. The label 2 is given for the emotion fear and the number of images under this class is 5121. There are 8989 images for the emotion happiness and they are labeled ad 3. 6077 images are accumulated under the class sadness. The label given to it is 4. Label 5 is given the emotion surprise and the number of images grouped under this class is 4002. 6198 images are considered for neutral expression and the label assigned is 6.

4.2 Haar Cascade Classifier in OpenCV

A Haar Cascade is basically a classifier which is used to detect the object for which it has been trained for, from the source. The Haar Cascade is trained by superimposing the positive image over a set of negative images. The training is generally done on a server and on various stages. The algorithm needs a lot of positive images that are images of faces and negative images that are images without faces to train the classifier. Then we need to extract features from it. The neural network contained a hidden layer with neurons. The approach is based on the assumption that a neutral face image corresponding to each image is available to the system. Each neural network is trained independently with the use of on-line back propagation.

The data used to build the final model usually comes from multiple datasets. In particular, three data sets are commonly used in different stages of the creation of the model. The model is initially fit on a training dataset that is a set of examples used to fit the parameters of the model. The model is trained on the training dataset using a supervised learning method namely gradient descent or stochastic gradient descent. The current model is run with the training dataset and produces a result, which is then compared with the target, for each input vector in the training dataset. Based on the result of the comparison and the specific learning algorithm being used, the parameters of the model are adjusted. Successively, the fitted model is used to predict the responses for the observations in a second dataset called the validation dataset. The validation dataset provides an unbiased evaluation of a model fit on the training dataset while tuning the model's hyper parameters. Validation datasets can be used for regularization by early stopping: stop training when the error on the validation dataset increases, as this is a sign of over fitting to the training dataset. This simple procedure is complicated in practice by the fact that the validation dataset's error may fluctuate during training, producing multiple local minima.

Figure 3. FER Dataset used in Experiments



4.3 Learning Procedure

Deep learning dominates computer vision studies in recent years. Even academic computer vision conferences are closely transformed into Deep Learning activities. Herein, convolutional neural networks are utilized to tackle this task. The model constructed is CNN with Keras using TensorFlow backend. The network model is constructed and trained. The first portion of the model consists of convolutional and max-pooling layers which act as the feature extractor. The second portion consists of the fully connected layer which performs non-linear transformations of the extracted features and acts as the classifier. Pooling layer is used immediately after the convolutional layer to reduce the spatial size. This reduces the number of parameters, hence computation is reduced. Using fewer parameters avoids overfitting.

To complete the training in less time, it is prefered to implement learning with randomly selected training set instances. That is the reason why train and fit generators are used. Also, loss function would be cross entropy because the task is multi class classification. The emotion detection for multiple faces is attempted using keras with tensorflow as backend. By extending openCV for multiple faces, the facial coordinates was obtained for more than one face present in a frame captured from the live video feed by the standard web cam.

5. RESULT ANALYSIS

This section presents the extensive result analysis of the experiments conducted with the help of webcam. The results presented are compared in the form of which emotions were identified for the same environmental conditions. The results from the standard webcam are shown wherein the emotions are identified with an accuracy rate of 70%. The results are displayed for all the seven emotions. Figure 4 illustrates facial emotion recognition from input images with single face.

Similarly, Figure 5 presents the facial emotion recognition from input images with multiple faces. It is inferred that the multiple faces could exhibit varied emotions as shown in Figure 5. On all validation and test sets the accuracy was higher than during the previous runs, underlining that more data and longer training can improve the performance of a network. Very high accuracy rates are obtained on happy 90%, neutral 80% and surprised 77%. These are in fact the most distinguishable facial expressions according to humans as well. Sad, fearful and angry were often misclassified as

Figure 4. Single face - various emotion recognition

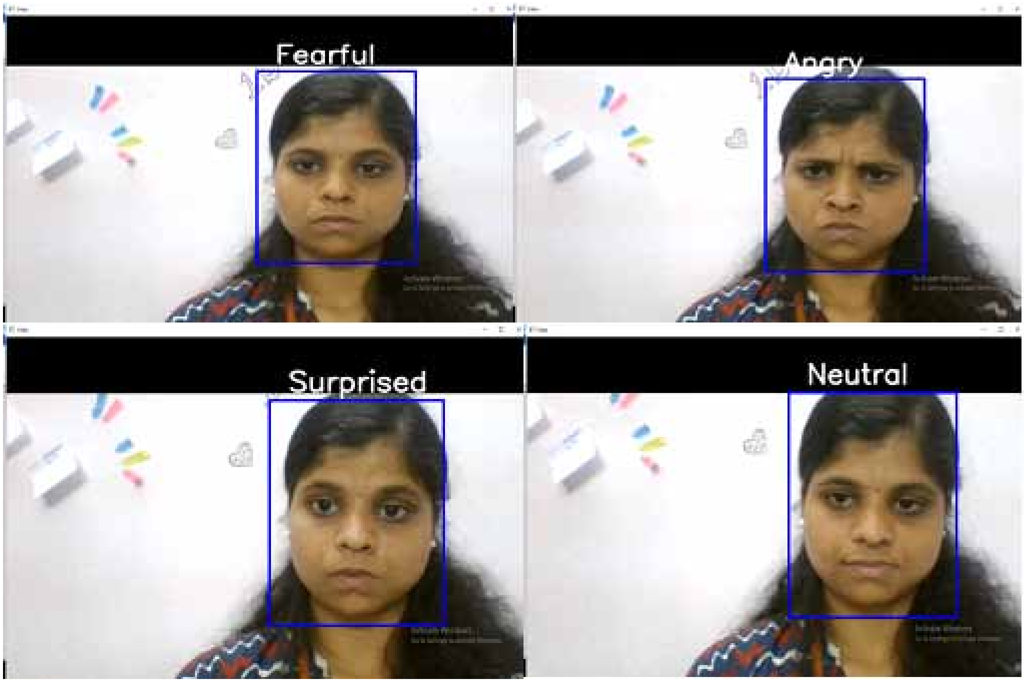


Figure 5. Multi-face emotion recognition

neutral too. The lowest accuracy was obtained in sad 28% and fearful 37%. Figure 6 plots the accuracy values obtained with increased number of epochs.

6. CONFUSION MATRIX FOR FER DATASET

Figure 7 as well as Figure 8 shows some of the images with various facial expressions for corresponding emotions. Confusion matrix obtained for the FER dataset used in the experiments is given in Figure 9. It shows that 642 happy images are recognized as happy emotions, 1035 neutral images are recognized

Figure 6. Accuracy of Emotion Recognition

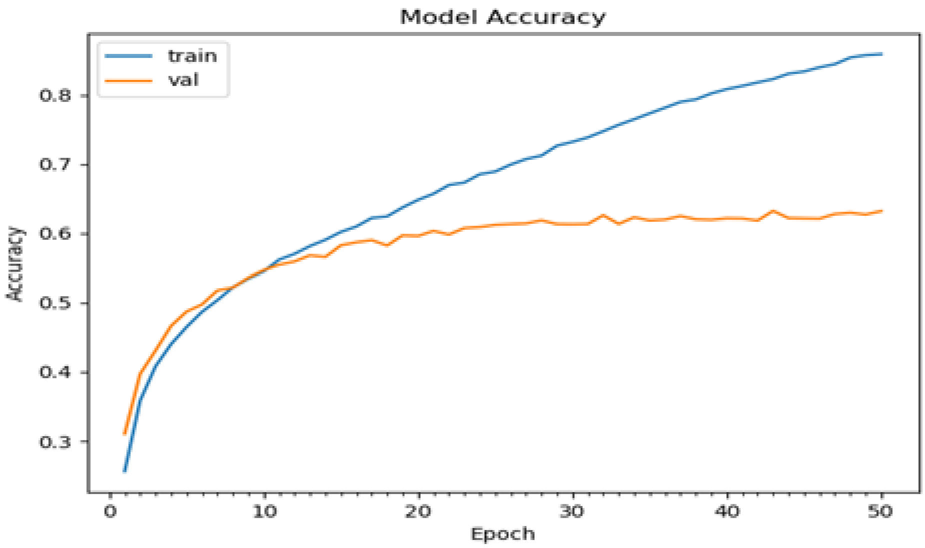


Figure 7. Images from FER Dataset

as neutral emotions, 287 sad images are recognized as sad emotions and 308 surprise images are recognized as surprise emotion.

From the confusion matrix obtained for the FER dataset used in the experiments as shown in Figure 9, the accuracy values of various emotions are obtained. The various emotions namely, angry, disgust, fear, happiness, neutral, sadness and surprise have obtained accuracy values of 53.52%, 36%, 46.46%, 69.03%, 80.23%, 63.50%, and 68.44% respectively. The graph plotting the various accuracy values are shown in Figure 10.

Typically, we can infer from the plotting that emotions neutral, happiness, sadness and surprise have been recognized with better accuracies. Emotions angry and fear are moderately recognized and disgust is the most hard to recognize emotion and further efforts on this could improve the accuracies.

Figure 8. More Emotions from FER Dataset

Figure 9. Confusion Matrix for FER Dataset

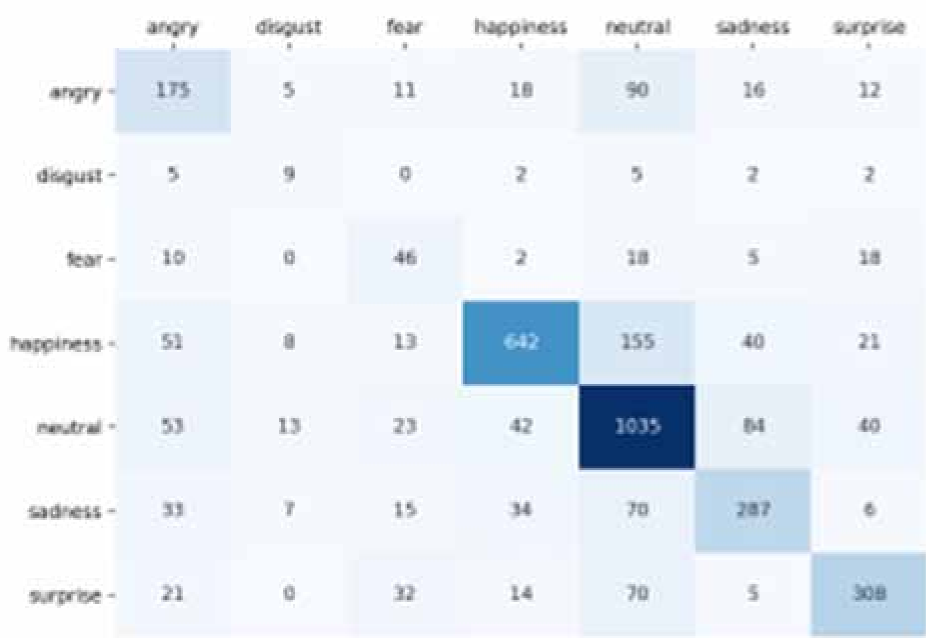
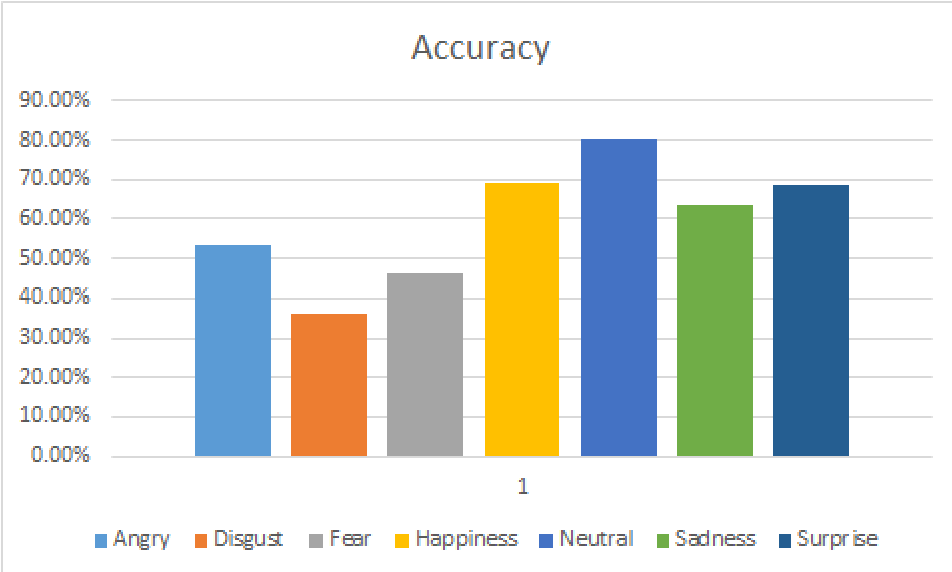


Figure 10. Accuracy values obtained for various Emotions



7. CONCLUSION

This paper presents a better model for recognizing facial emotions with multiple faces. In this work, even when the model predicts incorrectly, the correct label is often the second most likely emotion. The facial expression recognition approach presented in this work contributes a better face recognition model based on extraction of multi-face features and model construction based on those features. The physiological characteristics of the human face with relevance to various expressions such as happiness, sadness, fear, anger, surprise and disgust are associated with geometrical structures which restored as base matching template for the recognition system. The developed facial emotion recognition model has been experimentally evaluated with FER dataset as well as with live videos from web cam and has achieved good accuracy. The various emotions namely, happiness, neutral, sadness and surprise have obtained high accuracy values of 69.03%, 80.23%, 63.50%, and 68.44% respectively.

REFERENCES

Choi, D. Y., & Song, B. C. (2020). Semi-Supervised Learning for Continuous Emotion Recognition Based On Metric Learning. *IEEE Access: Practical Innovations, Open Solutions*, *8*, 113443–113455. doi:10.1109/ACCESS.2020.3003125

Ekman, P., Rolls, E. T., Perrett, D. I., & Ellis, H. D. (1992). Facial expressions of emotions: An old controversy and new finding discussion. *Pill Trans. Royal Soc. London Ser. B. Biol. Sci.*, *335*(1273), 63–69. doi:10.1098/rstb.1992.0008

Guo, J., Lei, Z., Wan, J., Avots, E., Hajarolasvadi, N., Knyazev, B., Kuharenko, A., Silveira Jacques, J. C. Junior, Baró, X., Demirel, H., Escalera, S., Allik, J., & Anbarjafari, G. (2018). Dominant And Complementary Emotion Recognition From Still Images Of Faces. *IEEE Access Special Section on Visual Surveillance And Biometrics: Practices, Challenges, and Possibilities*, *6*, 26391–26403. doi:10.1109/ACCESS.2018.2831927

Li, S., & Deng, W. (2019, January). Reliable Crowdsourcing and Deep Locality Preserving Learning for Unconstrained Facial Expression Recognition. *IEEE Transactions on Image Processing*, *28*(1), 356–375. doi:10.1109/TIP.2018.2868382 PMID:30183631

Mishra, S., & Dhole, A. (2013). A Survey on Facial Expression Recognition Techniques. *International Journal of Science and Research*. https://pdfs.semanticscholar.org/e241/25e4e9471a33ba2c7f0979541199caa02f8b.pdf

Mustaqeem, M. S., & Kwon, S. (2020). *Clustering-Based Speech Emotion Recognition by Incorporating Learned Features and Deep Bilstm* (Vol. 7). IEEE Access.

Savoiu, A., & Wong, J. (2017). *Recognizing Facial Expressions Using Deep Learning*. Stanford University. http://cs231n.stanford.edu/reports/2017/pdfs/224.pdf

Shahin, I., Bou Nassif, A., & Hamsa, S. (2019). Emotion Recognition using Hybrid Gaussian Mixture Model and Deep Neural Network. *IEEE Access: Practical Innovations, Open Solutions*, *7*, 26777–26787. doi:10.1109/ACCESS.2019.2901352

Song, T., Zheng, W., Lu, C., Zong, Y., Zhang, X., & Cui, Z. (2019). MPED: A Multi-Modal Physiological Emotion Database for Discrete Emotion Recognition. *IEEE Access: Practical Innovations, Open Solutions*, *7*, 12177–12191. doi:10.1109/ACCESS.2019.2891579

Vaibhavkumar, J. M., & Goyani, M. M. (2013). A literature survey on Facial Expression Recognition using Global Features. *International Journal of Engineering and Advanced Technology*. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.645.5162&rep=rep1&type=pdf

Yu, D., Liu, X., Dong, S., & Lei, Y. (2019). Group Emotion Recognition Based on Global and Local Features. *IEEE Access: Practical Innovations, Open Solutions*, *7*, 111617–111624. doi:10.1109/ACCESS.2019.2932797

Zhang, S., Zhang, S., Huang, T., Gao, W., & Tian, Q. (2018, October). Learning Affective Features With A Hybrid Deep Model For Audio–Visual Emotion Recognition. *IEEE Transactions on Circuits and Systems for Video Technology*, *28*(10), 3030–3043. doi:10.1109/TCSVT.2017.2719043

Padmapriya K. C. is an undergraduate student of the Department of Computer Science and Engineering, Anna University, Chennai. Her research interests include image processing and machine learning.

Leelavathy V. is an undergraduate student of the Department of Computer Science and Engineering, Anna University, Chennai. Her research interests include image processing and machine learning.

Angelin Gladston is working as Associate Professor at the Department of Computer Science and Engineering, Anna University, Chennai. Her research interests include software engineering, software testing, image processing, social network analysis, and data mining.