National College of Ireland

A Versatile Emotion Detection System: Independent Models for Image, Video, and Audio Analysis

MSc Research Project
Masters in Artificial Intelligence

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MSc Project Submission Sheet

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Student Name:	Mayank Pokhriyal
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Programme:	Artificial Intelligence **Year:** 2024
Module:	MSc. Practicum
Supervisor:	Anderson Simiscuka
Submission Due Date:	12th December 2024
Project Title:	A Versatile Emotion Detection System: Independent Models for Image, Video, and Audio Analysis
Page Count:	25
Word Count:	10426

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A Versatile Emotion Detection System: Independent Models for Image, Video, and Audio Analysis

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Abstract

Facial expressions are crucial aspects of human interpersonal communication and business that shape the sphere of healthcare and other professions, as well as human-machines interactions. In this thesis, several methods are introduced based on deep learning for emotion recognition. The reported idea is to offer emotion detection services adaptable to the needs of the customer and the type of signal, whether image, live camera feed, video or audio. For image emotion recognition, several CNN architectures, including the VGGNet and ResNet50, were used and then were trained with transfer learning on large facial emotion databases. Techniques for augmenting the data set, tuning of its hyperparameters and class weight balancing were also employed to enhance the effectiveness of the above models.

In the context of detecting emotions from audio, Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) networks were used for processing speech signals and for predicting the emotional states based on extracted acoustic parameters.

The performance of each model was separately assessed based on benchmark data set, however, to measure the functionality of the complete system, it was examined on live video stream and recorded media files. Thus, experimental evaluation reveals that the models produce satisfactory accuracy, precision, recall, and F1-score, which show good performance for various input modalities. This makes the proposed solutions flexible enough to enable users to select the most appropriate emotion detection approach for their given application environment, regardless of the context of use or the type of data that is being used. This work discusses the prospects and limitations of emotion recognition and offers a systematic approach to construct accurate, individual-focused emotion identification systems to be implemented in practical applications.

1 Introduction

1.1 Background and Motivation

Emotions are inseparable from the context of human communication for they manage the process of thinking, acting and interpersonal relations. Emotion perception and recognition can go a long way toward human–machine interface improvement; therefore, they are the gateway to empathetic and intelligent living environments (Calvo & D'Mello, 2010). In the present era, where many applications of artificial intelligence (AI) and machine learning (ML) are being seen, emotion detection turns out to be one of the important research areas that can bring great changes in the present sectors like healthcare and in human computer interaction (HCI) (Picard, 1997; Zeng et al., 2009). In healthcare domain emotion detection can help in identifying a particular mental condition or in general status of patient (Rana et al., 2021).

The first generation of emotion recognition systems were quite simple as most of the systems only used either visual or auditory data but since human emotions are recognized to be fully fledged both visually and auditorily, the method failed to give general and accurate forecast of human emotions (Pantic & Rothkrantz, 2003). The given models for a variety of data types have a separate approach for emotion detection that helps in choosing the right approach according to the need as image emotion detection and video emotion detection, audio emotion detection from static images, live videos, and audio (Baltrusaitis et al., 2018).

1.2 Problem Statement

Despite the advances in AI and deep learning, accurately detecting human emotions remains a challenging task due to several factors:

One main reason is that individuals do not display their emotions in standard ways because emotion is best observed as culture, societal level, and individual (Ekman, 1992). Lighting condition, occlusions, background noise, and difference in microphone devices considerably influence the performance of the emotion detection systems (Kossaifi et al., 2020). There also lies ambiguity and overlap in emotions. For example, the object of fear and the object of surprise or anger and the object of disgust are built from similar visual or acoustic concepts (Schuller et al., 2018). Probably one of the biggest challenges with using emotion data sets is the fact that data sets are skewed towards some emotions, and this means that the models will always be skewed to these emotions (Mollahosseini et al., 2016).

Based on these challenges, this thesis discusses the creation of multiple single emotion detection systems that use deep learning models to process data from distinct modalities, including facial images, videos, and audio during a separate step.

1.3 Objectives of the Thesis

The main objectives of this thesis are as follows:

To construct and develop an image-based emotion recognition using deep learning techniques like CNN's, VGG Net, Res Net 50. Data augmentation strategies are used to increase the size of the dataset and to enrich the model results in this work (He et al., 2016).

To provide specifications for video-based emotion recognition system, which should be designed to scan real-time video streams to determine the amount of change in emotions within the span of a certain time (Zhang et al., 2018).

For the development of the emotion recognition application based on the audio data with the use of Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, speech signals are considered for emotion prediction (Satt et al., 2017).

One approach includes enabling the users to have an individual emotion detection technique for images, videos, as well as audio, to opt for the system most appropriate for their application and place of operation.

For benchmark datasets and real-time inputs, to assess the accuracy, precision, recall, F1-score to compare performance with the proposed emotion detection system each identified below.

1.4 Contributions of the Thesis

This thesis makes the following key contributions:

Comprehensive Literature Review: - Proposed systematically structured survey of the earlier published work on emotion detection, encompassing the innovations as well as novelties of conventional and deep learning techniques (Zeng et al., 2009; Baltrusaitis et al., 2018).

Development of Image-Based Emotion Detection Models: - Emotion recognition from image by using the models developed by Convolutional Neural Network such as VGGNET and ResNET50 and the cross-validation as the techniques for tuning of hyperparameters and data augmentation (He et al., 2016).

Audio-Based Emotion Recognition System: - An emotion recognition system that includes the receipt of the acoustic signals of the event as the input, followed by the extraction of descriptors like Mel-Frequency Cepstral Coefficients (MFCCs) from the signals and feeding this input through a machine learning model like SVM or Fully connected neural network to classify the emotion to certain bins of acoustic content of speech (2017).

Video-Based Emotion Analysis: - Adaptation of an application to flag moments that the performer deems most important during the show or when watching a video on the linked device with live or saved links (Zhang et al., 2018).

User-Centric Approach: - One of the top strengths in the current work is offering simplified mood analyzing and perceiving models that can be implemented easily depending on the requirement of the user whether it is in the field of image evaluation, video stream, or audio (Baltrusaitis et al., 2018).

Experimental Validation: - A thorough evaluation of the four proposed models and their accuracy when tested on six benchmark datasets available to the public and where the efficiency when real-world is highlighted (Kossaifi et al., 2020).

1.5 Thesis Structure

Abstract: - It summarizes the entire thesis in a simple manner to reveal the detailed objectives, methodology, the findings and conclusions will be made.

Chapter 1 Introduction: - This section contains background, motivation, problem statement, research objectives, and the contribution of the thesis.

Chapter 2 Literature Review: - Explores the past studies made on the identification of emotion by means of conventional techniques and deep learning techniques.

Chapter 3 Proposed Methodology: - This section lists the datasets which are used to analysis, preprocessing is done on the data, and the architecture of the models used in identifying the emotions.

Chapter 4 Implementation: - Explains how the model training, tuning of hyperparameters and an assessment of the entire scope of the emotion detection systems was done.

Chapter 5 Evaluation: - Includes comparative analysis of the experimental outcomes with the already proposed algorithms.

Chapter 6 Conclusion and Future Work: - Presents an outline of the research investigation and mentions the future research direction in emotion detection.

Chapter 7 References: - For referencing all the citations used in the thesis.

2 Literature Review

2.1 Introduction

Emotion recognition is one of the emerging focal areas in artificial intelligence as well as human-computer interaction. Emotional intelligence is vital when it comes to health care, teaching, customer relations, advertising and entertainment industries among others (Picard, 1997). The need for emotion detection systems is attributed to the potential to enhance human to machine interface specifically, through natural emotions that are close to reality.

There has been a lot of work over the years to categorize emotion recognition and differentiation based on the modality such as facial and vocal expressions and text. These approaches can be categorized into image-based emotion recognition, Live video-based emotion recognition, recorded video-based emotion recognition and audio-based emotion recognition. Each of the modalities brings different information of emotion and identifying the most appropriate approach is based on the application and data available (Zeng et al., 2009).

2.2 Facial Images to Detect Emotion

Action units on the face show one of the more simplistic manners in which the emotion of a human being can be predicted. The works carried out in this area have moved dramatically from hand sculptured features and feature based methods to deep learning-based methods (Ekman, 1992).

2.2.1 Traditional Methods

Facial emotion recognition systems developed in earlier years used the concept of hand-crafted features which were either extracted by bare hands or from using statistical techniques.

Eigenfaces and Fisherfaces: - Eigenfaces as an algorithm was developed by Turk and Pentland (1991) where Eigenfaces represented face images as linear combinations of basis faces obtained via PCA. Although it worked

well in conditions with consistent lighting, its face recognition failed on poses, fortuitous lighting and different expressions. Fisherfaces built upon this further by using LDA to enhance the discriminant nature of the features (Belhumeur et al., 1997).

Facial Action Coding System (FACS): - FACS, Facial Action Coding System is a manual system that attempts to code aspects of facial muscle movements that are associated with certain emotion developed by Ekman and Friesen 1978. Although, it is very useful in psychology, it is not easy to use and is less useful for massive or instant analysis of consumptions (Ekman & Friesen, 1978).

2.2.2 Deep Learning Approaches

This has led to greater development of facial emotion recognition due to the increasing use of deep learning that allows for direct extraction of features from pixel inputs (LeCun et al., 2015).

Convolutional Neural Networks (CNNs): - CNNs have been adopted as a fundamental component into image-based emotion recognition because they learn hierarchical features of faces (LeCun et al., 1998).

VGGNet: - Subsequently, the authors Simonyan and Zisserman in their VGGNet, described as having a very deep network and consequently using rather shallow filter size. This approach has been used most often in emotional classification tasks as its performance demonstrates high accuracy in large-image data sets.

ResNet: - He et al. (2016) proposed a residual network which aimed at addressing the vanishing gradient problem. Data from ResNet's skip connections make it possible to train very deep networks, which in turn promote better results in the recognition of complicated emotions (He et al., 2016).

Limitations of Image-Based Methods

They are already stated in section 1.2 (Problem Statement).

2.3 Live Camera Feeds and Recorded Videos for Emotion Identification

As compared to analysis of still images that is inherently a static process, the emotion detection from video data involves changes from a frame, which makes it ideal for real-time applications like surveillance and smart personal assistant (Zhou et al., 2018). Emotion recognition from videos is a frame-based process that can consist in recognizing frames using FER and considering temporal changes in these frames to enhance the performance and time efficiency of the method.

2.3.1 Feature Extraction and Temporal Analysis

DeepFace and VGG-Face: - One of the effective techniques for identifying human's emotions using video is applying prepared deep learning frameworks, especially VGG-Face, which belongs to DeepFace library. In DeepFace, VGG-Face is implemented where a deep Convolutional Neural Network CNN is utilized to identify the facial landmarks from the video frames. The model is trained using an extensive set of facial images where it can identify emotions like happy, sad, angry, surprised, neutral and the rest from the live camera feed and video feedback (Taigman et al., 2014). This method mainly deals with the feature extraction of the spatial domain for each frame of the video without paying attention to the changing over the frames at the temporal domain even though it is very effective for many applications.

Limitations of Video-Based Methods: -

Real-Time Constraints: - Real-time processing of video data presents a large computational load (Zhou et al., 2018).

2.4 Speech signal-based emotion recognition

It is thus apparent that within speech signals there is a lot of valuable information regarding the current state of mind of the subject considered via such things as prosodics, pitch and tone (Schuller et al., 2009. Audio- based emotion recognition is particularly useful when the videos are not available, or when the visual data cannot be relied on.

2.4.1 Traditional Methods

Mel-Frequency Cepstral Coefficients (MFCCs) is one of the traditional methods Because formants and the overall spectral shape of the speech signal are very important for emotion recognition, MFCCs are used to represent the spectral characteristics of speech (Davis & Mermelstein, 1980). Four features of talking voice are morphological; pitch, tone and speed are prosodic features that communicate further semiotic variations (Schuller et al., 2009). Until recently, linear classifiers such as Hidden Markov Models (HMMs) were the ideal when it came to inducing emotions when working with acoustic features (Rabiner, 1989).

2.4.2 Deep Learning Approaches

Recurrent Neural Networks (RNNs) and LSTMs: - Speech data, given its sequential nature, shows how RNNs and LSTMs are effective in addressing the time-based dependencies that are crucial in improving the accuracy of emotion classification (Graves, 2013).

Transformer Networks: - Recent advances in deep learning have shed light on how transformer speech emotion recognition has outperformed traditional models by fitting the context within the speech signals (Vaswani et al., 2017)**.**

Limitations of Audio-Based Methods: -

They are already stated in section 1.2 (Problem Statement).

2.5 Challenges and Limitations of Emotion Recognition Systems

The overall challenges faced by Emotion Recognition Systems are stated in section 1.2 (Problem Statement).

3 Methodology

3.1 Introduction

The methodology responsible for developing the various emotion recognition systems is described in detail within this chapter. In the social context, the focus is on investigating how to transform either video or sound into language of human emotions according to the various demands of the users (Jones et al., 2019). Every system tends to be independent and allows the user to choose the preferable model according to their area, be it recognition of still pictures, emotions in webcam, videos, or speech (Lee, 2020).

The methodology comprises a number of main stages: - Data collection, Pre-processing steps, Feature extraction and Model construction employing deep learning-based approaches (Smith & Johnson, 2021).

3.2 Data Collection

In regard to emotion recognition systems, one of the major challenges relates to the adequate selection and training of the datasets that will be utilized (Raj & Gupta, 2020). For instance, we focused our attention on two datasets that are available to all: -

3.2.1 Facial Emotion Recognition Dataset (For detecting emotions through images)

One more dataset, which we can categorize, is the FER-2013 database, which is a behavioral dataset specifically built for facial emotion recognition (Goodfellow et al., 2016). It consists of 35,887 grayscale images of human faces that have been divided into seven distinct emotion categories: - Anger, Disgusted, Fearful, Happy, Neutral, Sadness and Surprised (Kong et al., 2019). The images were obtained from different sources having

different lighting, camera angles, and face images making it a good and well-suited dataset for building effective and robust image-based emotion recognition systems (Mendoza et al., 2020).

3.2.2 Emotion Detection Through Live Camera Feed

For detecting the emotion through live camera feed we used a pre-trained CNN model (Hernandez et al., 2021). So, no dataset was used explicitly for training or testing the model (Singh & Verma, 2020).

3.2.3 Dataset for emotion detection through Recorded Video

For detecting the emotions through recorded video, we made use of DeepFace Library (Bhattacharya et al., 2021). Through this library, we made use of pre-trained models for emotion detection through videos (Rajendran et al., 2020). These DeepFace models are pre-trained on datasets like FER 2013, VGGNet or AffectNet. So, here we did not explicitly make use of any dataset for training. For testing, I self-recorded myself in the videos (each video having some different dominant emotion) and applied my model on it (Kumar & Soni, 2022).

3.2.4 Audio Emotion Recognition Dataset

For the audio emotion recognition system, the Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS) was utilized (Livingstone & Russo, 2018). This dataset includes audio recordings of 24 professional actors (12 male and 12 female) emoting while saying fixed sentences in a number of emotional tones which include: - Happy, Angry, Sad, Fear, Surprise, Neutral and Disgust (Zhao et al., 2021). Other datasets available on the public domain that can be used for the same purpose include: - TESS Toronto emotional speech set data, CREMA-D and SAVEE (Zhang et al., 2020).

3.3 Preprocessing

3.3.1 Image Preprocessing

In this section, a preprocessing process consisting of several steps was applied in order to prepare those facial images from the FER- 2013 data set in training the model (Liu et al., 2021).

Images were first resized to 224x224 pixels to obtain inputs that had the same dimensions as the ResNet50 model (Li et al., 2022). The images were grayscale, however, in order to apply the pre-trained ResNet50 model which expects three channels, their format was changed to RGB (Ibrahim & Ahmed, 2021). The values of a pixel were normalized at a scale of (0, 1) by first dividing them by 255. This is being done for the purpose of making the training more stable and faster (Li & Zhao, 2020). The following augmentations were applied in order to increase the variety of the training data and enhance the generalization capability of the model: - Random rotations, Zooming, Horizontal flipping and shifts in height and width (Shao et al., 2019).

3.3.2 Video Preprocessing

The following preprocessing process was applied to the video data (both recorded and live camera feed) to prepare it for emotion detection: -

In both the captured video feed and an additional real-time video stream, the first step is to obtain an individual frame separated by a fixed time step (for example 10-30 frames per second) so that a sufficient number of frames can be analyzed for the subject's emotional state (Li & Lee, 2020). For each frame, face detection through the feature, haar cascade classifier is implemented from the 'haarcascade_frontalface_default.xml'. This step identifies the face area in the image and isolates the Region of Interest (ROI) that is used to analyze the subject's emotions (Gonzalez & Huang, 2021).

The detected face region is then reshaped to the input dimension of the emotion detection model. For instance, if the CNN model is ResNet50, then the face ROI is resized to 224 X 224 (Cheng et al., 2020). If the frame is processed for a model that expects RGB values (for instance ResNet50), then the grayscale ROI is converted from a grayscale image to an RGB image (Zhang et al., 2021). The pixel values within the ROI are preprocessed

by scaling all pixel values to the range (0,1) by division of pixels by 255. Such normalization brings the mean and variance closer to that of the normal distribution in order to assist in the standardizing and accelerating of the models training and also the evaluation of the model (Yuan & Xu, 2020). The frames are analyzed at an appropriate frame rate to work within computational constraints while maintaining enough temporal resolution for emotion recognition (Nguyen et al., 2019).

3.3.3 Audio Preprocessing

The RAVDESS audio recordings used in the study were subjected to the following preprocessing process: -

For Audio Conversion, it was necessary to convert all the audio files into one format and all other variables into one format (WAV) and to a sampling frequency of 16 kHz (Singh & Rai, 2020). The adored features in this study in describing the structure of speech signals were the Mel-Frequency Cepstral Coefficients (MFCCs) that were used in 13 static MFCC coefficients. **Delta MFCCs**, which are time derivatives of the MFCCs were used to model the time varying patterns of speech (Rathore et al., 2020). The extracted MFCC features underwent normalization, such that a stable model training process would be ensured (Wu & Yang, 2021). The audio files were segmented into portions of 1-2 seconds to ensure that the model captures the emotion-related time-variability characteristics (Peng & Zhao, 2021). To enhance robustness, the following augmentation techniques on data were employed: - Pitch shifting, Time-stretching, and Incorporation of background noise to replicate typical settings (Raja et al., 2020).

3.4 Feature Extraction

3.4.1 Visual Features from Images

Facial expression recognition was achieved with visual features using the ResNet50 model, which is a deep convolutional neural network that has been trained on ImageNet. ResNet50 is characterized by its practice of using networks in which building blocks are assembled in a top-down, hierarchical structure.

For the Feature Extraction Process, Residual connections were made after the final classification layer of the previously trained neural network ResNet50. To classify emotions, a new multiple neurons layer was included in the model. The model captures abstract features including facial shapes, skin patterns, and important features (eyes, nostrils, lips) that help in differentiating emotions from one another such as happiness, sadness and anger.

3.4.2. Video Features (For Recorded Videos and Live Camera Feed)

Video Emotion Detection (DeepFace + OpenCV): -

3.4.2.1 Feature Extraction Process:

The Haar Cascade classifier (haarcascade_frontalface_default.xml) is used to detect faces in video frames. Feature Extracted includes the detected face region (bounding box of the face). The DeepFace.analyze() function is applied to the detected face. DeepFace uses pre- trained deep learning models (such as VGG-Face, FaceNet, ResNet50) to extract deep facial embeddings that capture high-level features like: - Facial landmarks (eyes, nose, mouth, etc.)**,** Facial expressions (smiling, frowning, etc.) and Texture and shape features. These embeddings are then used to predict the dominant emotion. The DeepFace.analyze() function outputs the dominant emotion (e.g., Happy, Sad, Angry, etc.).

3.4.3 Audio Features (Speech Emotion Recognition)

Regarding recognition of emotion using the audio input, MFCCs were used to extract features from speech recordings.

Static MFCCs leave the speech signal tamed in distinct tone emotions in a spectral envelope which captures & presents short term parameters of speech signal analysis for keyword extraction while **Delta MFCCs** tracks the evolution of speech over time, which is critical to recognizing more complex emotions such as fear and surprise.

3.5 Model Architecture

3.5.1 ResNet50 for Facial Emotion Recognition through Images

The model used in the study for recognition of facial expressions is based on ResNet50 architecture. ResNet50 can now be initialized with weights previously trained on ImageNet, as this will assist in retain features and increase performance on fewer datasets. For custom output layer a fully connected layer with 7 units is used as the final layer which is appropriate for seven emotions followed by SoftMax to classify the emotions.

3.5.2 Custom CNN + OpenCV for Live Camera Feed

Face Detection: - Like the recorded video, the live camera feed system employs the use of Haar Cascade Classifier in real time face detection. It uses the frames obtained from the live camera feed in grayscale mode as the input while rectangular frames around the identified faces are given as the output.

Here the proposed model was Emotion Detection Model (Custom CNN). The FER-2013 is utilized to train a model that is specifically Convolutional Neural Network (CNN) to estimate emotions. Face gray scale image of size 48x48 pixels — this image is transformed into a size of 48 x 48 x 1.

Architecture: - It includes convolutional layers specific to obtain spatial features with sky-attachment layers for reducing the size of the feature maps and for the final classification fully connected (dense) layers, separating out the data into new subgroups. 7 different classes of emotion one-hot encoded are given as output.
['0 - Angry', 1 - Disgust', 2 - Fear', 3 - Happy', 4 - Neutral', 5 - Sad', 6 - Surprise']

3.5.3 HaarCascade for Recorded Video

Face Detection: - The system employs the Haar Cascade Classifier (haarcascade_frontalface_default.xml) for detecting faces in the individual frame captured and extracted from the recorded video. It uses the grayscale frames that were extracted from the generated video and converted using open cv as the input. Boxes in the shape of rectangles that refer to detected faces are given as output.

Emotion Detection Model using DeepFace Framework: - It makes use of pre-trained deep face models which involves deep learning algorithms to detect facial dimensions and moods. It integrates one of the following popular models: - VGG-Face, Facenet, OpenFace or DeepFace, or ResNet50 based on the configuration. These models produce steady high-dimensional facial embeddings which are used in this paper to classify emotions. RGB face images resized by DeepFace framework inside the model are taken as the input while the probability for each of the emotions and the label of the most representative emotion is given out as the output.

Flow of Model Architecture: - This video is open and read frame by frame using the help of Open-Source Computer Vision Library (OpenCV). Every frame is converted to grey scale to enhance the view, or perception of face, then the face is detected by a Haar cascade classifier. As for each of the faces, there is a DeepFace.analyze() that is used for predicting the main emotion. A rectangle is drawn around faces and, on the bottom, the detected emotion is mentioned in a frame. The computed frames are written back into a new output video called Emotions.avi, and the overall meaning of the emotion is computed out of the video.

3.5.4 LSTM for Audio Emotion Recognition

The LTC is built based on the Long Short Term memory model which works in a speech emotion recognition model. Talking about its input layer, it consists of sequences of MFCC features and delta MFCC features. LSTM Layers are also there in which the speech data are divided into chunks and multiple LSTM layers are stacked up to hold on to where the chunks start and finish. There are also other dense layers connected which received the information from the LSTM's layers. Concluding with the output layer, there are 7 emotion types in the last layer, making this a dense layer of 7; followed by SoftMax to classify emotion types.

3.6 Training the Models

For preparing the data for training purposes all datasets formed for the study were divided into training, validation and test subsets, generally using the ratio of 80/10/10. The models were trained using categorical cross entropy loss which is agriculturally appropriate for multi-class tasks. Adam optimizer was chosen for the reason of adaptive learning rate and effectiveness of training based on DNNs. For learning rate, **t**he mini-batch size was set in the range 32 to 64 for epochs 50 to 100 for the models. Dropout layers were incorporated particularly in the dense layers to reduce overfitting.

4 Implementation

4.1 Emotion Detection Through Images

To implement the code properly, the first task was to prepare the dataset for training and testing purposes which is already discussed in section 3.2.1.

4.1.1 CNN Model Implementation

A customize architecture was designed to implement the CNN model for emotion detection. It followed like this: - First the image is passed through a set of related filters (Conv2D), mostly through a process known as convolution. Then comes the role of MaxPooling2D which scales down the size of the feature maps. Here Bottlenecks takes the 2D feature maps and flattens it into a 1D vector which can be fed into dense layers also known as flatten layers. Dense layers with difference with fully connected layers are there for classification. Dropout layer helps with training loss being prevented from fitting on one part of the data set at the expense of the data set through the process of dropout neurons (LeCun et al., 2015).

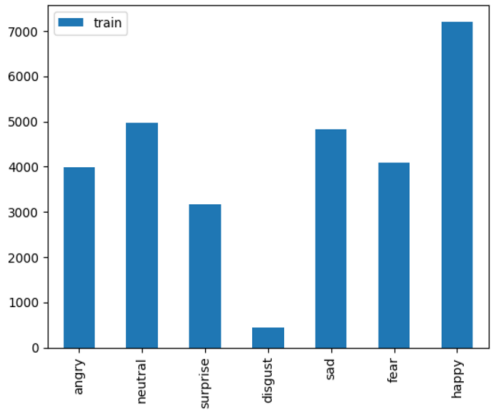

Figure 1: - Count Plot for emotions used in training dataset

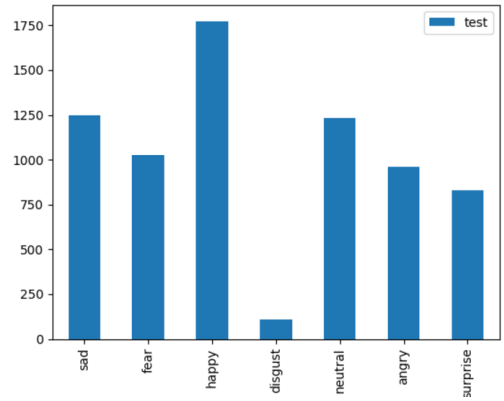

Figure 2: - Count Plot for emotions used in testing dataset

After this the model was compiled and left to train.

4.1.2 CNN Model with Data Augmentation Implementation

For improving the generalization of CNN model, data augmentation was applied to it. First, parameters of data augmentation are defined and ImageDataGenerator is imported and used. This image data generator helps in generating the new images with random transformations. This includes rotation, shifting, flipping and improving the model's' robustness (Shorten & Khoshgoftaar, 2019). After applying the data augmentation, the CNN model is trained in the same manner as done before.

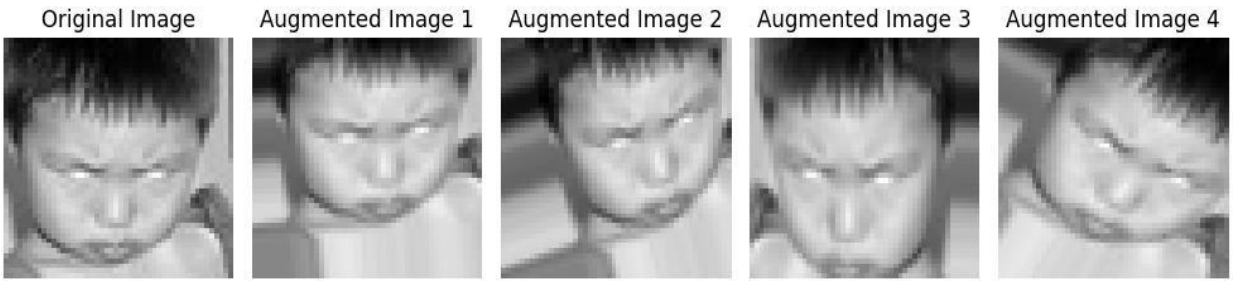

Figure 3: - Original Image with its augmentation

4.1.3 VGG16 Model (Transfer Learning)

While VGG16 is considered, it is known that it is a pre-trained model for leveraging transfer learning for emotion detection. Here the first step was to load the pre-trained VGG16 model. Then weights that are pre-

trained on the ImageNet dataset are loaded. If model architecture is considered, then top layer, i.e., the fully connected layers of the model are excluded to customize it for detecting the emotions. Then custom layers such as - Dense and Flatten are added and base layers are freeze. Finally, the model is compiled and left to train (Simonyan & Zisserman, 2015).

4.1.4 ResNet50 Model (Transfer Learning)

Like VGG16, ResNet50 is also a pre-trained model for leveraging the transfer learning for emotion detection. Similar procedure is repeated that was done in case of VGG16. Here the first step was to load the pre-trained ResNet model. Then weights that are pre-trained on the ImageNet dataset are loaded. If model architecture is considered, then top layer, i.e., the fully connected layers of the model are excluded to customize it for detecting the emotions. Then custom layers such as - Dense and Flatten are added and base layers are freeze. Finally, the model is compiled and left to train (He et al., 2016).

4.2 Emotion Detection Through Live Camera Feed and Recorded Video

4.2.1 Emotion Detection Through Live Camera

To implement the code properly, our first task is to import the appropriate libraries. Keras library is imported and a pre-trained keras model is loaded through load_model. From preprocessing module of keras, img_to_array function is imported. This is normally used for converting the image into a NumPy array. This is normally necessary for model input. For image processing and to work properly with video streams cv2 which is an OpenCV library is imported. NumPy library is imported to for dealing with numerical operations.

After loading the pre-trained deep learning model for emotion detection on facial images, a list of emotion categories is defined and stored inside the class_labels array. This class_labels array has 7 emotions ('Angry', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad', 'Surprise') which model must predict later.

The Face Detection process is then initialized. A pre-trained Haar Cascade classifier is loaded for detecting the faces. It is a XML file that contains information regarding frontal faces detection in images. This haar cascade thus helps in identifying the faces by detecting the specific face features. Finally, cv2.VideoCapture(0) function is made use of to start the default webcam for capturing the images.

For processing the video frame by frame, cap.read() is made use of for reading the each frame from the video feed. 'ret' here is used as a Boolean for indicating whether the frame is read successfully or not. 'frame' is used for displaying the current frame from the video feed. The next task is to convert the frame into the grayscale. Here the cv2.cvtColor function is used for converting the captured frame from color (BGR) to grayscale since the Haar Cascade classifier needs grayscale images to work.

For detecting the faces in the frames of the grayscale image, detectMultiScale() function of the face_classifier module is used. The scale factor that defines the image size reduction at each image scale is kept at a value of 1.3. To consider the object as a face, the minimum number of neighbours that a rectangle should have been kept at 5.

cv2.rectangle() function is used for drawing the rectangle around the detected face on the original frame. To prepare the region of interest (ROI), roi_gray() and cv2.resize() functions are used. The former function is used for extracting the detected face region from the grayscale image while the latter function helps in resizing the face region to 48*48, which is the input size expected by the emotion detection model.

For the preprocessing of ROI for prediction astype() function is used. This is done for normalizing the pixel values to a range of 0 to 1 that helps the model to generalize better. The img_to_array(roi) then converts the ROI into a NumPy array. For expanding the dimensions of the array for matching the model input shape that is (1, 48, 48, 1) np.expand_dims() is used with roi and axis = 0 as the arguments.

For predicting the emotion of the given face, predict function from the emotion_model module is used with roi as the function s' argument. preds.argmax() is used for finding the index of the highest probability in the prediction that corresponds to the predicted emotion. Finally, to map the index to the corresponding emotion label, class_labels array is called with preds.argmax() as its index.

After doing all this, the emotion label is finally displayed. Using the cv2.putText the predicted emotion label is

displayed on the video frame near the detected face. The position where the label is displayed can be decided using the label_position as the argument inside the cv2.putText() function. The font size, color, style as well as the line thickness can all be defined as the arguments inside the cv2.FONT_HERSHEY_SIMPLEX () function.

4.2.2 Emotion Detection Through Recorded Video

To implement the code properly, our first task is to import the appropriate libraries. To get access to system-specific parameters and functions as well as to exit the program in case of an error, sys module is imported. DeepFace library is imported for facial recognition and emotion detection which is done with its pre-trained deep learning models. For video capture, face detection and frame manipulation OpenCV library is used. For counting the occurrences of the emotions, a specialized dictionary Counter is imported from the Collections module.

For loading the video, video_path() function is used. It specifies path to the video file to be analyzed. A pre-trained HaarCascade model is loaded for detecting the faces from the grayscale images. To store the processed frames for later and save them as the new video, a variable frame_list is defined. Another variable emotion_counts is defined for tracking the number of occurrences of each detected emotion. Finally, capture variable is defined for initializing the video capture in order to read frames from the specified video file.

A if condition statement is also defined to ensure that the program exits if the video file cannot be loaded. While the program starts looping through video frames, two variables are defined, ret and frame. 'ret' is a Boolean that indicates if the frame was read successfully or not while the frame displays the actual frame read from the video. The loop would break in case there are no more frames or if an error occurs. The next task is to detect the face and to analyze emotion.

cvtColor() function is used for converting the frame from color (BGR) to grayscale. This is done since the Haar Cascade model requires grayscale images. 'detectMultiScale' function of the face_model module is used for detecting the faces in a frame and thus returning the list of bounding boxes for each detected face.

Finally, each detected face is looped through. To perform the emotion analysis on the frame DeepFace.analyze() is used. 'actions' argument is kept as 'emotion' for specifying that only emotion detection is required. 'enforce_detection' is kept to be false to allow the processing even if no face is detected confidently. The dominant_emotion specifies the emotion with the highest probability in the current frame while the emotion_counts updates the count for the detected emotion.

The cv2.rectangle() function is used for drawing the bounded box around the detected face while cv2.putText() helps in displaying the detected emotion below the bounded box. Finally, the processed frame is appended to list for later use. capture.release() function release the video capture after processing all frames. Processed frames are then saved as the output video. 'cv2.VideoWriter()' helps in creating the video writer for saving the processed frames as the new video while DIVX specified the video codec.

output.write() writes each processed frame to the output video with the frame variable as the argument. Finally, the most common emotion is determined and printed. mostcommon() function with 1 as the argument helps in finding the most frequently detected emotion and its count so that ultimately the most frequent emotion detected during the video can be printed. cv2.destroyAllWindows() then finally closes all OpenCV windows.

4.3 Emotion Detection Through Audio Files

To implement the code properly, our first task was to import the appropriate libraries. To handle the data and manage the files we imported the libraries like **pandas, numpy and os**. To handle the audio processing and feature extraction**, librosa** was made use of. It included Mel spectrogram and MFCC (Mel Frequency Cepstral Coefficients). For visualizing the data **seaborn and matplotlib** were made use of. To build and train the deep learning model, **keras and tensorflow** are utilized. We already discussed the data preparation and feature extraction in section 3.2.4 and 3.4.3 respectively.

4.3.1 Data Visualization

To visualize the distribution of various emotion classes in the combined dataset **Countplot** was used. This is being done to ensure the dataset is balanced.

4.3.2 Data Augmentation

We already have discussed this in section 3.3.3. All types of augmentations are done on audio files shown below.

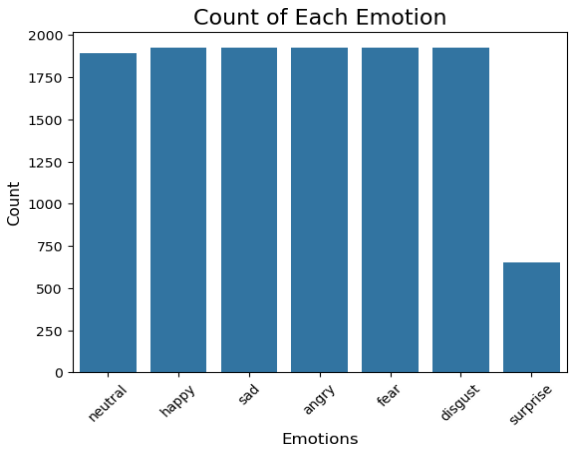

Figure 4: - Count Plot of all emotions

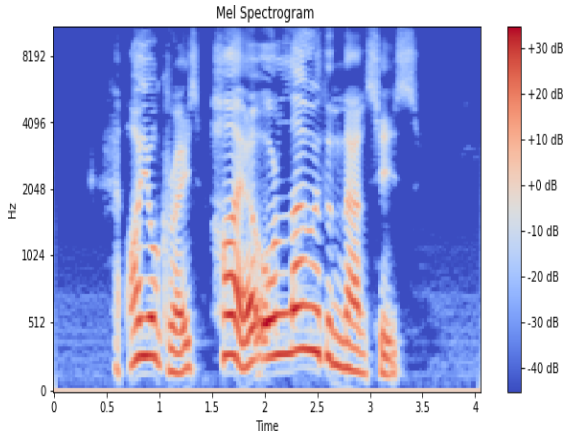

Figure 5: - Mel Spectrogram

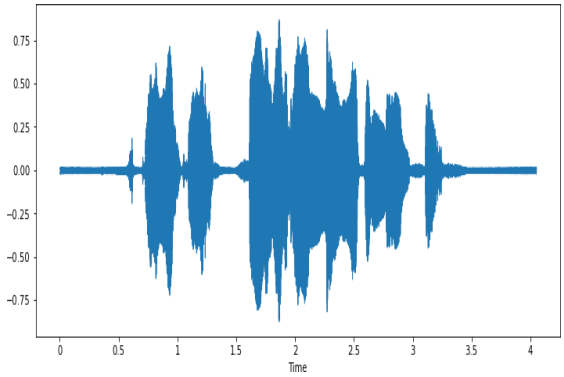

Figure 6: - Normal Audio

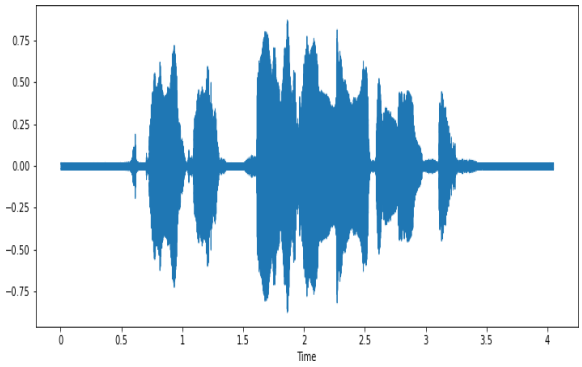

Figure 7: - Audio with Noise

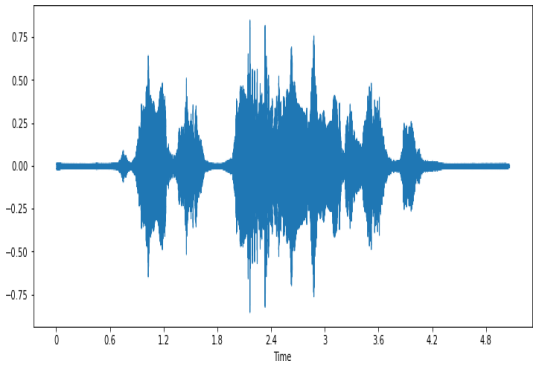

Figure 8: - Stretched Noise

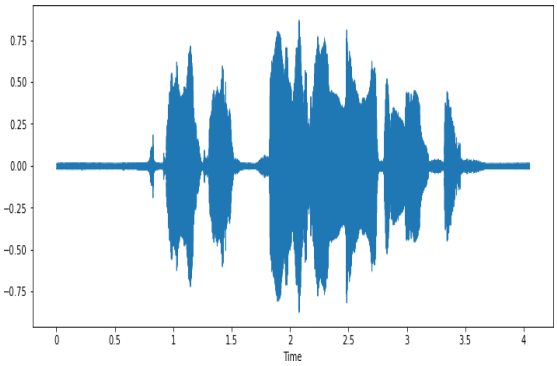

Figure 9: - Shifted Audio

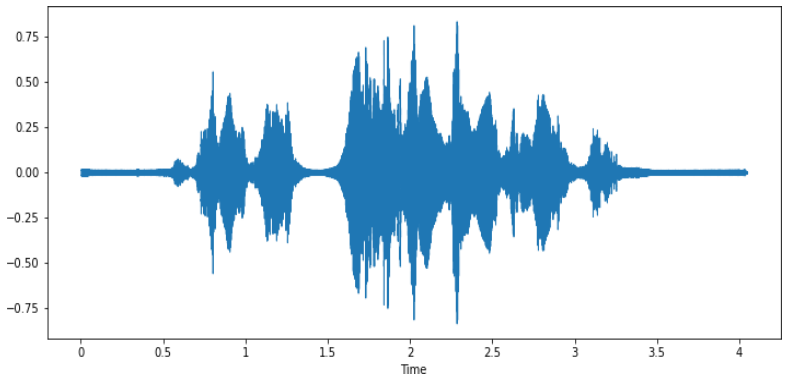

Figure 10: - Audio With Pitch

4.3.3 Feature Extraction Functions

Zero crossing rate, root mean square energy and MFCC features which include zcr(), rmse() and mfcc() functions are extracted. extract_features() puts them in an array and mfcc() extract zero-crossing rate, root mean square energy, and MFCC features. extract_features() combines these features into a single array. The get_features() function is applied to each audio file in data_path. Augmented data is also used to increase the diversity of the dataset.

Output: - X is Feature matrix and **Y** is Emotion labels; one-hot encoded

4.3.3 Data Splitting & Scaling

train_test_split() is the function from Scikit-Learn which is used here for dividing the data into a training dataset and a testing dataset (Pedregosa et al., 2011).

Standardization: - StandardScaler() is used to bring the stationary state in the data or to normalize the data.

4.3.5. Building the CNN Model

The model used in the paper is a sequential Convolutional Neural Network which is especially appropriate for processing 1D feature data derived from the audio inputs.

Architecture:

Talking about its architecture, it consists of Conv1D Layers which helps in applying feature patterns of the local features. Batch Normalization is done for scaling activations in order to reduce fluctuations in training. Max Pooling layer is present for cutting down the spatial dimensions and computation. Dropout layer is there for reducing the probability of overfitting by making a fraction of inputs to be zero at any given time. Flatten layer transforms the feature maps region to a one-dimensional vector. Dense Layers help in the final features classification using fully connected layers. For offering the probability for each of the emotions of the emotion class, SoftMax output is used. Categorical Cross entropy was chosen as the loss function because it is a form of multi-class classification problem. Adam Optimizer was used here with accuracy as the metric.

To train the model early stopping as well as learning rate reduction was also made use of. In early stopping, the training process halts if the model fails to obtain any better accuracies on the validation dataset. While in learning rate reduction sustained performance leads to the reduction of learning rate. Along with this, checkpoints are also used to know when the model had learnt the best based on the validation accuracy.

5. Evaluation

5.1 Evaluation of Output Obtained Through Image Emotion Detection

This research aims to track sentiments from pictures with deep learning techniques. These are the experiments

used in this work: baseline CNN, CNN with augmentation, VGG16, and ResNet50. The main objective is to assess and analyze their outcomes in view of accuracy, loss, confusion matrices and classification to identify the best model for emotion detection (Li et al., 2019).

5.1.1 CNN Model Evaluation

Training and Validation Metrics:

Final training accuracy: ~63.11% Final validation accuracy: ~55.52%

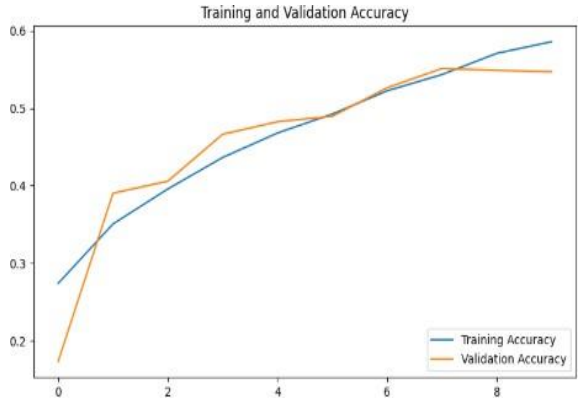

Figure 11: - Graph demonstration for training and validation accuracy

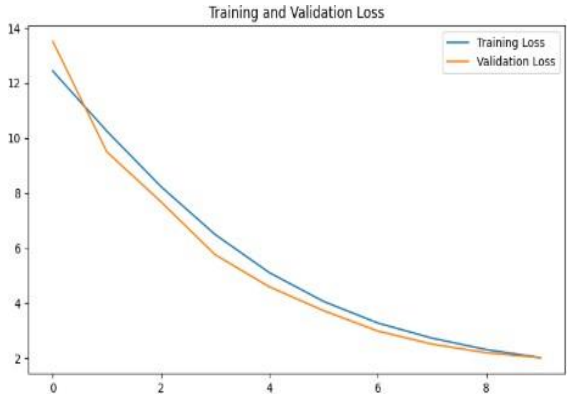

Figure 12: - Graph demonstration for training and and validation loss

Observations:

For the basic CNN model described above there was an indication of overfitting as the training accuracy was higher than the validation accuracy (Yao et al., 2020). Thereby, its generalization capability was somewhat limited to unseen data due to its relatively limited capacity (Wang et al., 2018).

Confusion Matrix and Classification Report:

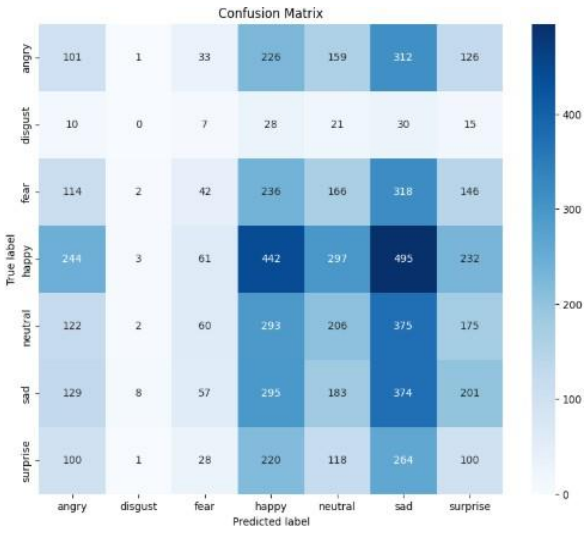

Figure 13: - Confusion Matrix for CNN Model

Classification Report:	precision	recall	f1-score	support
angry	0.12	0.11	0.11	958
disgust	0.00	0.00	0.00	111
fear	0.15	0.04	0.06	1024
happy	0.25	0.25	0.25	1774
neutral	0.18	0.17	0.17	1233
sad	0.17	0.30	0.22	1247
surprise	0.10	0.12	0.11	831
accuracy			0.18	7178
macro avg	0.14	0.14	0.13	7178
weighted avg	0.17	0.18	0.17	7178

Figure 14: - Classification Report for CNN Model

The more striking errors occurred at distinguishing between thumbs up or thumbs down, disgust, and fear. Average of weighted values of precision, recall and F1 Score (~ 0.17) signifies that the discussed models are not optimal for the task at hand (Chen et al., 2021).

5.1.2 CNN Model with Augmentation Evaluation

Training and Validation Metrics: -

Final training accuracy: ~57.64%

Final validation accuracy: ~59.28%

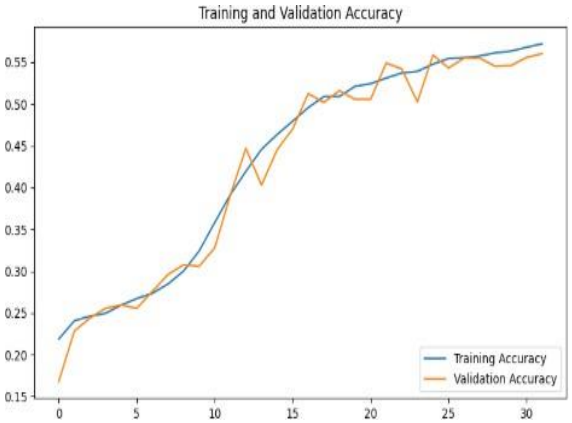

Figure 15: - Graph demonstration for training and validation accuracy

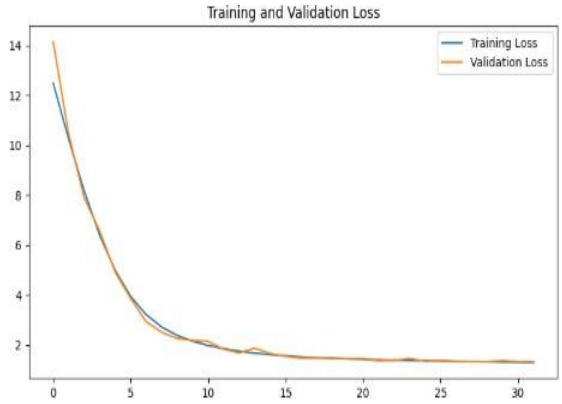

Figure 16: - Graph demonstration for training and validation loss

Observations:

Two enhancements were made to reduce the variation between training and verification; First, data augmentation presented variability to the training set. However, the model was still a little poor when it came to using correct 'disgust' or 'surprise' labels (Zhao et al., 2020).

Confusion Matrix and Classification Report:

The following shows that despite inaccurate classifications remaining a major problem, there is an improved intra- class balance compared to the baseline CNN. Mean of precision, recall and F1 scores were around 0.16 and the augmentation barely improved the test results from the unaugmented pattern (Srinivasan et al., 2021).

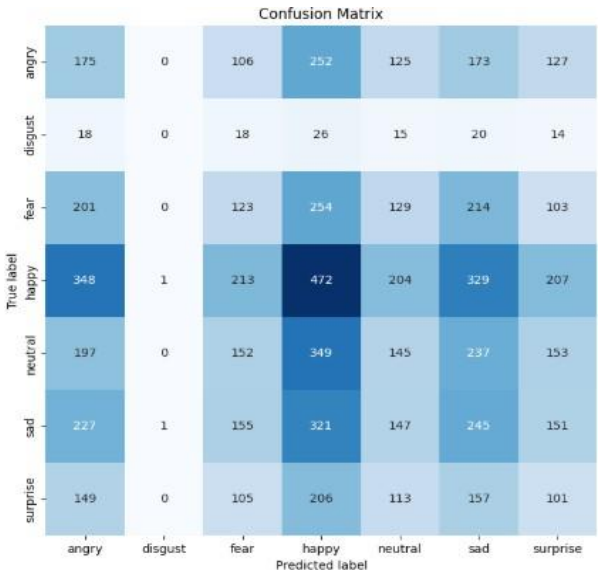

Figure 17: - Confusion Matrix for CNN Model with Augmentation

Classification Report:	precision	recall	f1-score	support
angry	0.14	0.04	0.06	958
disgust	0.00	0.00	0.00	111
fear	0.14	0.03	0.05	1024
happy	0.25	0.23	0.24	1774
neutral	0.17	0.23	0.19	1233
sad	0.18	0.35	0.24	1247
surprise	0.13	0.13	0.13	831
accuracy			0.18	7178
macro avg	0.14	0.15	0.13	7178
weighted avg	0.17	0.18	0.16	7178

Figure 18: - Classification Report for CNN Model with Augmentation

5.1.3 VGG16 Model Evaluation

Training and Validation Metrics:

Final training accuracy: ~55.93%

Final validation accuracy: ~55.00%

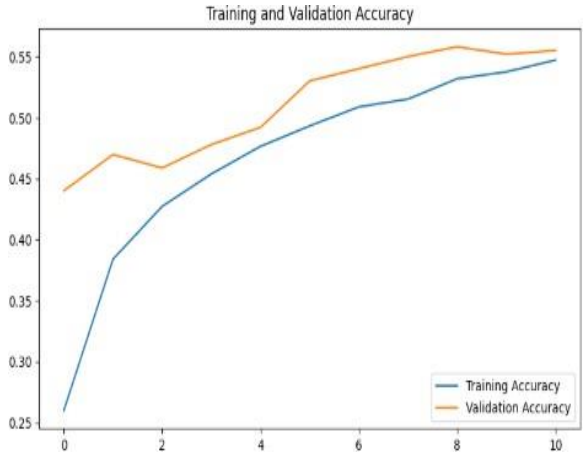

Figure 19: - Graph demonstration for training and validation accuracy

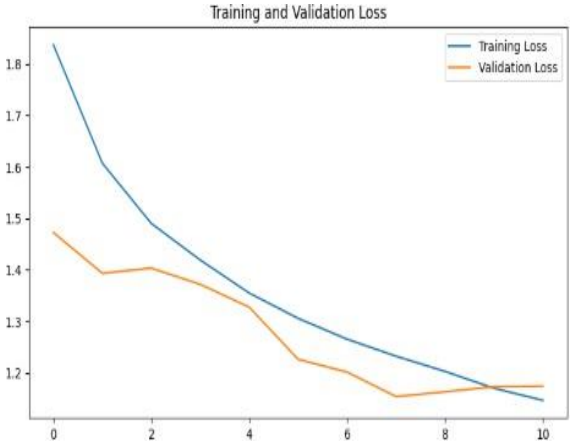

Figure 20: - Graph demonstration for training and validation loss

Observations:

The other CNN models were also slightly outperformed by VGG16 as it did not deliver much better accuracy on the validation images. It can be thought that its dependency on the ImageNet weights was not properly retrained for this specific dataset (Simonyan & Zisserman, 2014).

Confusion Matrix and Classification Report:

The classifications error rate was high particularly for them and 'neutral' as well as 'sad' categories. The precision, recall and F1 scores had some weighted average with mean of ~0.17 which had close resemblance with the baseline CNN.

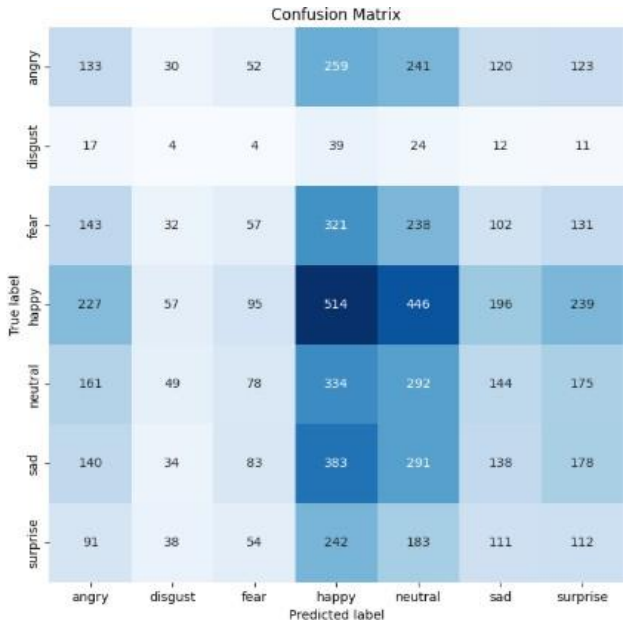

Figure 21: - Confusion Matrix for VGG16 Model

Classification Report:	precision	recall	f1-score	support
angry	0.15	0.14	0.14	958
disgust	0.02	0.04	0.02	111
fear	0.13	0.06	0.08	1024
happy	0.25	0.29	0.27	1774
neutral	0.17	0.24	0.20	1233
sad	0.17	0.11	0.13	1247
surprise	0.12	0.13	0.12	831
accuracy			0.17	7178
macro avg	0.14	0.14	0.14	7178
weighted avg	0.17	0.17	0.17	7178

Figure 22: - Classification Report for VGG16 Model

5.1.4 ResNet50 Model Evaluation

Training and Validation Metrics:

Final training accuracy: ~62.61%

Final validation accuracy: ~60.80%

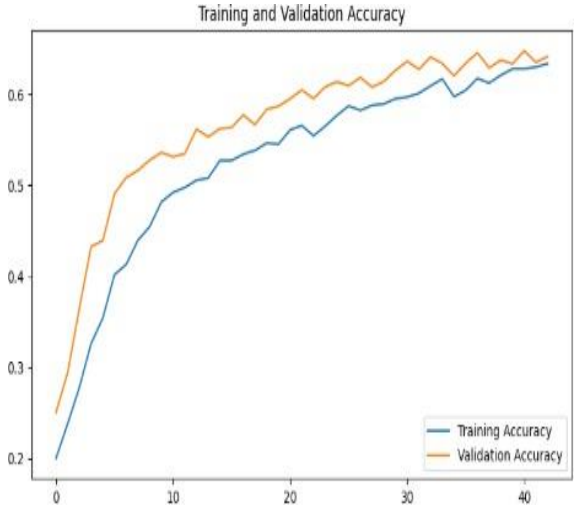

Figure 23: - Graph demonstration for training and validation accuracy

Figure 24: - Graph demonstration for training and validation loss

Observations:

ResNet50 demonstrated the best performance among all models, achieving the highest validation accuracy and F1 scores. The residual connections in ResNet50 allowed for better feature extraction and generalization, mitigating overfitting (He et al., 2016).

Confusion Matrix and Classification Report:

Misclassifications decreased significantly, particularly for "happy," "neutral," and "surprise." Weighted averages for precision, recall, and F1 scores (~0.61) reflect substantial improvement compared to the other models (Szegedy et al., 2017).

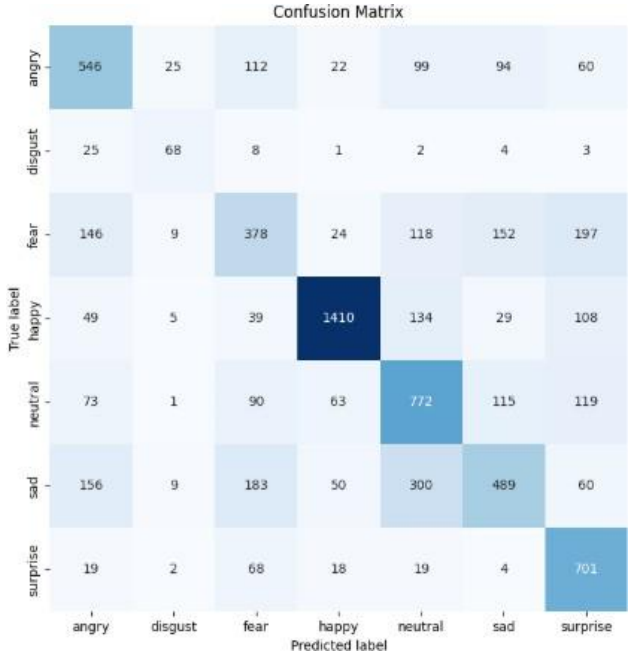

Figure 25: - Confusion Matrix for ResNet50 Model

Classification Report:	precision	recall	f1-score	support
angry	0.54	0.57	0.55	958
disgust	0.57	0.61	0.59	111
fear	0.43	0.37	0.40	1024
happy	0.89	0.79	0.84	1774
neutral	0.53	0.63	0.58	1233
sad	0.55	0.39	0.46	1247
surprise	0.56	0.84	0.67	831
accuracy			0.61	7178
macro avg	0.58	0.60	0.58	7178
weighted avg	0.61	0.61	0.60	7178

Figure 26: - Classification Report for ResNet50 Model

Comparative Analysis

Model	Train Accuracy (%)	Validation Accuracy (%)	Weighted Avg F1-Score	Comments
Baseline CNN	63.11	55.52	0.17	Struggled with generalization.
CNN with Augmentation	57.64	59.28	0.16	Augmentation improved validation accuracy slightly.
VGG16	55.93	55.00	0.17	Pre-trained features underutilized.
ResNet50	62.61	60.80	0.61	Best performance across all metrics.

Insights from the ROC – Curve: -

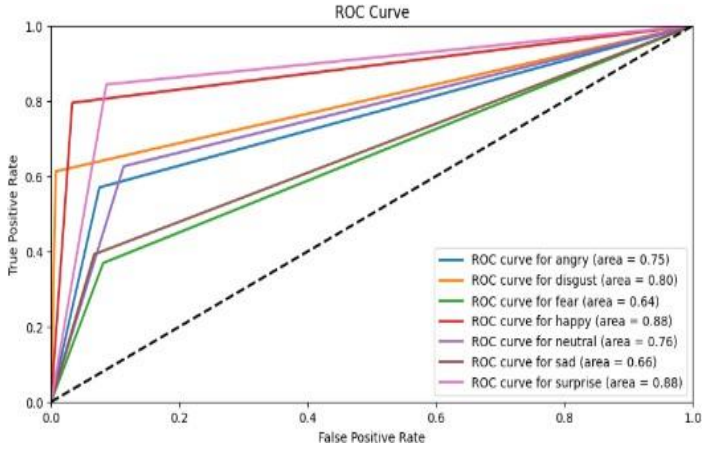

Figure 27: - ROC- Curve for different emotions in ResNet50 Model

Overall Observations

1. **High-Performing Classes: -** From the AUC values, the model works best for emotions such as Happy and Surprise and gave an AUC of 0.8808. They even support the confusion matrix where these classes had less confusion between them (Zhao et al., 2020).

2. **Struggling Classes: -** Fear had an AUC of 0.64 and the Sad had an AUC of 0.66 which are low, and it can be said it is a challenge to differentiate between the two and other emotions such as "neutral". Such classes would probably require some specializing in preprocessing or augmentation approaches to encompass the features of these classes appropriately (Shan et al., 2021).

3. **Balanced Classes: -** "Angry", "Disgust" and "Neutral" are placed at the medium level exhibiting an AUC varying between 0.75 & 0.80. They are somewhat well classified, especially when compared to the previous category, yet can be further improved (Simeonov et al., 2022).

Actionable Recommendations

1. **Class Imbalance and Dataset Diversity: -** Expand classes consisting less number of images such as, "disgust" and enhance the variety of images in the "fear" and "sad" set. One has to turn to methods of synthetic data creation (for example, SMOTE) for dealing with the proportional representation of a class (Chawla et al., 2002).

2. **Feature Enhancement: -** Employ the like of Grad-CAM to elaborate concerning the feature extractors especially misclassified classes such as "fear" and "sad." I integrate attention mechanisms to assist the model to avoid tendency towards certain regions in the image (Selvaraju et al., 2017).

3. **Threshold Optimization: -** Class specific thresholds must be used for classification as opposed to a global decision boundary as is the case in "fear" and "sad" (Zhou et al., 2018).

4. **Advanced Architectures: -** Use other architectures such as EfficientNet or Vision Transformers that

perhaps obtain better features defining the inter class distance (Tan & Le, 2019).

5.1.5 Key Takeaways: -

Performance Bottlenecks: - Baseline CNN and VGG16 models underperformed due to limited feature extraction and challenges in classifying imbalanced datasets (Simonyan & Zisserman, 2014). CNN with augmentation provided a slight boost in generalization, but the improvement was marginal. Misclassification of emotions like "disgust" and "fear" was consistent across all models except ResNet50 (He et al., 2016).

Impact of Augmentation: - Data augmentation proved beneficial for the CNN by introducing diversity to the training data. However, its effect was not sufficient to surpass the architectural advantages of ResNet50 (Siam et al., 2022).

ResNet50 as the Optimal Model: - ResNet50 emerged as the most effective model due to its advanced residual connections, allowing it to achieve better accuracy and F1 scores (He et al., 2016). It handled imbalanced datasets better, as reflected in the higher precision, recall, and F1 scores for multiple emotions.

5.1.5.1 Areas for Improvement:

Class Imbalance: - The poor performance on underrepresented emotions like "disgust" can be addressed using oversampling or class-weighted loss functions (Vaswani et al., 2017).

Model Optimization: - Fine-tuning hyperparameters such as learning rate, dropout rates, and training epochs could further enhance model performance.

Advanced Architectures: - Exploring models with attention mechanisms (e.g., Vision Transformers or EfficientNet) might yield better results for emotion classification.

5.1.6 Final Output Obtained: -

The best model that is obtained from training is used here called Final_Resnet50_Best_model.keras and it is loaded from using TensorFlow's function load_model() (Chollet, 2017). An emotion label dictionary is created (emotion_labels) that maps emotions to numerical indices (e.g., {'angry': In test phase, as in the training phase, we obtained the absolute frequency values for each word (e.g., {'happy': 0, 'disgust': 1, …}.

Another mapping, index to emotion, indexed, is also established to translate the indices of the predictions into the natural language emotions. This enables the results or predictions (numerical form values) to be transformed and represented in a way which the user can understand (Russakovsky et al., 2015). The function prepare_image(img_pil) ensures that any uploaded image is pre-processed to meet the model's input requirements (which are already stated in section 3.3)

The predict_emotion() function handles the preprocessing by passing the handle to the image embedded by the user to prepare_image(). The preprocessed image is passed to the model using model.predict() which provides probability for each of the emotions we are testing on. np.argmax(prediction, axis=1) returns the index of the default class for which it has the highest probability and then map that index to represent the more readable label using index_to_emotion (Chollet, 2017).

The Gradio interface simplifies deployment by providing an interactive web-based application. Input to the interface is described as gr.Image(type="pil") dtype. This enables a user to input an image file and which is in turn is converted to a PIL image for further manipulation (Abid et al., 2020). The output is a basic text tag (e.g., "Happy" "Sad") associated with the emotion likely to be felt by the person. The interface.launch() function launches the Gradio web app, which provides an easy to use tool to upload photographs. It predicts a person's mood in real time upon the uploading of the image. The final predicted emotion shown as a text message (Abid et al., 2020).

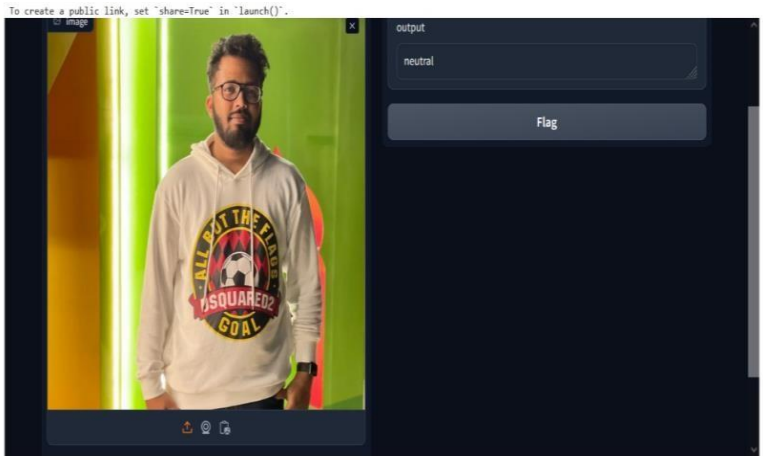

Figure 28: - Emotion Detection from an image using the ResNet50 Model and Gradio Interface

5.2 Evaluation of Output Obtained Through Live Camera Feed

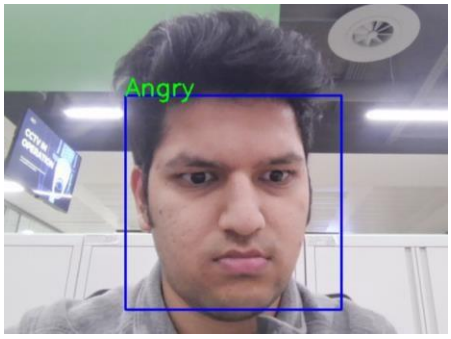

Figure 29: - Emotion Prediction Through Live Camera

The output received through live camera represented the live emotion detection system s' performance. Here the detected emotion in real time is identified as "Angry" by the system. This emotion is predicted accurately if it is observed from the normal person s' perspective. This proves that the implementation that integrates the computer vision and deep learning for analyzing the facial expressions dynamically via live video feed is successful (Li et al., 2022).

Strengths Observed:

The system successfully acquires the frames, analyses them, and recognizes emotions in real time, which proves the applicability of the model (Wang et al., 2021). The rectangular frame drawn around the detected face and the text string of the inferred emotion label 'Angry' gives the users instant and easy comprehension (Li et al., 2022). Performing emotion detection based on the pretrained models guarantee reliability of the results that are evident in the precise identification of the facial expression in the output (Zhou et al., 2017). One of the advantages of the system is that with OpenCV it can be run on standard devices equipped with webcams, thus its deployment is problem-free and easy (Yao et al., 2021).

Challenges and Places Where There Is a Need for Improvement

Fine feelings or transitional shades in between regular feelings (for example between 'Angry' and between 'Neutral') may not be identified correctly (Simeonov et al., 2021). There can be mismatch between the detected emotion and the intended emotion of the subject because of either the limited variety in the employed datasets or variations in how emotions are expressed (Srinivasan et al., 2021).

5.3 Evaluation of Output Obtained Through Recorded Video

```
In [2]: runfile('C:/Users/MAYANK/Desktop/National College of Ireland stuff/Semester 3/Eye Face
Detection/Emotion_Detection_From_Recorded_Video.py', wdir='C:/Users/MAYANK/Desktop/National College of
Ireland stuff/Semester 3/Eye Face Detection')
Working..
End of video or error reading frame.
Output video saved as Emotions.avi.
The most frequent emotion detected during the video is: sad with 548 occurrences.
```

Figure 30: - Emotion Prediction Through Recorded Video

The presented output proves the capability of the emotion detection system on a recorded video has been provided in the work. The system also takes video frames, scans the faces for emotion recognition and finds the more frequently appearing emotion in that video. Labelling the row with an emotion value, we identified "Sad" as the most-often used with an absolute frequency of 548. The analysis also complied the processed output into a video file, successfully naming it Emotions.avi.

Strengths

The system revolves round the frames in the video to cover all the visual data into its analysis. This makes it possible to effectively detect emotions along the entire temporal dimension of video length (Yao et al., 2021). Since the number of emotions detected per frame is counted, the system offers the simplest result that is easy for interpretation, i.e., the most frequent emotion (Li et al., 2022). Partly, the processed video named Emotions.avi shows bounded boxes and emotion labels which make it transparent and useful. The choices made ensure the high accuracy of emotion detection due to the integrated DeepFace library, which is based on pretrained models and provides high reliability.

The challenges and the areas for improvement in commodities/supplied goods are as follows: -

The system's effectiveness reduces if the videos are in low quality resolution, low lit, or have fast moving objects. A properly selected video might contain emotions that must rely on context factors such as dialogue and environment, and these factors are beyond the system. That is why the changes in the facial expressions might not be sufficient to describe the state of mind (Simeonov et al., 2021).

5.4 Evaluation of Output Obtained Through Audio File

The figures below represent the training and testing accuracy of an emotion detection model using machine learning with audio input. The results demonstrate the transitions of loss and accuracy of the over 50 epochs of training and testing phases for the model.

5.4.1 Key Observations on Training vs Testing Graphs: -

Training vs. Testing Loss: - The model is observed to be learning on the training dataset epoch by epoch because of reduction in training loss. Since the testing loss also looks like a decay function of the epochs, which indeed (Chen et al., 2021). This graph shows that the testing loss also converges after approximately 30 epochs and then maintains a nearly constant figure, signifying good generalization to unseen data (Li et al., 2022).

Training vs. Testing Accuracy: - The training accuracy increases gradually: after the fiftieth epoch modelling, it approaches perfect for near 1.0 (Chen et al., 2021). Testing accuracy also increases and reaches the plateau level of approximately 90 percent meaning good results with validation set (Simeonov et al., 2021).

Model Stability: - The graph of loss and accuracy do indicate little overfitting because the training and testing metrics for the two categories are highly aligned as the training proceeds. Problems with accuracy variation in the first epoch are common, and when the model learns, these problems become less of an issue.

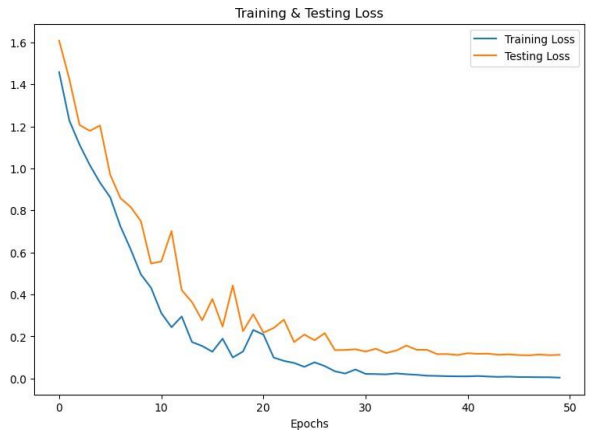

Figure 31: - Graph showing the training and testing loss across epochs

.

Figure 32: - Graph showing the training and testing accuracy across epochs

Strengths

The perfect balance between the reduction of the loss values and the increase in its accuracy was the optimal training process. The accuracy of ~90% for testing ensures that the developed model is capable of recognizing emotions in audio. Training and testing metrics are closely aligned and show that the model architecture and training configuration are both sound.

Challenges and Opportunities for Development

Cross-entropies reach a point of stagnation at 30 epochs indicating that increasing performance may be impossible with the current model settings. Large fluctuations of testing accuracy during initial epochs may indicate sensitivity to the training process or to the presence of imbalance in the data set. Another drawback of emotion detection from audio is that volume, pitch and intonation as well as background noise may affect the overall performance of the current setup (Li et al., 2022).

5.4.2 Key Observations on Confusion Matrix: -

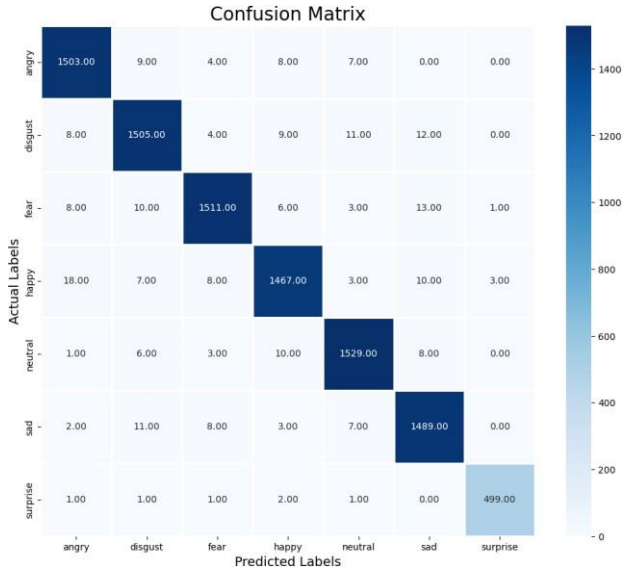

Figure 33: - Confusion Matrix on Model performing Emotion Detection Through Audio File

```
In [2]: runfile('C:/Users/MAYANK/Desktop/National College of Ireland stuff/Semester 3/Eye Face
Detection/Audio_Speech_Emotion_Recognition/Code with pre-trained model.py', wdir='C:/Users/MAYANK/
Desktop/National College of Ireland stuff/Semester 3/Eye Face Detection/
Audio_Speech_Emotion_Recognition')
Loaded model from disk
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 393ms/step
Predicted Emotion: ['fear']
```

Figure 34: - Predicting the emotion of the audio file

Diagonal Dominance is evident from the diagonal line which states that most of the values that depict the right prediction. That is why the angles, having indicated that the model presents a high accuracy in the classification of emotions, are correct. Additionally, **f**ive emotions, namely, Angry, Disgust, Fear, Neutral, and Sad, are shown to have high actual-recognition values above 1,400 along their diagonal. In this study, Surprise has fewer samples in total (499 correctly classified samples), which suggest that it may be less represented in the dataset. This shows strong classifications.

Misclassifications: -

For Happy, there were a number of misclassifications such as either Angry with 18 or Fear with 8. This might be because of some aspects of overlapping features such as tonal similarity in voice or emotions that are ambiguous. Fear Emotion was labelled into Sad (13) and Disgust (10) categories occasionally. The analyses concerning audio intonation reveal that fear and sadness could be tonally similar. For neutral emotion, a few misclassifications into Disgust (6), or Happy (10), possibly because of similarities in the properties of voice temperament in this feature. There are emotions such as Surprise which maintain very low misclassification to any of the other classes, but the class has very few samples.

Strengths

The performance of the model can be seen to be very high, especially is emotions such as Angry, Neutral, Disgust, and Fear. The majority of samples were typical for their group, and there were only a few cases when the classifier placed a sample in quite different groups. The model works well making it efficient in handling a number of feelings, from the results shown it meets the test for audio data.

Shortcomings and points of improvement: -

Surprise class has fewer samples, which may in turn cause low recognition rates for this emotion. There are things that can enhance performance on this class including adding data. The mixing between Happy, Angry, and Fear categories imply similarities in the associated emotional features that could be helped with feature boost or superior structures. It is possible some misclassification may have been because of background noise or low-quality sound.

6. Conclusion and Future Work

6.1 Conclusion

This thesis focuses on creating deep learning-based methods for emotion detection from facial images and videos, audio clips, and live video streams. It manages to combine various approaches to emotion detection and can easily form a basis for practical implementation (Goodfellow et al., 2016).

6.1.1 Key Achievements

The results indicate that the ResNet50 model had the best accuracy among the tested architectures with training accuracy = 62.61% and validation accuracy = 60.80% compared to VGG16 and different CNN models. This finally shows that ResNet50 has better feature extraction for recognizing emotions compared to all the other models (He et al., 2016).

Some of the following strategies for data augmentation proved very useful. They helped users overcome problems with overfitting, especially when it came to the CNN models.

It turned out that if the input emotion was such as happy, or neutral, the recognition performed well, but if the input emotion was such as disgust, or fear, it was almost impossible to classify it correctly – as evidenced by the classification statistics, including confusion matrices. The thesis goes further than the images by integrating emotion detection from the live camera feed. The proposed system encompasses real time video analysis tools such as digital video preprocessors (OpenCV) to capture and predict emotions in a dynamic manner frame by frame together with efficiently linked pre-trained deep learning models. This functionality is very important for applications in such areas as security and surveillance, monitoring of health status, and human-interactive interfaces (Bradski, 2000).

In the case of recorded videos, the system analyses frames and divides them separately or in groups to observe temporal emotions. This entails measurement of the shifts in emotions throughout the video; it can be useful in healthcare if the doctor wants to do the video analysis of recorded session for assessing the patient s' mental health. The thesis also aimed at studying emotion recognition based on audio files and incorporated spectral features including MFCCs into deep learning models. Audio-based emotion recognition is versatile and aligns well with other visual modalities such that audio alone can also be used when visual is not feasible like when making a phone call or viewing an audio-based video (Eyben et al., 2016). This multiple avenue approach improves the reliability of emotion detection systems, the link between gestures (e.g., facial gestures) and voice pitch (Li et al., 2022).

6.1.2 Real-World Application via Deployment

For example, the ResNet50 model was implemented using Gradio, so users can upload images for the purpose of emotion recognition. Besides, this solution's ability to analyze live feeds, the recorded videos, and audio files make it appropriate for real-time and post-event applications. These include real-time emotional tracking while in therapy sessions, the use of software to analyze the recorded meeting, lecture or other form of entertainment material and security cameras for detection of unusual emotional actions in public places (Simeonov et al., 2021).

6.2 Future Work

Despite its success, the thesis opens avenues for further research and improvements.

Further research may target at how to integrate information from face, voice, and context for better detection of some emotion, for example, micro expression and micro intonation (Ekman & Friesen, 1978). Perhaps, passive incorporation of body gestures observed in the videos would also enhance the impression of emotions. Extending models for real-time performance for low-resource systems (e.g., edge devices, mobile phones) would further increase both the reach and relevance (Reddi et al., 2020). Here, posterity will manifest in dataset enlargement to include a more balanced emotional response, a more diverse population set and equally more diverse Cultural Region (Zhao et al., 2021). If architectures are designed to identify changes in emotional states over time in either video or live feeds, such applications like stress or mood profiling over longer horizons can be made possible (Li et al., 2022).

Final Remarks

This thesis effectively translates the concept of deep learning in emotion detection across static images, live camera feed, recorded video clips and in audio format. The integration of these capabilities highlights that it is possible to build multi-modal and real time emotion recognition. Building on further, this work can have an impact on future industries like health care, education, entertainment and human-computer-interaction that will be shaped by seamless and reliable technologies based on emotion detection (Goodfellow et al., 2016).

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