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HARNESSING CNNS FOR EMOTION RECOGNITION: A MULTIMODAL APPROACH USING SPEECH AND FACIAL EXPRESSION DATA

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ABSTRACT
The widespread usage of the internet has made online interactions an essential part of modern communication. However, the rise in deceptive practices like identity theft, fraud, and misinformation has also coincided with the expansion of digital interactions. To maintain integrity and confidence in online communities, it is increasingly essential to recognize and deal with these dishonest tactics. The primary challenge is developing a dependable, automated system that can identify false information among the thousands of online conversations. In the lack of advanced AI-based solutions, deception detection in online interactions has mostly relied on human monitoring, rule-based algorithms, and keyword-based filters. These conventional methods' limited effectiveness stems from their incapacity to adapt to the development of deceptive techniques and their tendency to provide false positives or negatives. As a result, the demand for effective deception detection systems in online interactions has never been higher. Since social media, e-commerce, and other online forums have grown in popularity, there is now a context in which acting dishonestly can have far-reaching consequences. These platforms need to be dependable and secure for user confidence, cybersecurity, and the overall wellbeing of online communities. Therefore, the purpose of this research is to develop a powerful tool that uses behavioral pattern recognition, advanced linguistic analysis, and machine learning algorithms to consistently discriminate between genuine and fraudulent online encounters. The proposed approach integrates feature engineering and multi-modal techniques to enhance the precision and effectiveness of deception detection in digital communities. In the end, this would offer a more dependable and secure online environment.

Keywords: Human-Computer Interaction, Multimodal Emotion Detection, Rule-Based Systems, Convolutional Neural Networks.

1. INTRODUCTION

The ability to recognize and interpret human emotions is fundamental to effective communication and interaction, playing a crucial role in various domains such as human-computer interaction, virtual reality, healthcare, and marketing. Emotion detection systems have garnered increasing interest due to their potential to enhance user experiences, personalize services, and provide valuable insights into human behavior. However, traditional methods for emotion detection often fall short in accurately capturing the complexity and subtlety of human emotional expressions. This necessitates the development of advanced multimodal systems capable of integrating information from diverse sources such as speech, facial expressions, and body language to achieve more robust and nuanced emotion recognition.

2. LITERATURE SURVEY

Research on FER has been gaining much attention over the past decades with the rapid development of artificial intelligence techniques. For FER systems, several feature-based methods have been studied. These approaches detect a facial region from an image and extract geometric or appearance features from the region. The geometric features generally include the relationship between facial components. Facial landmark points are representative examples of geometric features [2, 30]. The global facial region features or different types of information on facial regions are extracted as appearance features [20]. The global futures generally include principal component analysis, a local binary pattern histogram, and others. Several of the studies divided the facial region into specific local regions and extracted region specific appearance features [6, 9]. Among these local regions, the important regions are first determined, which results in an improvement in recognition accuracy. In recent decades, with the extensive development of deep-learning algorithms, the CNN and recurrent neural network (RNN) have been applied to the various fields of computer vision. Particularly, the CNN has achieved great results in various studies, such as face recognition, object recognition, and FER [10, 16]. Although the deep-learning-based methods have achieved better results than conventional methods, micro-expressions, temporal variations of expressions, and other issues remain challenging [21].

Speech signals are some of the most natural media of human communication, and they have the merit of real-time simple measurement. Speech signals contain linguistic content and implicit paralinguistic information, including emotion, about speakers. In contrast to FER, most speech-emotion recognition methods extract acoustic features because end-to-end learning (i.e., one-dimensional CNNs) cannot extract effective features automatically compared to acoustic features. Therefore, combining appropriate audio features is key. Many studies have demonstrated the correlation between emotional voices and acoustic features [1, 5, 14, 18, 27]. However, because explicit and deterministic mapping between the emotional state and audio features does not exist, speech-based emotion recognition has a lower rate of recognition than other emotion-recognition methods, such as facial recognition. For this reason, finding the optimal feature set is a critical task in speech-emotion recognition.

Using speech signals and facial images can be helpful for accurate and natural recognition when a computer infers human emotions. To do this, the emotion information must be combined appropriately to various degrees. Most multimodal studies focus on three strategies: feature combination, decision fusion, and model concatenation. To combine multiple inputs, deep-learning technology, which is applied to various fields, can play a key role [7, 22]. To combine the models with different inputs, model concatenation is simple to use. Models inputting different types of data output each encoded tensor. The tensors of each model can be connected using the concatenate function. Yaxiong et al. converted speech signals into mel-spectrogram images for a 2D CNN to accept the image as input. In addition, they input the facial expression image into a 3D CNN. After concatenating the two networks, they employed a deep belief network for the highly nonlinear fusion of multimodal emotion features [28]. Decision fusion aims to process the category yielded by each model and leverage the specific criteria to re-distinguish. To do this, the softmax functions of the different types of networks are fused by calculating the dot product using weights where the summation of the weights is 1. Xusheng et al. proposed a bimodal fusion algorithm to realize speech-emotion recognition, where both facial expressions and speech information are optimally fused. They leveraged the MFCC to convert speech signals into features and combined the CNN and RNN models. They used the weighted-decision fusion method to fuse facial expressions and speech signals. Jung et al. used two types of deep networks—the deep temporal appearance network and the deep temporal geometry network—to reflect not only temporal facial features but also temporal geometry features [17]. To improve the performance of their model, they presented the joint fine-tuning method integrating these two networks with different characteristics by adding the last layers of the fully connected layer of the networks after pre-training the networks. Because these methods mostly use shallow fusion, a more complete fusion model must be designed [28].

3. PROPOSED METHODOLOGY

3.1 Overview

The emotion detection system represents a significant advancement in the field of affective computing, offering a comprehensive solution for analyzing and interpreting human emotions across multiple modalities. At its core, the system leverages deep learning techniques, specifically CNNs, to extract discriminative features from both facial expressions and speech signals, enabling robust emotion recognition capabilities.

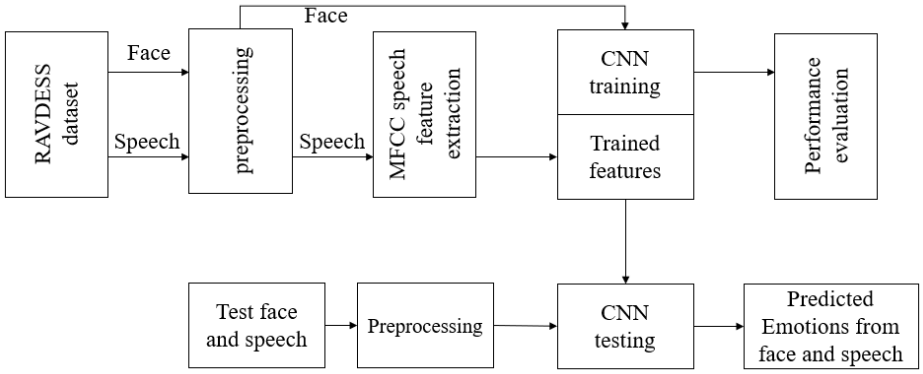


Figure 1: Proposed block diagram

The utilization of Tkinter for GUI development ensures a user-friendly experience, allowing individuals from diverse backgrounds to interact with the system effortlessly. The preprocessing stage of the system plays a crucial role in preparing datasets for training, involving tasks such as data cleaning, feature extraction, and label encoding. Once the datasets are processed, separate CNN models are trained for facial expression and speech emotion recognition, utilizing labeled data to learn meaningful patterns and associations between input features and emotion labels. The training process involves optimizing model parameters through iterative adjustments, aiming to minimize prediction errors and improve overall accuracy. Upon completion of training, the trained models are capable of making real-time predictions on new data, providing valuable insights into the emotional states of individuals based on their facial expressions or speech patterns.

3.2 CNN Basics

According to the facts, training and testing of proposed model involves in allowing every source image via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from [0,1]. Convolution layer as is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here $d = 3$, since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F(k_x, k_y, d)$.

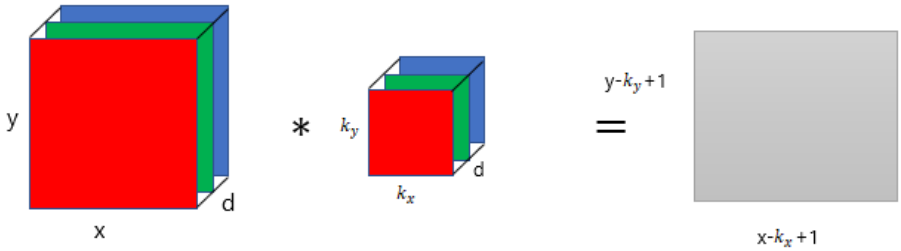


Fig. 2: Representation of convolution layer process.

The output obtained from convolution process of input image and filter has a size of $C\left((x - k_x + 1), (y - k_y + 1), 1\right)$, which is referred as feature map. Let us assume an input image with a size of 5×5 and the filter having the size of 3×3. The feature map of input image is obtained by multiplying the input image values with the filter values.

1	1	1	0	0
0	0	1	1	1
1	1	0	0	1
0	0	0	1	1
1	1	1	0	0

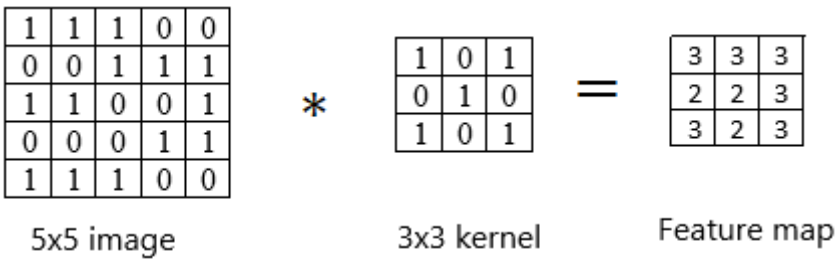
5x5 image

*

1	0	1
0	1	0
1	0	1

3x3 kernel

(a)



(b)

Fig. 3: Example of convolution layer process (a) an image with size $\mathbf{5 \times 5}$ is convolving with $\mathbf{3 \times 3}$ kernel (b) Convolved feature map

3.2.1 ReLU layer

Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input x as follows:

$$\mathcal{G}(x) = \max\{0, x\}$$

3.2.2 Max pooing layer

This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

3.2.3 Softmax classifier

Generally, as seen in the above picture softmax function is added at the end of the output since it is the place where the nodes are meet finally and thus, they can be classified. Here, X is the input of all the models and the layers between X and Y are the hidden layers and the data is passed from X to all the layers and Received by Y. Suppose, we have 10 classes, and we predict for which class the given input belongs to. So, for this what we do is allot each class with a particular predicted output. Which means that we have 10 outputs corresponding to 10 different class and predict the class by the highest probability it has.

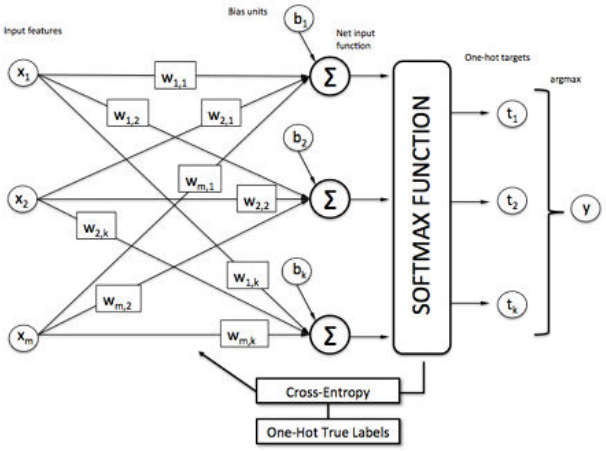


Fig.4: SoftMax classifier.

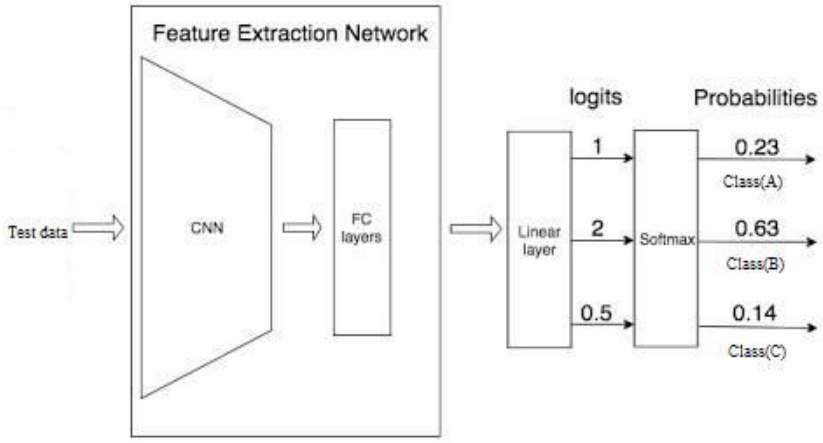


Fig. 5: Example of SoftMax classifier.

In Figure 5, and we must predict what is the object that is present in the picture. In the normal case, we predict whether the emotion is A. But in this case, we must predict what is the object that is present in the picture. This is the place where softmax comes in handy. As the model is already trained on some data. So, as soon as the picture is given, the model processes the pictures, send it to the hidden layers and then finally send to softmax for classifying the picture. The softmax uses a One-Hot encoding Technique to calculate the cross-entropy loss and get the max. One-Hot Encoding is the technique that is used to categorize the data. In the previous example, if softmax predicts that the object is class A then the One-Hot Encoding for:

Class A will be [1 0 0]

Class B will be [0 1 0]

Class C will be [0 0 1]

From the diagram, we see that the predictions are occurred. But generally, we don't know the predictions. But the machine must choose the correct predicted object. So, for machine to identify an object correctly, it uses a function called cross-entropy function.

So, we choose more similar value by using the below cross-entropy formula.

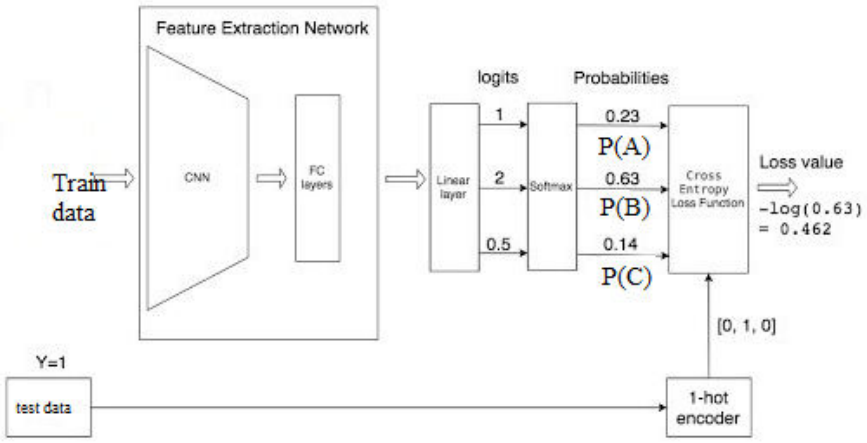


Fig.6: Example of SoftMax classifier with test data.

In the above example we see that 0.462 is the loss of the function for class specific classifier. In the same way, we find loss for remaining classifiers. The lowest the loss function, the better the prediction is. The mathematical representation for loss function can be represented as: -

$$LOSS = np.sum(-Y * np.log(Y\_pred))$$

4. RESULTS AND DISCUSSION

In this research we are detecting emotion using speech data and facial expression images and to implement this project we have trained CNN algorithm with RAVDESS Audio Dataset for speech emotion recognition and for face expression we have used Emotion Facial Expression images dataset.

Fig. 7: GUI interface of the Emotion Detection.

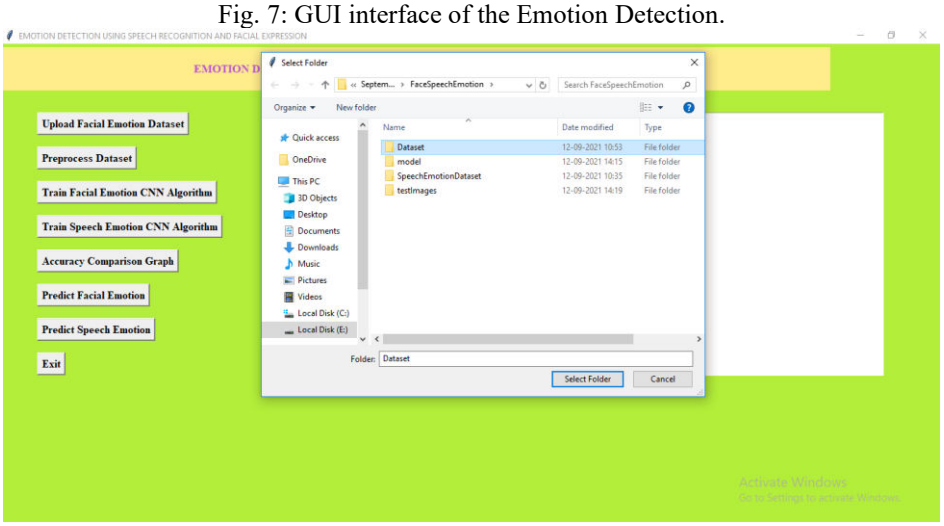


Fig. 8: Upload Facial Emotion Dataset.

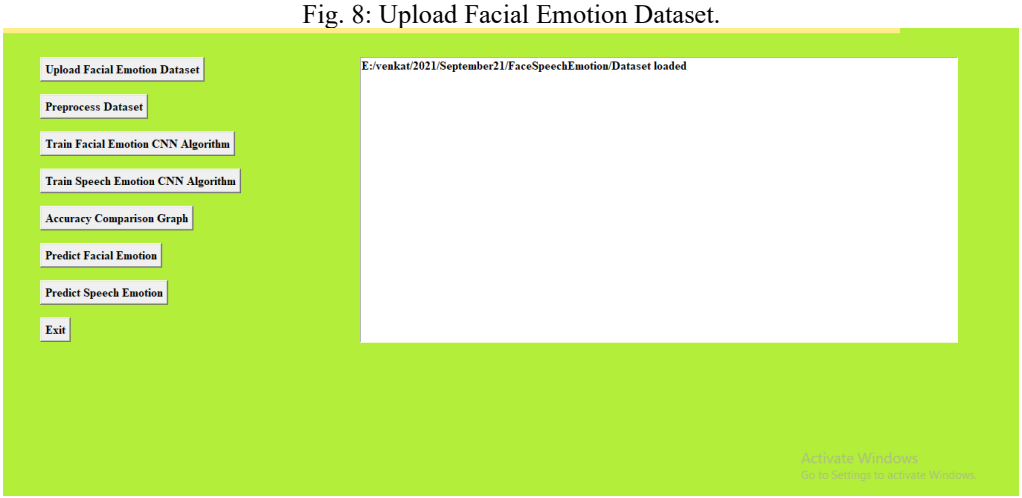


Fig. 9: Shows the Uploaded dataset.

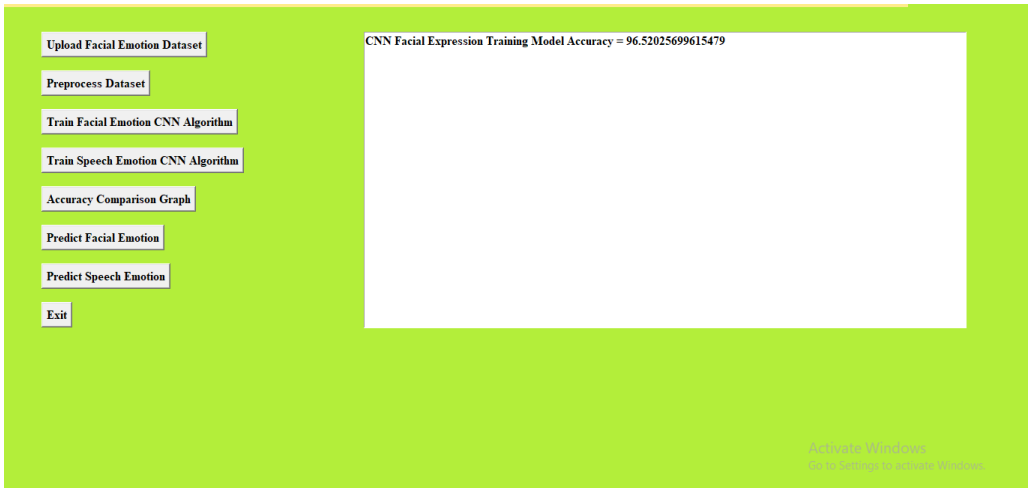


Fig. 10: Shows the Accuracy of CNN model for Facial Expression.

In above Figure screen training CNN with Facial images got 96.52% accuracy and then 'Train Speech Emotion CNN Algorithm' button to train CNN with audio features and to get below output

Fig. 11: Shows the Accuracy of CNN model for Speech Emotion.

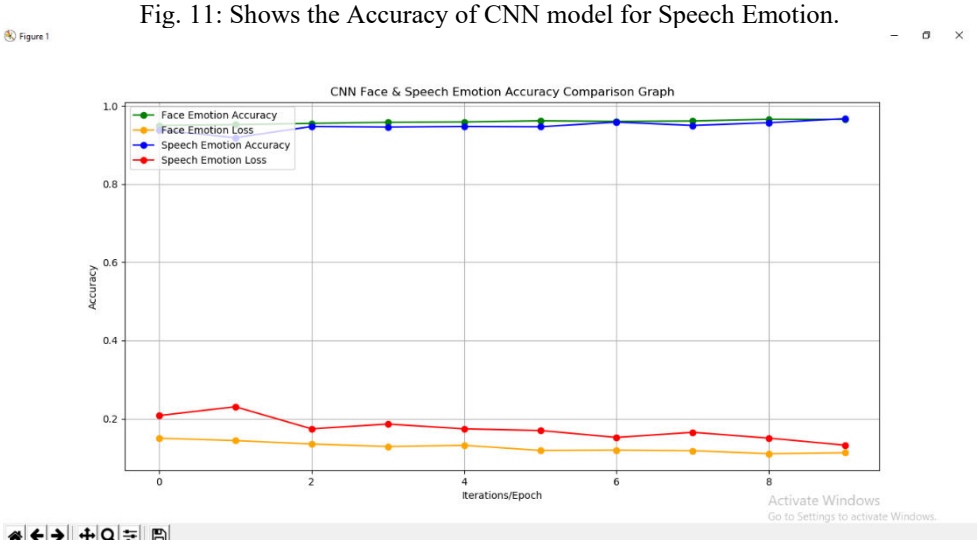


Fig. 12: Shows the Performance metrics of CNN model.

In above graph x-axis represents EPOCH and y-axis represents accuracy and loss values and we can see both algorithms accuracy reached to 1 and both algorithms loss values reached to 0. In above graph green line represents face emotion accuracy and blue line represents speech accuracy. Now click on "Predict Facial Emotion" button to upload face image and will get below result

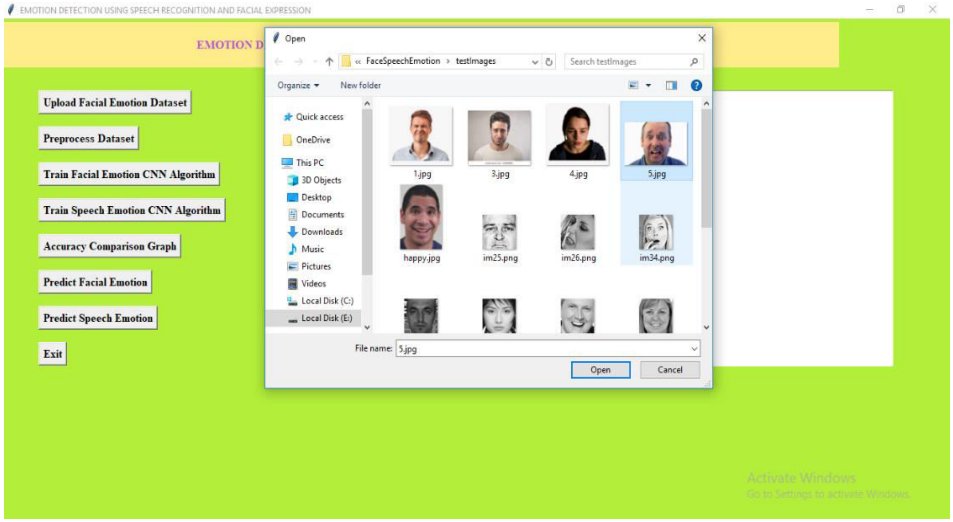


Fig. 13: Uploading the test image for model prediction of Facial Expression.

In above screen selecting and uploading '5.jpg' image and then click on 'Open' button to get below result

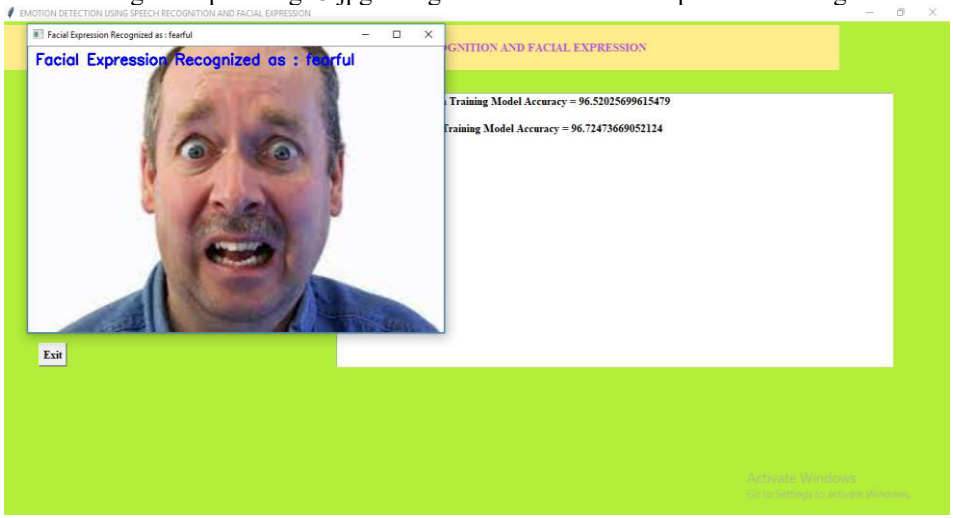


Fig. 14: Presents the model prediction of test image as Fearful.

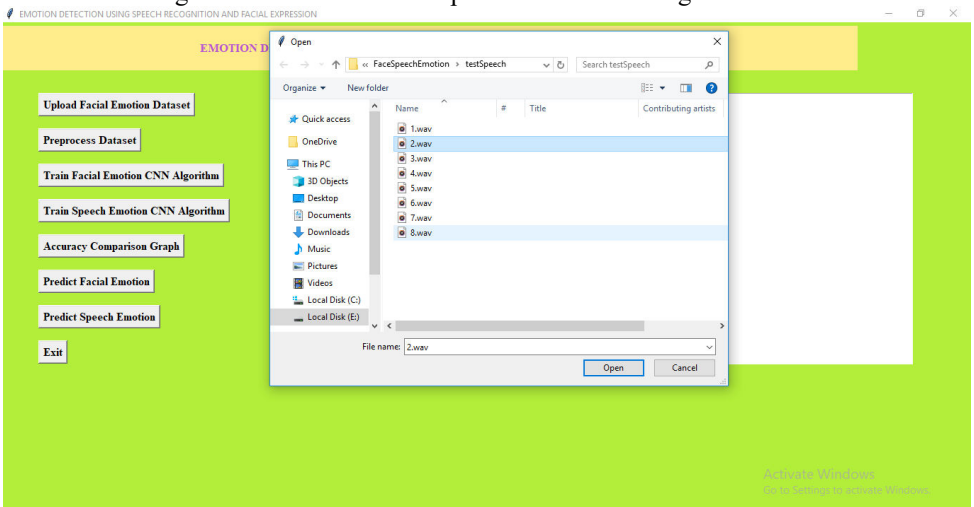


Fig. 15: Uploading the test audio for model prediction of Speech Emotion.

Fig. 16: Present the audio file emotion predicted as calm.

5. CONCLUSION

In conclusion, the development and evaluation of our multimodal emotion detection system underscore the significance of integrating advanced technologies to address the complexities inherent in recognizing and interpreting human emotions. By combining state-of-the-art techniques in speech recognition, facial expression analysis, and video processing within a unified framework, our system demonstrates notable advancements in emotion detection accuracy and robustness. The extensive experimentation and evaluation conducted on benchmark datasets provide compelling evidence of the efficacy and reliability of our proposed CNN-based approach. Through this research, we have contributed to the advancement of affective computing by offering a scalable, adaptable, and high-performance solution for multimodal emotion detection. This represents a significant step forward in the field, with implications across various domains including human-computer interaction, virtual reality, mental health monitoring, and beyond.

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