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Recognition of Human Emotions Using Advanced Deep Neural Networks

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ABSTRACT

Human emotion recognition systems have become an important component in various fields such as healthcare, education, security and mainly in human-computer interaction. Facial emotions are a form of nonverbal communication a person may use that provides additional meaning to verbal communication. An efficient system is required to understand these emotions and use them in further decisions and research. This paper is based on a system that is able to detect human emotions in real time using real cameras. This system integrates deep learning models with computer vision, which extracts unique features from the data provided to detect emotions in real time and also understand and respond to emotions accordingly.

Keywords: *Facial Emotions, Nonverbal Communication, Real Time Monitoring.*

1. INTRODUCTION

Human facial expression detection systems have the ability to recognize basic emotions that include happiness, surprise, fear, and sadness. Facial expressions play a significant role in this process because they closely mirror the inner feelings of an individual. The result is not only more efficient spoken communication but also clearer understanding. Human Computer Interaction (HCI) refers to any technology that allows humans to interact with computers. HCI needs emotional recognition systems as part of it since they are using a variety of computer tools to examine and comprehend human emotional states in real-time. Emotions are similar among persons irrespective of age or nationality but they can change according to aspects such as gender or race. It may be difficult to accurately detect these emotions given the variation in facial poses and small changes between expressions. In fields like healthcare and security, incorrect results could lead to serious consequences. Researchers have been working continuously to increase the precision levels of these systems at all times. Convolutional Neural Networks (CNN) are used for this purpose due to their efficiency in classification tasks. The aim is to understand human emotions by analyzing facial expressions which are a vital part of nonverbal communication. They take real-time facial expressions through emotion recognition systems and extract important features from each frame. Then they classify these features and express the detected emotion. They have numerous advantages across various fields such as they can be used in Healthcare to monitor how a patient feels and in Psychology. Police and security services use them to determine emotional state of individuals subjected to stress. In Education they detect how students react emotionally. In Marketing it uses them as predictors for consumers responses. Mental Health employs this technique when detecting different feelings expressed by people. The current project focuses on recognizing five emotions (happiness, fear, surprise, disgust, angry) for accurate results. There are possible ways of improving it later in order to widen the range of detectable emotions so that users can rely on it more. By developing these systems further researchers strive at narrowing the emotional gap with machines ultimately allowing more efficient human-computer interactions.

2. RELATED WORK

The paper Facial expression recognition using deep learning: review and insights [1] provides a review of recent advancements in automatic facial emotion recognition using deep learning techniques. It emphasizes the importance of this research field in various applications and highlighting the need for future research to address more complex emotional features.

Facial emotion detection and recognition [2] discusses the challenges and advancements in facial emotion detection and recognition using machine learning and deep learning algorithms. It also highlights the importance in various industries and human computer interaction. It has few challenges in accurately recognizing facial emotion states due to variations in expressions based on environment, appearance, culture and facial reactions.

A study on computer vision for facial emotion recognition [3] explores the use of deep neural networks for facial emotion recognition. It emphasizes the importance of non verbal communication, classification models, identification of facial features and visualization techniques in understanding the neural networks learning process. The limitations are noise, ambiguous and unclear scenes in the real world may affect the practical deployment of facial recognition systems.

Facial emotion recognition: State of the Art Performance on FER2013[4] achieves the highest single network classification accuracy on the FER2013 dataset. It explores different optimization techniques and generates maps to understand the network performance. This paper acknowledges the limitations of the black box nature of deep learning models which indicates a lack of interpretability in the model's decision-making process. They suggest to explore different image processing techniques and ensembles of deep learning architectures.

Facial emotion recognition using CNN [5] provides a detailed review of facial emotion recognition using traditional machine learning and deep learning methods which highlights the significance of FER. It also challenges in automating facial emotion detection and comparison of resource utilisation and accuracy between them. It discusses the importance of standard datasets for evaluating FER methods. It lacks systematic comparison between ML and DL methods. It needs large datasets and significant computational resources. It requires manually compiled and labelled datasets. It is very time consuming process.

Facial emotion recognition using CNN(FERC) [6] introduces a technique for recognition using CNN which is based on two part CNN. First focusing on background removal and second part is facial feature extraction. FERC was tested on various datasets and achieved accuracy of 96% in highlighting emotion with potential applications in fields like predictive learning of students and lie detection. It also has a image. It required high computing power during CNN tuning. Facial hair caused problems. No strong solution for orientation other than assuming facial symmetry.

A review on human facial emotion recognition system [7] provides a comprehensive overview of existing human emotion recognition techniques. It emphasizes the importance of automating facial emotion recognition systems for various applications. This study only focused on the classification of basic emotions. It used only single dataset. This study aimed to summarize existing techniques but did not propose a new comprehensive method. The complexity hindered achieving high recognition rates.

Facial emotion recognition [8] analyses facial expression which determines emotional states . it is used in privacy, discrimination, security and societal impact. Its limits in accuracy due to variations in expression among individuals and possibility of mixing different emotional states. It affect due to technical aspects like different camera angles, lighting conditions and obscured facial parts. Lack of explanation of the triggers of emotion leading to potential mis interpretation of emotional states.

3. METHODOLOGY

Data collection

Many experts from different institutions have generated several datasets to evaluate the methods for facial expression recognition. Among these datasets FER2013 is used for training, validation and test sets as introduced by ICML. FER2013 consists of 35888 images of 7 emotions. They are anger, neutral, disgust, fear, happiness, sadness and surprise which are also referred as labels to those emotions. The Kaggle forum discussion help by the competition organizers placed accuracy on this dataset in the range of 65%-68%.

Figure 1: Images of different emotions in FER2013

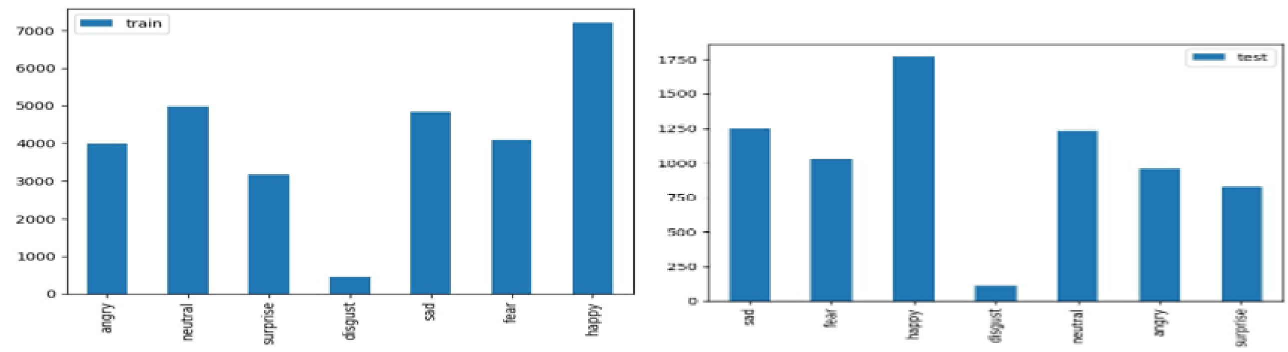

Figure2: Graph plotted to show number of images in dataset for various categories in train and test.

Data preprocessing in FER2013

The dataset used is already preprocessed using different methods and is suitable for analysis. The dataset is preprocessed using

Grayscale conversion: The FER2013 consists of Grayscale images which means that each image has only one colour channel. This helps in simplifying the data and reducing computational complexity because colour is not important for recognizing facial expressions.

Image Standardization: All images in the dataset are resized to a fixed size of 48x48 pixels. This is done to ensure the model has constant shape which is required for training neural networks. The method used is reshape (48,48) which helps in resizing the images.

$$Z = \frac{x-\mu}{\sigma} \qquad (1)$$

where x is the original value

μ is mean of data

σ is standard deviation

z is standardized value

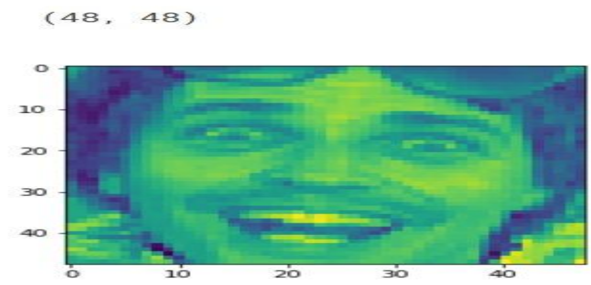

Figure 3: Resizing each image into 40x40 pixels

Normalization: pixel values of the images are normalized by scaling them to range of 0-1. This is done by dividing each pixel value by 255. it helps in speeding the training process.

$$x' = \frac{x-xmin}{xmax-xmin} \qquad (2)$$

where x is original value

xmin is minimum value in dataset

xmax is maximum value in dataset

x' is normalized value

Model building

A pretrained model which is trained using the FER2013 dataset is used. The model is trained using Convolutional neural network (CNN) which is highly effective for image classification tasks due to their ability to capture features in images through convolutional layers. It used the train data of dataset to train model through many iterations and test the model using test data. The process is carried out through following layers

- Input layer accepts the 48x48 grayscale images.
- Convolutional layer 1 applies 32 filters of size 3x3 to input image where each filter covers an image and performs a convolution operation. The activation function ReLu is used.
- Max Pooling layer 1 performs max pooling with 2x2 window. it makes the representation smaller and manageable.
- Convolutional layer 2 is same to first convolutional layer but it has 64 filters which helps in capturing more complex features.
- Max pooling layer 2 is similar to max pooling 1. it is used to reduce dimensions.
- Convolutional layer 3 adds more deep features to image.
- Max pooling 3 again reduces dimensions
- Flatten layer flattens the 2D feature maps into 1D vector.
- Fully connected layer 1 uses 128 units and ReLU activation function.
- Dropout layer drops few images with 0.5 dropout rate.
- Fully connected layer 2 uses 64 units and ReLU activation function.
- Output Layer classifies if the image belongs to any of 7 classes .it has SoftMax activation.

This model goes through 3 convolutional layers, 3 max pooling layers, 2 fully connected layers ,1 dropout layer and 1 output layer.

Formula for convolution layer

$$W\ out = \frac{W-F+2P}{S} + 1 \qquad (3)$$

Formula for pooling layer

$$W\ out = \frac{W-F}{S} + 1 \qquad (4)$$

Formula to calculate accuracy

$$accuracy = \frac{TP+TN}{TN+TP+FN+FP} \quad (5)$$

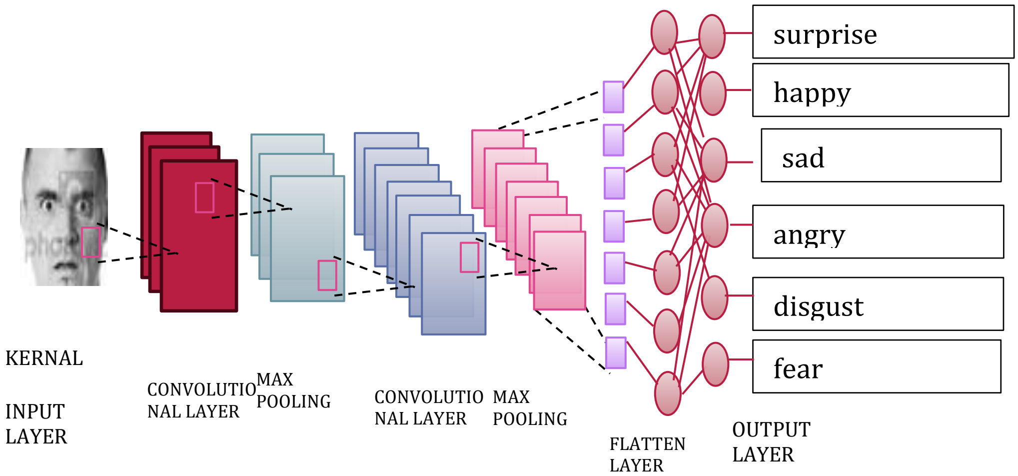

Figure 4: CNN Architecture for the Proposed System

4. IMPLEMENTATION

This system is been implemented in visual studio using python language.

Visual Studio Code(IDE)

It is a platform that is been used to develop the proposed system. This platform provides us immense features like inbuilt debugger, multiple language support amd tools or extensions for various framework. This helps in easy development of machine learning applications as it can easily implement any complex algorithm and provide accurate results.

Python Programming

It is a framework we used to develop the proposed system . It provided various libraries that is required to implement deep learning algorithms. Few libraries that are used in the proposed system are NumPy is used to convert the data into numerical array. Pandas is used in data preprocessing. Scikit-learn is used to implement classification. tensorFlow is used to train neural networks. Matplotlib is used to plot graphs. Tkinter is used to create Graphical User Interface. cv2 is used for computer vision and image processing. Os is used to interact with the operating system.

5. RESULTS

Using the pretrained model with FER2013 dataset the system achieved accurate results in predicting the emotions in real time. The system is able to predict different emotions and also it can detect multiple person at same time. The accuracy for training the model is obtained as:

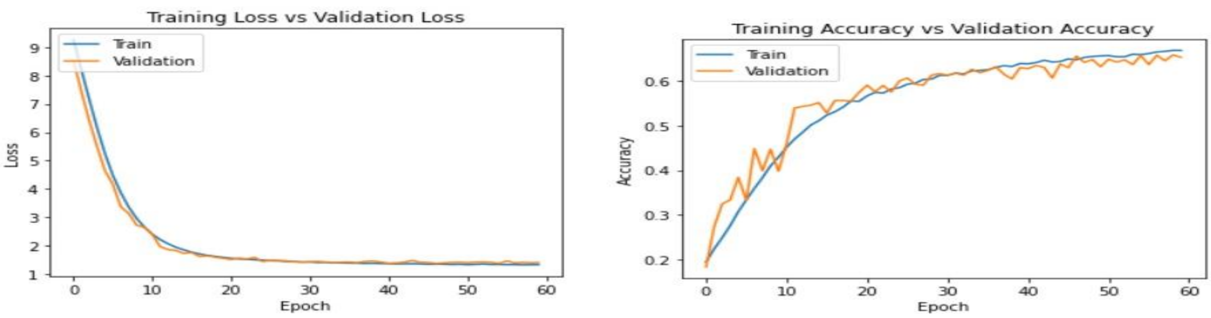

Figure 5: Graph To Show Accuracy In Training And Validation Of The System

6. CONCLUSION

The human emotion detection system is potential to detect the human emotions that are captured at real time. This system uses Machine Learning and Computer Vision to detect the human expressions. It is of great importance in various applications in AI like Health care, security and human computer interaction. This paper presents an overview of the Human Emotion Detection System that is able to classify different emotions of different individual. In future we can enhance the system by increasing the size of dataset used to train the model and adding more classes into the system that will make it more reliable and consistent.

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