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Final Year Dissertation

MULTIMODAL EMOTION RECOGNITION

HERIOT-WATT UNIVERSITY, DUBAI



April 2022

Declaration

I, Ayushi Madhukumar Amin confirm that this work submitted for assessment is my own and is expressed in my own words. Any uses made within it of the works of other authors in any form are properly acknowledged at any point of their use. A list of the references has been included.

Signed: Ayushi Madhukumar Amin

Date: 21/04/2022

Abstract

The field of Human-Computer Interaction and Affective Computing has been slowly gaining prominence in Artificial Intelligence. One of the most challenging problems in these two fields is Automatic Emotion Recognition since humans express emotions through multiple modalities. Nonetheless, Emotion Recognition has a variety of applications in the health, education, and psychology fields, among others. Numerous studies have proposed and tested various approaches that use multiple modalities such as visual, EEG (Electroencephalography), text, audio, etc. However, most Multimodal Emotion Recognition research focuses on text and audio modalities, with only a few including the visual modality in addition to the text and audio modalities.

This project aims to:

**Keywords:** *Multimodal Emotion Recognition, Audio, Visual, Text, Deep Learning, Neural Networks*

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Table of Contents

[**Declaration**](#Declaration)**i**

[**Abstract**](#Abstract)**ii**

[**Acknowledgement**](#Acknowledgement)**iii**

[**Table of Contentsiv**](#Table_of_contents)

[**List of Figuresv**](#List_of_figures)

[**Abbreviations**](#Abbreviations)**v**

**1 Introduction1**

1.1 Motivation1

1.2 Aim1

1.3 Objectives1

1.4 Organization2

**2 Literature Review3**

2.1 Classification of Emotions3

2.1.1 Plutchik’s Wheel of Emotions3

2.1.2 The Geneva Emotion Wheel3

2.1.3 Ekman’s Basic Emotions4

2.2 Introduction to Emotion Recognition5

2.2.1 Types of Emotion Recognition Algorithms5

2.3 Background Topics8

2.3.1 Machine Learning9

2.3.2 Deep Learning9

2.3.3 Neural Networks and their types9

2.3.4 Machine Learning Workflow10

2.4 Dataset Analysis11

2.4.1 Natural Datasets vs. Acted Datasets11

2.4.2 [Available Multimodal ER Datasets](#avail_DS)12

2.5 Key steps involved in Multimodal Emotion Recognition14

2.5.1 Feature Extraction 15

2.5.2 Feature Fusion 17

2.6 Related Work & Critical Review17

**3 Project Implementation24**

3.1 Hardware and Environments used24

3.2 Important Terminologies 3

3.2.1 Word Embeddings 3

3.2.2 Attention 3

3.2.3 Transformers 4

3.3 Getting the Data24

3.4 Data Processing24

3.4.1 Textual Data Pre-Processing3

3.4.2 Modifying the Emotion Scores 4

3.5 Feature Extraction24

3.5.1 Extraction of Audio and Visual data3

3.5.2 Extraction of Textual data4

List of Figures

[**Figure 2. 1**: Plutchik’s Wheel of Emotions [9] 3](#_Toc94176719)

[**Figure 2. 2**:The Geneva Emotion Wheel [10] 4](#_Toc94176720)

[**Figure 2. 3**: (a) A sample from the dataset illustrating the visual feature and the utterance, along with their associated emotion and sentiment type (b) The above bar chart depicts the proportion of the seven emotions for each character [7] 12](#_Toc94176721)

[**Figure 2. 4**: The above pie charts illustrate the proportion of each of the ten emotions in the dataset that has been taken from the two sessions (a) choreographed (b) impromptu [20] 13](#_Toc94176722)

[**Figure 2. 5**: (a) A sample from the dataset illustrating the visual feature and its associated audio and text feature (b) The above bar chart depicts the proportion of each of the six emotions in the dataset [30] 14](#_Toc94176723)

[**Figure 2. 6**: The proposed MMFA-RNN Architecture [6] 18](#_Toc94176724)

[**Figure 2. 7**: The proposed crossmodal fusion transformer with EmbraceNet architecture [25] 19](#_Toc94176725)

[**Figure 2. 8**: The proposed Multi-task Gated Contextual Cross-Modal Attention Architecture [27] 20](#_Toc94176726)

[**Figure 2. 9**: The proposed Deep Learning-based Hierarchical model [28] 21](#_Toc94176727)

[**Figure 2. 10**: The proposed Deep Higher-Order Sequence Fusion network [29] 22](#_Toc94176728)

[**Figure 3. 1**: The implementation procedure followed 24](#_Toc94176731)

[**Figure 3. 2**: The CMU-MOSEI dataset hierarchy [47] 25](#_Toc94176732)

[**Figure C. 1**: Gantt Chart 46](#_Toc94176786)

[**Figure C. 2**: The Scrum Methodology Model 47](#_Toc94176787)

Abbreviations

|  |  |
| --- | --- |
| **AI** | **A**rtificial **I**ntelligence |
| **ML** | **M**achine **L**earning |
| **ER** | **E**motion **R**ecognition |
| **NN** | **N**eural **N**etwork |
| **RNN** | **R**ecurrent **N**eural **N**etwork |
| **LSTM** | **L**ong **S**hort-**T**erm **M**emory |
| **GRU** | **G**ated **R**ecurrent **U**nit |
| **MER** | **M**ultimodal **E**motion **R**ecognition |
| **DL** | **D**eep **L**earning |
| **ANN** | **A**rtificial **N**eural **N**etwork |
| **CNN** | **C**onvolutional **N**eural **N**etwork |
| **NLP** | **N**atural **L**anguage **P**rocessing |

Chapter 1 - Introduction

Unlike most words in the English language, there is no clear and precise definition for “Emotion” in today’s society. On the other hand, emotions play an essential role in human communication and interaction because one can perceive another’s emotional state by seeing their facial expression, body language, voice tone, or reading their texts if they are messaging each other [[1]](#ref_1). Understanding one’s emotions can help two people or a group communicate more effectively but identifying the correct emotions has always been challenging because humans can express several emotions at different times. Researchers aspire to accomplish the idea of robots or computers gaining human-like characteristics in the ever-evolving field of Human-Computer Interaction [[2](#ref_2)]. In other words, this idea is known as Affective Computing. This area is concerned with making computers comprehend human-like characteristics such as comprehension, interpretation, and recognition [[3](#ref_3)]. A primary goal of this field is to effectively recognize and identify the right emotion that a person is displaying so that appropriate responses can be generated by the computers with which the person is interacting [[4](#ref_4)]. This study seeks to investigate some of the previously deployed ER models and propose an approach for recognizing and classifying human emotions effectively.

* 1. Motivation

Initially, ER researchers focused on proposing and implementing unimodal models, which are models that solely focus on one modality, such as facial expressions. However, these kinds of models are not very accurate and reliable as human emotions, are difficult to interpret because they can be exhibited in a variety of ways at the same time, such as changes in voice tone, facial expressions, text messages, heart rate, etc. For example, the dialogue “*Great, now he is waving back*” [[7](#ref_7)] from the *Friends* TV show can be classified as “Happy”, but while uttering this dialogue, the character has a frown on their face indicating “Sadness”. As shown by the given example, a single modality is insufficient for developing an ER model because humans tend to express emotions through multiple modalities. Since human communication is a mix of verbal and nonverbal means [[50](#ref_50)], using multiple modalities as input to an ER model is more efficient than using a single modality. Hence, researchers are now focusing on developing Multimodal ER models, that take in multiple modalities as input, such as text and visual features, fuses them, and feeds the result to an ML/DL classifier. The majority of MER research focuses on the utilization of audio and textual information as input. Only a few MER models consider facial characteristics (visual features) in addition to textual and auditory input. Besides the voice tone and text medium, facial expressions play a significant influence in determining a human’s emotion. Along with audio and textual inputs, we will also use visual features as input for this project, with the goal of improving the efficiency of a MER model.

* 1. Aim

This project aims to develop a simple and robust Deep Learning Multimodal Emotion Recognition model that precisely classifies human emotions such as anger, happiness, sadness, etc. using three modalities (audio, textual, and visual features). Our primary goal is to investigate various existing MER models and propose and develop a rather simpler MER model. To test the efficiency of our proposed model, we would be comparing our results to those obtained by the previously implemented models.

* 1. Objectives

1. To conduct in-depth research into the area of MER and the methodologies used to develop existing MER models.
2. To investigate and select a MER dataset that includes labeled data from online sources such as TV shows, vlogs, and other media.
3. To research and select appropriate methods for extracting the most relevant features for each of the modalities (audio, text, and visual) from the data provided as input.
4. To examine and select an appropriate method for fusing the extracted features obtained for each of the three modalities.
5. To find and pick a suitable DL model that can be trained on the fused features and can serve as a classifier for ER.
6. To compare the model’s accuracy and other key ML metrics to those obtained by the previously implemented MER models.
   1. Organization

The document organization is described as follows:

* [**Chapter 1**](#chap_1) – This chapter provides a brief introduction of the topic alongside the aims and objectives of the project.
* [**Chapter 2**](#chap_2) – This chapter covers the background of Multimodal Emotion Recognition as well as a critical review of some of the existing models in this field.
* [**Chapter 3**](#chap_3) – This chapter describes how the project was implemented. Additionally, the chapter also briefly explains some of the challenges faced during the implementation.
* [**Chapter 4**](#chap_4) – This chapter includes a critical evaluation of our work as well as a comparison to existing MER models.
* [**Chapter 5**](#chap_5) – This chapter summarizes our implementation, briefly explains some of the challenges faced during the implementation, and future work.

Chapter 2 - Literature Review

This chapter describes the various methods used for classifying emotions, provides an introduction to ER, describes the multiple algorithms of ER and its limitations, briefly elaborates on important topics of ML and DL, provides an analysis of the various available MER datasets. The feature extraction and feature fusion methods are also discussed briefly. Additionally, the chapter also includes a critical discussion of the prior work in MER.

2.1 Classification of Emotions

2.1.1 Plutchik’s Wheel of Emotions

The Plutchik’s Wheel of Emotions is given below, designed by psychologist Robert Plutchik in 1980 [[8](#ref_8)].



**Figure 2. 1**: Plutchik’s Wheel of Emotions [[9](#ref_9)]

Robert Plutchik proposed eight basic emotions: Joy, Trust, Fear, Surprise, Sadness, Disgust, Anger, and Anticipation. These eight emotions are represented in the diagram above, each positioned opposite to a specific emotion. Joy, for example, is placed opposite sadness, whereas anger is positioned opposite Fear. This is because these positions represent the polar opposite of the relevant emotion. The intensity levels of each primary emotion are depicted on the wheel of emotions. For example, the lowest level of intensity for Anger is Annoyance, whereas the highest level of intensity is Rage. Each of these eight emotions can be combined to create an emotion distinct from the basic ones. Contempt, for example, has been derived from the combination of Anger and Disgust [[9](#ref_9)].

2.1.2 The Geneva Emotion Wheel

Given below is the Geneva Emotion Wheel, another popular metric used for the classification of emotions.

Diagram

Description automatically generated

**Figure 2. 2**:The Geneva Emotion Wheel [10]

The wheel is made up of 20 different emotions, each of which belongs to a separate emotion family. The intensity levels of each emotion have also been depicted, in which the element closest to the center of the wheel represents the lowest level of intensity, and the element farthest from the center represents the highest level of intensity [10]. Aside from these 20 emotions, the wheel also contains the emotion ‘Neutral,’ which is positioned in the center of the wheel. If the user is experiencing an emotion that is not one of the 20 discrete emotions listed in the wheel, the section ‘Other’ is set aside to list that emotion [11].

2.1.3 Ekman’s Basic Emotions

Ekman’s basic emotions are considered to be one of the most frequent approaches for categorizing emotions in most studies in the subject of Human Emotions and Affective Computing. Throughout his years of research, Dr. Paul Ekman discovered that there are six primary universal emotions: Anger, Disgust, Fear, Joy/Happiness, Sadness, and Surprise [12].

In the field of Emotion Recognition, most of the previous works have used Ekman’s basic Emotions as the metric to classify the emotions, and hence, for this project, we would be using Ekman’s basic Emotions for the classification.

2.2 Introduction to Emotion Recognition

**Emotion Recognition (ER)** is the process of recognizing human emotions exhibited through various means such as facial expressions, changes in voice tone, heart rate, text messages, breathing cycles, etc. [5]. The importance of recognizing emotions stems from the desire to strengthen the relationship or communication between two or more people. People can tend to misinterpret the emotional state of the person to whom they are speaking, which might interfere with their relationship. As a result, academics are turning to AI and Affective Computing methods to help overcome this challenge.

2.2.1 Types of Emotion Recognition Algorithms

Some of the modalities used in ER have their own algorithms, which we will be describing in this section.

Facial Emotion Recognition (FER)

Humans express their emotions most often through facial expressions, making facial expressions the most common type of non-verbal communication. When communicating face-to-face or via video call, one can usually perceive the other’s feelings by looking at their facial expressions. One of the most popular subfields in Computer Vision is **Facial Emotion Recognition (FER)** [13]. The goal of FER is to offer machines ways to detect human emotions by examining facial expressions [14]. Some of the popular databases used in FER are JAFFE, FER-2013, CK+, etc.

FER faces some limitations, no matter how popular it is in the field of emotion recognition. Some of the images in the dataset might not have proper lightning or might not be entirely clear. Another limitation is that there is a chance that the FER model might detect and classify the wrong emotion as some emotions share similar features; for example, lowering of the eyebrows can indicate confusion or even annoyance at times [15].

Speech Emotion Recognition (SER)

Speech is the most common type of communication between two or more people. People tend to express their feelings through speech, even if they are not aware of it. When speaking with someone face-to-face or over the phone, a person may notice a change in the speaker’s voice tone, which can aid in understanding each other’s emotional conditional [16]. By analyzing the conveyed speech signals, **Speech Emotion Recognition (SER)** aims to assist machines in understanding a human’s emotional state [6]. Some of the popular databases used in SER are EmoDB, DES (Danish Emotional Speech Database), SUSAS, etc.

SER has certain drawbacks, which we will go over briefly. The vast majority of SER databases are limited to a single language. The DES database, for example, has utterances in Danish, while the EmoDB database contains utterances in German. When such databases are used to create SER models, they can only be used for that particular language, and they cannot be used for another language. There are not many databases that have a variety of languages in them. Aside from that, most SER databases contain data that has been acted out by professional actors/actresses just to create the database. Some actors will even modify their voice to convey a feeling. The SER systems trained on these databases will not deliver remarkably accurate findings of the emotion detected because this does not represent the actor’s actual emotion [17].

Textual Emotion Recognition (TER)

As FER and SER have been gaining popularity, **Textual Emotion Recognition (TER)** has progressively risen to prominence in Emotion Recognition. This is because of many social networking applications such as Instagram, Twitter, Facebook, and WhatsApp. Many people utilize these platforms to meet new people or chat with their peers. Aside from that, many people utilize social media platforms to express their views on a specific subject by posting, commenting, or tweeting about it. Websites such as TripAdvisor and Rotten Tomatoes allow individuals to share their opinions about a specific restaurant, amusement park, movie, and so on. An entire text does not always reflect the emotional state of the individual [18]; only certain words in the text help to detect the human’s emotional state. A machine can determine a user’s emotional state from their texts, comments under a post, reviews, tweets, etc., by extracting these specific words, classifying them as positive/negative/neutral with the help of Sentiment Analysis [19], and using TER. Some of the popular databases used in TER are ISEAR, EMOBANK, Fairy Tales, etc.

In its field, TER is also faced with various difficulties. Apart from textual data, most of the databases used to build TER models, such as IEMOCAP and MELD, also contain other data such as audio, visual features, and so on. There is a scarcity of databases that only include textual data. Because TER extracts particular words and a TER system assigns an emotion based on these phrases, this is not always accurate, as humans sometimes use such words for sarcasm or exaggeration. As a result, in the field of emotion recognition, TER has proven to be the most difficult [21].

Physiological Emotion Recognition

Human physiological signals are the most reliable modality for emotion recognition because, unlike other modalities such as facial expressions, speech signals, and textual information, these signals cannot be altered or controlled and are genuine. Heart and breathing rate, skin temperature, etc., are some of the physiological signals given out by the human body. Biosensors such as ECG (Electrocardiography), EEG (Electroencephalography), and EMG (Electromyography) are used by researchers to measure these signals. Using the data (signals) acquired by the biosensors to recognize and classify the emotions accurately is the primary goal of **Physiological Emotion Recognition**. Because people with Autism Spectrum Disorder (ASD) do not freely express their emotions, FER and SER models will not give reliable results because ASD people exhibit unusual behavior at times; using physiological signals released by the body can help determine their true feelings. Hence, Physiological Emotion Recognition is especially useful for detecting emotions in ASD people [22]. Some of the popular databases used in Physiological Emotion Recognition are SEED, DEAP, ASCERTAIN, etc.

No matter how reliable and accurate physiological signals are, Physiological Emotion Recognition still faces limitations and raises ethical issues. The physiological signals emitted by the body largely depend on the environment the human is currently in. Some might feel joyful, fearful, or upset. Suppose in an experiment conducted for Real-Time Physiological Emotion Recognition, the participants attached to biosensors are seated in a similar regular environment. In that case, they might all emit similar signals, and it would be hard to express a particular emotion via physiological signals [23]. Hence it would not be easy to detect the different types of emotions emitted by the participants. Furthermore, accurately labeling the acquired signals to a particular emotion is difficult when constructing datasets for Physiological Emotion Recognition, as some emotions generate similar signals at times [24].

Multimodal Emotion Recognition (MER)

Because using single modalities for emotion recognition has several limitations, as we have shown, researchers are now experimenting with multiple modalities for emotion recognition, which have produced better results than single modalities. **Multimodal Emotion Recognition (MER)** fuses multiple modalities, such as audio, visual, physiological signals, etc., and uses the resulting output to detect the emotional state [26]. Most of the available datasets used for emotion recognition consist of multiple modalities like gestures, facial expressions, textual information, etc. Some of the popular databases used in MER are IEMOCAP, HUMAINE, MELD, etc.

In this project, we would be using the Multimodal Emotion Recognition algorithm as previous works show that MER is more reliable, efficient, and accurate. The modalities which we would be looking into are – Audio, Text, and Facial Expressions. Physiological signals will not be considered in this experiment, as the available datasets for Physiological signals might not be as accurate as those of the available MER datasets.

2.3 Background Topics

2.3.1 Machine Learning

**Machine Learning** is described as the challenge of training computers in such a way that they can produce precise results based on their knowledge acquired via learning [33]. ML has become a very popular area in today’s society attributable to its applications in a variety of fields such as healthcare, power utilities, transportation, as well as security. It has also aided in the recognition of emotions, the improvement of social skills in autistic children, the detection of spam emails, and other tasks.

2.3.2 Deep Learning

**Deep Learning (DL)**, a branch of ML, has been steadily gaining prominence, particularly in the domains of Computer Vision, Real estate, Autonomous Vehicles, and Language Translation models. The process of DL has been illustrated in the given example - In Facial Emotion Recognition, an image illustrating an emotion is provided to the deep learning model. The neural network had previously been trained to inform users about which emotion has been detected from a picture provided as input. The input image is sent through a sequence of hidden layers that extract the edges and other appropriate features, with the ultimate output being the intended emotion [34].

2.3.3 Neural Networks and their types

**Artificial Neural Networks (ANN)** are a type of ML model that is typically used for classification. ANNs resemble the human neuron, and just like them, the nodes of ANNs are also interconnected with each other. The nodes apply specific weights to each input received using the Learning Rule approach, and then pass them to the next layer of the topology. The activation function is also computed before transmitting the weighted input to the next layer of the topology [35]. There are many different types of ANNs available, however in this project we will only look at two of them.

Convolutional Neural Networks (CNN)

**Convolutional Neural Network (CNN)** takes unstructured data as input, such as images. As it travels through the hidden layers to learn this input, the CNN uses filters to apply methods like edge detection and blurring to the input. This is done in order for the CNN to learn about the input provided to them by extracting the features. The desired output is generated after the CNN successfully interprets the input [36]. CNNs are frequently used for image data and image extraction applications, including autonomous driving and facial expression recognition.

Recurrent Neural Networks (RNN)

**Recurrent Neural Networks (RNN)** are similar to CNNs in that they accept unstructured data, but they deal with sequential data such as raw audio or text. RNNs, unlike CNNs, have their own memory, making them suited for applications involving data sequences. The most popular tasks for RNNs are language translation, speech recognition, sentiment analysis, etc. However, typical RNNs, suffer from the problem of exploding or vanishing gradients [6]. To resolve this problem, researchers have turned to different types of RNNs, such as the Long-Short Term Memory (LSTM) or the Gated Recurrent Unit (GRU), which do not have the same limitations as traditional RNNs.

2.3.4 Machine Learning Workflow

We will now elaborately describe the typical ML workflow used to deploy multiple ML projects [32].

1. **Getting the data** – Before beginning any ML project, one must first analyze and select a suitable dataset to work with. Some researchers may prefer to work with open-source datasets, seek permission to access a dataset that is not publicly available or even construct their dataset. The datasets are fed into the ML model to be trained appropriately and produce precise and appropriate results. Before passing a dataset into a model, it should be split into train and test datasets, with an 80:20 train:test ratio in most projects.
2. **Cleaning and preparing the data –** Some data might contain noise or unnecessary distortions that affect the model’s performance. Methods like grayscale conversion, reshaping, augmentation of data, etc., help clean (pre-processing) the data. The most relevant features are then extracted after cleaning the data.
3. **Training the model –** The ML model is trained on the pre-processed extracted features to ensure that it learns effectively and produces accurate results and predictions. More data is allocated to the training set when the dataset is split for training and testing, allowing the model to train and learn the data efficiently.
4. **Testing the model –** The model is then tested using the test set and predicted values (generated by the model in most cases) to compute numerous metrics such as accuracy, recall, true positive rate, ROC curve and score, precision, F1-score, false-positive rate, etc. Methods such as K-Fold Cross Validation are sometimes used to guarantee that sample bias is not an issue.
5. **Improvements of the model –** Modifications to the model could be done once it has been adequately trained and tested to examine and see if any improvements to the performance and majority of the metrics have been made.

2.4 Dataset Analysis

2.4.1 Natural Datasets vs. Acted Datasets

Generally, two types of datasets are available for MER: Natural and Acted Datasets.

Natural datasets are made up of data gathered from TV shows, movies, news channels, and online sources such as YouTube videos. These types of datasets usually give the model more accurate results when it comes to recognizing and classifying emotions. However, annotating the gathered data takes a while since there can be noise present in the data, and it can be difficult to identify a certain emotion to a specific segment because the actors can express complicated emotions at times [31].

At times, professional actors or actresses act out a specific emotion in accordance with a script or situation while wearing face markers or sensors on their bodies purely for the purpose of creating Acted Datasets. In general, labeling the emotions takes less time for these types of datasets because the dataset producers already know which performance is related to which emotion. Models trained on these datasets, on the other hand, may not achieve the same high accuracies as Natural datasets because there may be background noise while recording, some participants may or may not hold the microphone nearby, etc. [17]

2.4.2 Available Multimodal ER Datasets

In this section, we have listed some of the datasets we came across in our research that solely include the three modalities we are working with in the project: audio, text, and visual. Along with the distribution of the emotions in the dataset, a brief description of the data in the dataset has been provided.

MELD

Graphical user interface, application

Description automatically generated Chart, bar chart

Description automatically generated

**Figure 2. 3**: (a) A sample from the dataset illustrating the visual feature and the utterance, along with their associated emotion and sentiment type (b) The above bar chart depicts the proportion of the seven emotions for each character [7]

The **Multimodal Emotion-Lines Dataset (MELD)** dataset [7] created in 2018 is a Natural dataset because the data was collected from the *Friends* TV Show. The dataset contains approximately 13,000 utterances from more than 1,400 dialogues gathered from conversations between the characters. Emotions were labeled as per Ekman’s Universal Emotions - Sad, Disgust, Surprise, Fear, Joy, and Anger. Alongside this list of emotions, an extra-label was also added, i.e., Neutral. Since the data was acquired from a TV show, MELD is open-sourced.

IEMOCAP

Chart, pie chart

Description automatically generated

**Figure 2. 4**: The above pie charts illustrate the proportion of each of the ten emotions in the dataset that has been taken from the two sessions (a) choreographed (b) impromptu [20]

The **Interactive Emotional Dyadic Motion Capture Database (IEMOCAP)** dataset [20] was created in 2008 by the University of Southern California’s Speech Analysis and Interpretation Laboratory. The IEMOCAP is an Acted Dataset as it involves ten actors and actresses from within and outside the institution who acted out the following emotions – Sadness, Surprised, Happy/Joy, Disgust, Neutral, Excited, Frustration, Fear, Anger, and Other. The ‘Other’ emotion label refers to any other emotional state that has not been included in the list of nine emotions above. The dataset comprises approximately twelve hours of data collected from two independently conducted sessions, Choreographed and Impromptu. To detect the emotion, sensors and markers were attached to the actors’ or actresses’ bodies. This dataset is not open sourced to safeguard the privacy of the actors and actresses.

CMU-MOSEI

Graphical user interface, application

Description automatically generatedChart, bar chart

Description automatically generated

**Figure 2. 5**: (a) A sample from the dataset illustrating the visual feature and its associated audio and text feature (b) The above bar chart depicts the proportion of each of the six emotions in the dataset [30]

The **CMU Multimodal Opinion Sentiment and Emotion Intensity (CMU-MOSEI)** dataset [30] was created in 2018 is a Natural dataset as it consists of data that has been extracted from online sources like YouTube, vlogs, etc. The dataset includes around 23,453 utterances from over 3,200 online videos, acquired from monologues or dialogues of about 1000 YouTubers or Vloggers. The videos collected consist of a variety of topics ranging from Reviews to Courses. Ekman’s basic emotions, i.e., Anger, Disgust, Fear, Joy/Happiness, Sadness, and Surprise was used to label the emotion data. Because the data was gathered from online videos, this dataset is open-sourced.

We will utilize the CMU-MOSEI for our project because it is the largest and most extensively used dataset in most research projects undertaken to provide an MER model or technique. According to the results produced in the previous works, the proposed models utilizing this dataset have produced exceptionally high accuracies.

2.5 Key steps involved in Multimodal Emotion Recognition

This section describes the essential steps of any MER model using the modalities – audio, text, and visual features.

2.5.1 Feature Extraction

When any MER model takes in an input, they are usually in their raw state. This raw audio, images, or text may have noise or other elements that degrade the model’s performance. Feature extraction methods are utilized to extract the most relevant or suitable features from the pre-processed input, and these features are then used throughout the MER procedure to ensure the model’s robust performance. Some popular methods for extracting features from visual, audio, and textual information are listed below.

Facial Features

Analyzing a person's facial features is the simplest technique to determine their emotional state. When a visual input is given to the MER model, it applies a feature extraction method to detect facial features such as widening of eyes and lifting of brows present in an input segment or image and extracts the most appropriate one for recognizing the emotion. Given below are some of the methods used for extracting methods from visual data.

1. **CERT**– The **Computer Expression Recognition Toolbox (CERT)** is a real-time open-source tool for recognizing face features developed by researchers at the University of California, San Diego. The CERT calculates the levels of intensity of the various Action Units (AU) found in the Facial Action Coding System (FACS) as well as Ekman's six main emotions when a user uses the software. The ones with higher intensities are selected and a threshold is defined to find the most appropriate feature [37].
2. **FACS** – The **Facial Action Coding System (FACS)** designed by Paul Ekman and Wallace Friesen, is a system used for detecting the facial features from a given input [37]. To find the facial expression type, the various facial features or AUs are computed for the input and evaluated.
3. **CNN/RNN** – CNNs are commonly used to process images and extract features from them. The input is interpreted by a sequence of convolutional layers in the CNN [38]. To extract these features, methods such as edge detection and blurring are used within these layers. When a video is passed in as an input to the MER model, some researchers use RNNs to extract facial features. This is due to the fact that when working with sequential data, RNNs are favored over CNNs for visual feature extraction.

Audio Features

Sometimes, the emotional condition of the user is conveyed by the speaker’s voice tone. These voice tones are fed into a MER model as audio signals to identify the speaker's emotional state. Because the emotional state is not present in the entire audio signal but only in select parts, feature extraction is utilized to extract the features that convey these emotions. Given below are some of the coefficients which are calculated for audio feature extraction.

1. **Mel Frequency Cepstral Coefficients (MFCC)** – The MFCC coefficients are used to extract certain features that can be used to detect a user's emotional tone, a reservation number, etc.
2. **Linear Predictive Cepstral Coefficients (LPCC)** - The LPCC coefficients are calculated to extract various features that can aid in detecting the speaker's characteristics, such as gender. [39]

OpenSMILE is a popular toolkit for SER and feature extraction from audio signals [6]. This toolbox also assists in the computation of the coefficients listed above.

Text Features

Because only specific parts of the textual input are useful for detecting emotion, it's required to extract features from the pre-processed text and construct word embeddings before passing them into the MER model. The two most prevalent ways for creating word embeddings are described briefly below.

1. **Bi-directional Encoder Representations from Transformers (BERT)** – This pre-trained NLP model only has one layer and constructs word embeddings of the relevant features embeddings by traversing the full sentence (input) from left to right [40], rather than top to bottom.
2. **Embeddings from Language Models (ELMo)** – ELMo employs a two-layer LSTM that passes parts of the sentence top-down and extracts the features of the sentence before forming word embeddings [40].

2.5.2 Feature Fusion

When a MER model is programmed to recognize and classify an emotion from three different modalities, it is critical that the modalities be merged before being sent into the classifier. After feature extraction, feature fusion is the phase that deals with the fusion of the three modalities. Most common example of a feature fusion model is the **Support Vector Machine (SVM)** model.

2.6 Related Work & Critical Review

In this section, we will examine and investigate some of the related works in the field of Multimodal Emotion Recognition using datasets that we have previously investigated.

Diagram

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**Figure 2. 6**: The proposed MMFA-RNN Architecture [6]

Researchers at the Chonnam National University proposed a mechanism called **Multi-Level Multi-Head Fusion Attention Recurrent Neural Network (MMFA-RNN)** for Multimodal Speech Emotion Recognition [6]. The proposed model used two modalities as input instead of one, namely audio and textual features. The MFCC technique was used with the OpenSMILE toolkit for speech signal pre-processing and feature extraction. As a result, the MFCCs were obtained from the raw signals that were fed into the model. The BERT model was used to extract features and produce word embeddings from the textual features sent in as input. The MFCCs and word embeddings were passed separately into two different self-attention based RNN structures in the next phase. The two different RNNs retrieve the corresponding audio and textual features per segment. The resulting outputs are then merged with the help of the multi-head attention mechanism. In the multi-head mechanism, normalization was performed on each of the audio and textual features (given as output from the self-attention RNN), and the result is then passed to a GRU. A GRU was used instead of a typical RNN since typical RNNs have the central problem of exploding or vanishing gradients. Since overfitting is a common problem in ML, a GAP layer was added for spatial dimensionality reduction. With the help of the softmax function, the probabilities of each emotion were calculated, and conclusions were drawn. Before calculating the softmax, the flattened output was taken as input by the two fully connected layers to reduce the data further. Three multimodal databases were used to test the proposed architecture against other works: IEMOCAP, MELD, and CMU-MOSEI. For the IEMOCAP dataset, the model achieved an accuracy of 73.23% for the ‘Mixed’ scenario, and for the ‘Improvised’ scenario, it achieved 76.98% as the accuracy. On CMU-MOSEI, it got an accuracy of 99.19%, whereas, for MELD, the model achieved 63.26% accuracy.

For better results, an LSTM could have been used instead of a GRU. The three datasets used in this experiment are pretty large, so using an LSTM could offer much better and more accurate results.

Diagram

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**Figure 2. 7**: The proposed crossmodal fusion transformer with EmbraceNet architecture [25]

Researchers at George Washington University proposed a method for detecting speakers’ emotions during a conversation [25]. The proposed architecture took in three modalities – audio, text, and facial expressions, as the input. There were three separate deep learning models created for each modality, and the dataset used in this experiment is MELD. In this paper, the authors have used three different models per modality for the feature extraction process. The ‘WaveRNN’ model was used for audio features, the ‘FaceNet+RNN’ model helped extract suitable features from the facial features (visual) modality, whereas text features used the ‘GPT’ model. The ‘WaveRNN’ and the ‘GPT’ model were already pre-trained by other existing datasets. Due to memory issues and the aim of achieving an efficient model, only 50 image sequences were extracted for the facial features modality. Since some of the sequences varied, zero padding was applied. To fuse the three modalities together for detecting the emotions, the Crossmodality Transformer architecture was used along with the Multi-Head mechanism, and to ensure the process of the combination of the modalities was robust, EmbraceNet was used. This EmbraceNet consisted of two separate layers, which helped with the task of emotion recognition. The model achieved an accuracy of 65% on the MELD dataset and other relevant metrics have also been provided in the paper.

In the paper, it is mentioned that the extracted features of the visual modality have variable lengths, and only some were downsized. Instead of downsizing some of the samples, all the extracted features could’ve possibly been downsized to a particular length.

Diagram, schematic

Description automatically generated

**Figure 2. 8**: The proposed Multi-task Gated Contextual Cross-Modal Attention Architecture [27]

This paper proposed an architecture – **Multi-task Gated Contextual Cross-Modal Attention** used for multimodal emotion and sentiment analysis [27]. Audio, text, and visual features were fed in as input to the model, and the CMU-MOSEI dataset was used for testing the model’s accuracy in detecting the emotion and sentiment. Since raw data might contain some noise or unnecessary distortions that affect the model’s performance, the raw input was fed to a Gated Multi-modal Unit (GMU) to remove these distortions. Because videos are sequential data, and the modalities for this experiment were taken from videos, the proposed model was based on RNNs. After being processed by the GMU, the modalities were fed into three separate Bi-GRUs. A framework called Contextual Cross-Modal Attention (CCMA) merged two modalities (Text+Audio, Text+Visual, Audio+Text, Audio+Visual, Visual+Text, Visual+Audio) and calculated the attention of each of these six combinations. The derived outputs were fused to predict the respective emotion and sentiment. The residual connections of each modality were fused to the outputs derived from the use of CCMA to allow the flow of gradients through the layers. Two separate GMUs were used for the sentiment and the emotion data. For the Sentiment prediction, the softmax function was used, whereas the sigmoid function was used for emotion recognition. The proposed model achieved an accuracy of 63.16% for emotion recognition and 80.15% for the sentiment analysis task.

The comparative analysis of the F1 Score and Accuracy between the proposed model and relevant work has been given briefly, but the paper does not provide any information about the Precision, Recall, TP Rate, and FP Rate. These metrics could have also been computed to ensure that the predictions were made correctly.

Diagram

Description automatically generated

**Figure 2. 9**: The proposed Deep Learning-based Hierarchical model [28]

The authors of this paper proposed an SER **Deep Learning-based Hierarchical** model that is built to take in unimodal and multimodal data [28]. The proposed model takes in just audio (speech signals) features for the unimodal section, whereas it takes in audio features and textual features for multimodal. Three databases were used for evaluating the model: IEMOCAP, SAVEE, and RAVDESS. The ELMO v2 framework extracted features and produced word embeddings from the textual features sent in as input. For the audio features, the Framing and Windowing method was used to split the raw audio input file for feature extraction, and the Librosa library was used to extract the spectral, prosody, and VQ (Voice Quality) based features. The computed MFCCs were merged with the above-extracted features, and the resulting output was merged with the word embeddings and fed into the Input Feature Vector. To ensure that the audio features were balanced, zero padding was added, normalization and feature scaling were performed to all the features, including the textual data, and oversampling was used to balance the imbalanced datasets. Because some emotions are distinct from others, the model begins by identifying these distinct emotions. Furthermore, the model separates the emotions present in the output depending on the arousal degree of the emotion, using the output obtained from the fusion of the text embeddings and the selected audio features. Since some of the datasets utilized in this experiment have more data for some emotions and less data for others, those with fewer data are placed at the bottom of the hierarchy tree. For the IEMOCAP dataset, the model achieved an accuracy of 74.5%. On RAVDESS, it achieved 81.2% accuracy, whereas, for SAVEE, the model achieved 81.7% accuracy.

Although the accuracies and ROC curves have been calculated for each dataset used and comparisons with previous works have been made, the paper presents hardly any information about the other important metrics like F1-Score, Precision, and Recall.

Diagram

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**Figure 2. 10**: The proposed Deep Higher-Order Sequence Fusion network [29]

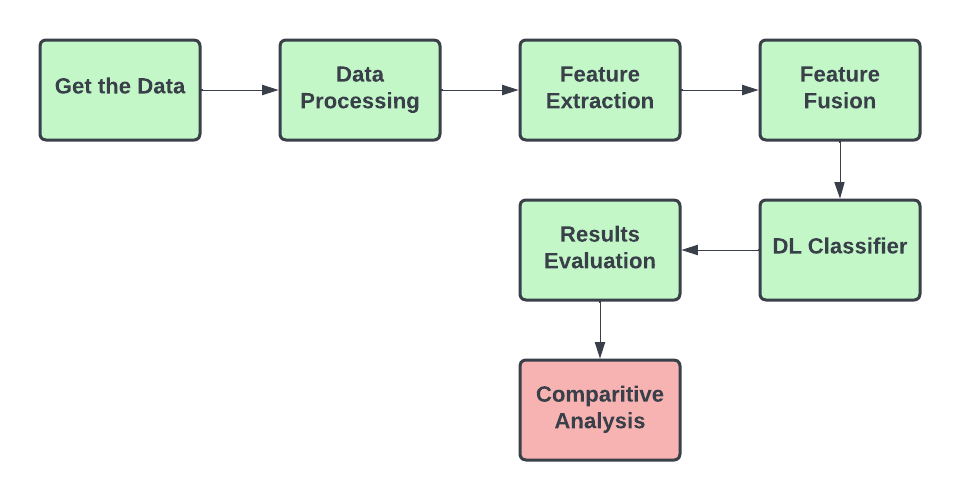
This paper proposed a methodology, **Deep Higher-Order Sequence Fusion,** for multimodal sentiment analysis (task of detecting whether a provided text is a positive/negative/neutral sentiment) using the CMU-MOSEI and CMU-MOSI datasets [29]. The model uses three modalities – Audio, Text, and Visual- and comprises two separate networks, namely, the Common and Unique networks. In the common network, the model extracts the information within each of the three modalities, and the model extracts the information across the three modalities. These data are then passed into three separate LSTMs for each modality. Using the output derived from the LSTMs, the tensor product is computed. In the unique network, the raw modalities are processed using feed-forward layers, and with the help of the obtained output, the tensor product of these values is also computed. The results derived from the common and unique networks are fused together using the pooling technique and feed-forward layers, and using the fusion, the model outputs whether the sentiment is positive or negative. An additional detail to note here in the architecture of the diagram is that the model processes the two tensor products computed with the common and unique networks using convolution layers. The proposed model achieved an accuracy of 44.17% for multi-class data, approximately 74.32% for the binary class, and 0.5438% for the correlations using the regression algorithm.

The paper presents extensive details relating to the evaluation results; however, since some of the accuracies vary considerably, like for the multiclass and binary class, the researchers could use K-Fold Cross Validation to ensure the sampling bias problem is not taking place.

Chapter 3 – Project Implementation

This chapter describes the various stages involved in the implementation of the project, i.e., Getting the Data, Data Cleaning and Processing, Feature Extraction, Feature Fusion, and implementation of the DL classifier. Alongside this, we have also briefly explained some important terminologies, that are essential in understanding the implementation. We also discuss the hardware and the environments we have used for this project.

As discussed in [Section C.2](#dev_metho_c2), we have implemented the project as per the project plan, while using the **SCRUM** methodology. The below flowchart provides a high-level overview of the steps involved in the implementation of the project.



**Figure 3. 1**: The implementation procedure followed

3.1 Hardware and Environments used

The program was developed using Python (*Version 3.7.13*) and the PyTorch DL library (*Version 1.10.0+cu111*) was used. Developed in 2016 by FaceBook’s AI Research Lab [44], PyTorch is a dynamic open-sourced ML Python user-friendly library that provides flexibility for building complex NN and DL architectures in a more object-oriented way [43]. Specifically due to its faster training and execution time [45], PyTorch was chosen over TensorFlow. The project was entirely implemented on Google Colab. Through Colab, we had access to 12.69 GB RAM and NVIDIA’s Tesla K80 GPU, which helped in executing our DL model and BERT.

3.2 Important Terminologies

In this section, we will be briefly explaining some important terms and logic, which is essential for understanding the implementation of our project.

3.2.1 Word Embeddings

When a NN operates on a piece of text, it doesn’t perform the relevant calculations on the individual characters in the string. It instead works on word embeddings. Word embeddings are a popular NLP technique used to represent documents (words or sentences) with vectors of fixed length [51]. In other words, word embeddings are known as the feature vector representation of a document. Feature vectors are a list of numerical values containing floating-point, positive or negative values.

Diagram

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**Figure 3. 2:** The word embeddings of some words and how these appear in a 2D vector space [53]

In Figure 3.2, we can see which few terms are semantically comparable to “**cat**” by looking at the word’s embedding. Word embeddings help in summarizing the semantic information of a word. Thus, capturing helpful information related to the context of the term [52] and making it a better method of representing documents than other text feature extraction methods like Bag of Words (BOW), One-hot encoding, etc. For this project, we will be using the BERT transformer model to generate our textual data embeddings. BERT embeddings are context-dependent. In other words, they have different embeddings for a particular word, depending on the situation it is used in. For example, consider two sentences, “My **left** arm hurts” and “She **left** for the movie a while back”. Methods like GloVe would produce identical embeddings for the term “left” present in the above two sentences. The BERT model’s embeddings generated for “left”, on the other hand, will be distinct for each of the two sentences.

3.2.2 Attention

The Attention Mechanism is a technique in NLP used for dynamically emphasizing the important features of an input sequence of textual data. Depending on the task, it calculates the attention scores for the input and assigns higher values to the most relevant words [54]. The model can focus on significant features of the sequence through these scores.

During the pre-processing stage, BERT makes use of the attention mechanism. In any dataset containing textual data, the raw sentences are usually of unequal length. Padding is added to them to ensure the sentences are all the same length. However, before passing the sentences to the BERT model for training, one must add the “attention mask”, which employs the Attention Mechanism described above. Input tokens having a significant relevance are assigned a score of 1, while padding tokens are given an attention score of 0 as they don’t contribute to the context of the input sentence. The scores are stored in an array containing 1s and 0s. Figure 3.3 depicts how the attention scores for a given sentence are assigned and represented.

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**Figure 3. 3:** Attention scores of each token in BERT

3.3 Getting the Data

As mentioned in [Section 2.4.2](#avail_DS), we have used the CMU-MOSEI (*CMU Multimodal Opinion Sentiment and Emotion Intensity*) dataset for this project. The dataset is open-sourced and is publicly available via the CMU MultiModal SDK [42]. Due to challenges faced while loading the dataset (explained in detail in 5.1.1), we opted to use an older version of the CMU-MOSEI dataset. This consists of data (Audio, Visual, and Text) already pre-aligned to the textual modality and as per their respective timestamp (referred to as the timestamp of the video from which the data was taken). As the data is already aligned and the sequences of each modality are of the same length, we are not required to perform the data alignment step before pre-processing the data. Therefore, since the pre-aligned dataset (the older raw version of CMU-MOSEI) is open-sourced, we decided to use the CMU-MOSEI raw dataset instead of the latest version present at the SDK [42].

For each modality (audio, text, and visual), the raw aligned dataset consists of three .h5 files – Train, Test, and Valid. Additionally, alongside the train, test, and valid files for each modality, the raw dataset contains three additional .h5 files, consisting of emotion scores ranging from [0, 3]. These emotion scores serve as labels for the data. The value “0” indicates that the emotion is not present, whereas “3” indicates a high presence of that particular emotion.

|  |  |  |
| --- | --- | --- |
| **Training Data** | **Testing Data** | **Validation Data** |
| 15290 | 4832 | 2291 |

**Figure 3. 4:** The sizes of the Training, Testing, and Validation data

3.4 Data Processing

Before performing feature extraction, it was critical to process the data as per our requirements and needs. This section will briefly explain how we processed our data.

3.4.1 Textual Data Processing

The textual data obtained from the raw aligned CMU-MOSEI dataset (discussed in [3.3](#getting_data)) was already embedded beforehand using the pre-trained GloVe embeddings. As we planned to make use of pre-trained BERT embeddings instead of ELMo or GloVe (discussed in [2.5.1](#feature_extra_lit_review)), we had to revert the GloVE embedded word vectors to get the words associated with the embeddings.

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**Figure 3. 5:** Creation of the dictionary

The creators of the dataset have provided two separate computational sequence (.csd) files on the respective dataset page [[42](#ref_42)], one containing a list of raw words (derived from the transcripts of the YouTube videos during the creation of CMU-MOSEI) and the other storing a list of GloVe embeddings associated to these words. As it has a faster lookup time **(*time complexity = O(1)*)** and doesn’t allow duplicate values, a dictionary was used in which the keys served as the GloVe embeddings and its respective word as the value. Since the average time to complete this step is approximately 25 minutes, the resulting dictionary was saved in a Pickle (.pkl) file. This helps increase efficiency we don’t have to re-create the dictionary and can simply load the pickle file elements. While reading the pickle file, its elements were saved in a new dictionary and this operation took 1 second to complete. For reverting our word/sentence vectors, we employed the following strategy. Within a for loop, the current GloVe embedded word vector is checked to see if it is a key in the newly formed dictionary (created from the .pkl file mentioned above). If that’s the case, we extract the value of the key (the word associated to the embedding) and each extracted raw word is saved in an empty list that holds the entire sentence (generated from the raw words). A large list was used to store the list containing this raw sentence. Finally, this large list is then used to create a csv file containing the raw sentence level transcripts that will be utilized to generate BERT embeddings.

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**Figure 3. 6:** (a) Script to revert the word vectors (b) A dataframe containing the raw transcripts and its length

We found the phrase “sp” appeared in almost all of the raw transcripts while reverting the GloVe embedded word vectors. The phrase “sp” refers to “Speech Pause”. It wasn’t removed from the raw transcripts because the features from the audio and video modality had already been extracted beforehand and it would be difficult to delete the specific audio and visual data accompanying the “sp”. Furthermore, because the data had already been pre-aligned (see [3.3](#getting_data)), removing the “sp” would cause the transcripts to become non-continuous and non-sequential, affecting the DL classifier results as we are dealing with continuous data [[50](#ref_50)].

3.4.2 Modifying the Emotion Labels

An emotion score can have a maximum value of 3 (indicating a strong presence of that emotion) and a minimum value of 0 (indicating that the emotion is not present). Under each emotion column (in the csv file containing the emotion labels) the scores have a value between [0, 3], indicating the presence level of the emotion. As we wanted our scores to be either 0 or 1 (0: Emotion is not present & 1: Emotion is present), we modified all the values under each of the emotion columns. Firstly, we determine which emotion column (Angry, Happy, Surprise, Sad, Fear, or Disgust) has the highest value for each row. This was done so that we could figure out which emotion has a high level of presence for that particular instance. The resulting column names (containing the highest emotion score) were then saved in a list. We modify the highest emotion score value to 1 for each row using this list, and the remaining scores are then converted to 0.



**Figure 3. 7:** Script to modify the emotion scores

3.5 Feature Extraction

3.5.1 Audio and Visual data

In addition to the GloVe embedded textual data, our dataset included the extracted relevant features of both the audio and visual modalities. FACET was used to produce and extract features for the visual modality, while the COVAREP software was used to extract audio features [30]. 35 visual and 74 audio features were created for each of the words found in the sentences (extraction of raw form explained in 3.4.1). We had initially planned to use FACET and COVAREP for feature extraction of the visual and audio data, respectively, as indicated in B.1. We opted not to re-extract the same features because they had already been extracted using FACET and COVAREP and instead utilized these provided features for our implementation.

3.5.2 Textual data

We chose the pre-trained BERT model to extract the textual features (embeddings) because of its ability to generate embeddings based on the context of the document. The BERT model was fine-tuned for our classification problem and was then used to produce the embeddings for our raw sentences. For this stage, we used the BERT model from Hugging Face’s transformers library (publicly available at [55]). This model has a total of 13 layers. The first layer is an input embedding layer, which maps each of the 30,000 tokens (size of the BERT vocabulary) to embeddings consisting of 768 vectors. The BERT model’s last 12 layers are Transformer layers stacked on top of one another.

**Formatting of the Input data and pre-processing**

Before feeding the raw sentences to the model, we had to prepare them into a particular format that the BERT model requires. After storing the train and validation sentences along with their emotion scores (1 and 0) in a DataFrame, we performed tokenization. As BERT is a pre-trained model, we had to use its tokenizer. The tokenizer splits the sentences into tokens (and sub-words) and automatically maps them to a unique ID. Before encoding our sentences to BERT’s format, we had to decide on an optimal length for padding the sentences. This step was crucial to be performed before encoding as most of our sentences had variable sizes. After experimentation, we found 45 to be the suitable length the sentences should be padded to. As part of BERT’s input formatting requirements, we had to add a few “special tokens” to the input data. These tokens are as follows:

* **[SEP]** – Needed for adding separation between sentences. This was appended to the end of each of our sentences.
* **[CLS]** – This token tells BERT that we are implementing a classification task and was prepended to the beginning of each sentence.
* **[PAD]** – Used for adding tokens that have no meaning. As discussed above, we had to add padding to our sentences. This token was appended to the end of every sentence to ensure we have sequences of equal length.

Additionally, to ensure the model focuses on only the important tokens, an attention mask was added that assigned an attention score of 0 to [PAD] tokens and 1 to the remaining relevant tokens (see 3.2.2). The above steps were performed via a custom class that we implemented. This custom class returns a dictionary consisting of the original sentences, token IDs, attention masks, and the emotion scores of the sentences.



**Figure 3. 8:** An example showing how the above-mentioned dictionary appears for a particular sentence

The dictionary was taken as an input to PyTorch’s DataLoader class. After testing the optimal batch sizes of 16 and 32 [56], we discovered that 32 produced faster and better outcomes in terms of training and embedding creation. Hence, the DataLoader generates the train and valid tensor datasets (used by the BERT model for training and validation) of 32 batches.

Text

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**Figure 3. 9:** The custom class used for BERT pre-processing

**Training the BERT model**

The model training, testing, and validation are done in batches of size 32. The BertForSequenceClassification model was used in this task as this model is designed to handle text classification problems with BERT. However, the BertForSequenceClassification model is designed to handle binary or multi-class problems. For a given sentence, as we had to predict the scores (1 or 0) for each of the 6 emotions, we manually modified the model’s class to use the BCEWithLogitsLoss() (Binary Cross-entropy with Logits) function instead of the CrossEntropyLoss() function (triggered for binary/multi-class classification tasks) and MSELoss() function (triggered for regression tasks). The BCEWithLogitsLoss() function allows us to assign the scores independently (for each class) based on their probability.

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**Figure 3. 10:** (a) Before modification of the BertForSequenceClassification model [57] (b) After modification of the same model

Inspired by [56], we chose the AdamW optimizer (offered by the Hugging face library) who had a learning rate of 0.00002. The model ran for 4 epochs and took approximately 35 minutes to complete. Training with batches of size 32 was faster than training with batches of size 16 (the alternate ideal batch size values stated in [56]), which took around an hour.

**Extracting the BERT embeddings**

We saved our fine-tuned model in a Binary file (.bin) as a backup. The same fine-tuned model stored in the Binary file was reloaded for testing. Using our custom class (Figure 3.9), the test data was pre-processed and formatted according to BERT’s requirements. We ran the model for 1 epoch after reloading it, and the train data sentence embeddings were saved in an empty list. Likewise, we saved the valid and test embeddings in the same list (as the train data) during the validation and testing stages. For the similar reasoning explained in 3.3.1, we saved this huge list of embeddings in a dictionary. The resulting dictionary was also imported into a Pickle (.pkl) file to access the BERT embeddings in another file. The dimensions of the 3 sets (consisting of the sentence embeddings) are as follows: **Train Set** =(15290, 768), **Valid Set** = (2291, 768), and **Test Set** = (4832, 768). Each of the sentence embeddings had a dimension of 768 features.

3.6 Data Preparation and Training Parameters

The following sub-sections discuss how the data was prepared before feeding it to the NN and which training hyperparameters were used for the model.

**Standardizing of data**

As the features for the Visual, Audio, and Text modalities have been obtained using three different models/software – FACET, COVAREP, and BERT, there is a probability that these features are of different scales. Due to this possible variation in scales, one of them could be significantly more valuable than the other two. Input features to the NN are typically standardized to a similar scale to be mathematically compared more precisely.

Diagram

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**Figure 3. 11:** Formula of Standardization

The features are standardized by converting the µ (mean) value to 0, and the standard deviation (σ) value is scaled to 1. In figure 3.11, “x” is the current sample that is being standardized. Standardization ensures that differences in input feature scales do not cause the model to become biased and that the model’s learning is unaffected. Thus, we standardized our data using sklearn’s StandardScaler(), which was fitted on our train dataset, and the test dataset was transformed using the same scaler. The data dimensions were not changed after standardization, as the StandardScaler() only alters the contents of the input data and doesn’t delete or add any data points.

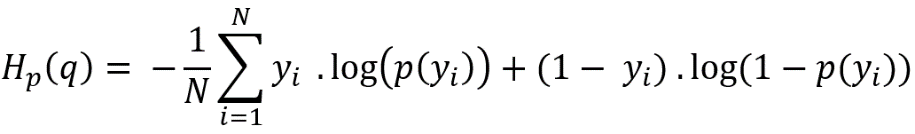
Text, letter

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**Figure 3. 12:** Standardization of our fused data

**Loss Function**

We conducted training and testing for each emotion class independently to compute the results (accuracy, F1-Score, Recall, etc.) for each emotion class separately. As a result, our NN was trained to be a binary classifier because our classification task is as follows: Given a fused feature, predict whether the emotion (the class, for example, Fear, Happy, etc. that the model is currently being trained on) is present (label = 1) or not (label = 0). Because we were working with a binary classification problem, we picked the Binary Cross-Entropy loss function instead of the usual Cross-Entropy loss function. BCELoss() and BCEWithLogitsLoss() are two Binary Cross-Entropy methods included in the PyTorch library. However, we used BCEWithLogitsLoss() for our model because it is a combination of the Sigmoid and BCELoss() functions. Moreover, in comparison to BCELoss(), the BCEWithLogitsLoss() function is more numerically stable.



**Figure 3. 13:** The Binary Cross Entropy function

**Optimizer**

For our optimizer, we chose “Adam” with a learning rate of 0.001. Before fitting the model, the initialized optimizer was used for clearing out any gradients. This step was done for each epoch. Additionally, at the end of every epoch, we update the NN’s (the model) weights by calling the step() function of the optimizer.

3.7 Feature Fusion and DL Classifier

In this section, we will be briefly explaining about feature fusion and the method we used for fusing our extracted features. Furthermore, we will also be describing our NN architecture.

3.7.1 Introduction to Feature Fusion

As we wanted to classify whether a particular emotion is present for a given trimodal data point, we had to first fuse the extracted features. Compared to the individual features, a fused feature will always have richer information about the modalities and better performance during the classification process. The following are the two primary types of feature fusion methods commonly employed in ML:

**Late Fusion**:

In this technique, each extracted feature is processed individually and passed through different streams [58]. These streams are usually referred to as the classifiers that predict whether a particular class is present (e.g., emotion is present) or not (e.g., emotion is not present) for a given individual feature (Audio, Visual, or Text features). The results from these independent streams are merged, and the output is derived.

Diagram

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**Figure 3. 14:** Late Fusion [59]

**Early Fusion**:

Early fusion involves fusing the extracted features before passing them to the classifier. However, after fusion, it is necessary to ensure the fused data is scaled (standardization/normalized) and aligned [58]. If the fused data has these properties, it can be fed to a classifier, and the necessary predictions (e.g., emotion is present/not present for a given data value) can be made.

Diagram

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**Figure 3. 15:** Early Fusion [59]

In addition to comparing our model (which deals with trimodal features) with previously implemented MER models (objective 6), we also decided to perform a comparative analysis between bimodal (Audio+Video) and trimodal (Audio+Video+Text) features. As a result, we chose the Early Fusion method because it allows us to make meaningful correlations between the modalities [58] since their features are fused before being fed to the classifier.

3.7.2 The DL Classifier – Feed Forward NN

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**Figure 3. 16:** The implemented model’s architecture

The dimensions of the features for the train, test, and valid sets were as follows:

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**Figure 3. 17:** Shapes of the sets before dimensionality reduction

As observed from Figure 3.17, the Audio and Video features were 3-Dimensional, while the Text features were 2-Dimensional. Dimensionality reduction was used to convert the audio and video arrays into 2D. This was accomplished by computing each array’s column-wise (dimension = 1) mean. As a result, we were able to gain the following new dimensions:

Table

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**Figure 3. 18:** Shapes of the sets after dimensionality reduction

Since all three modalities were of the same dimension, we carried out the process of Early Fusion on our data. We first fused the Audio and Video train features along the column, and a Torch Tensor of shape **(15290, 109)** [*74+35=109*] was obtained. The resulting tensor was then fused with the Text train features along the same dimension. Finally, we got a tensor of shape **(15290, 877)** [*109+768=877*]. Similar fusion steps were carried out for the valid and test sets. Tensors of dimensions **(2291, 877)** and **(4832, 877)** were created for the valid and test sets, respectively.

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**Figure 3. 19:** Script to perform Early Fusion

As discussed in section 3.6, we standardized our data to ensure the scales of the input features were similar. This was done to prevent the model’s learning from being hindered.

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**Figure 3. 20:** The class that handles the 3-layer Feed-Forward Neural Network

The resulting scaled data was converted into a PyTorch DataLoader object and was passed to the hidden layers of our Feed Forward NN. The Feed Forward NN takes in an input vector with a dimension of 877 and gives an output vector of size 1. The DataLoader object is initially passed through the first layer of our NN, and the ReLU activation is applied to the resulting value. At times, while training a NN, the parameters of its preceding layers tend to get modified. This impacts the distribution of each layer, slowing down the training process [60]. To reduce this issue and before shifting to the following linear layer, we apply Batch Normalization to the ReLU activation and the current batch that the model is training on.

The above steps are repeated for the subsequent layers. To minimize overfitting, we have applied the dropout regularization (value = 0.1) to the result of the last hidden layer. The final output is sent to our loss function, BCEWithLogitsLoss().

Chapter 4 – Results and Evaluation

In this chapter, we will be critically evaluating the performance of our model for each of the six emotion classes. We also analyze our results with a few previously implemented MER models (discussed in 2.6). Additionally, a comparative study between the use of trimodal and bimodal features has also been included in this chapter.

4.1 Evaluation Strategy

To evaluate our results, we will use the key metrics generally used for assessing any ML project. The metrics are described in detail below.

**Accuracy:**



**Figure 4. 1:** Formula for Accuracy

The accuracy, which is one of the popular metrics in ML, is calculated as the ratio of the correct number of predictions to the total predictions made [61].

**Precision:**

**Text

Description automatically generated with medium confidence**

**Figure 4. 2:** Formula for Precision

The precision is defined as the proportion of the correctly identified emotions to all positive predictions [61].

**Recall:**

Text

Description automatically generated

**Figure 4. 3:** Formula for Recall

Recall indicates how many emotions the model correctly identified out of all the positively identified emotions [62].

**F1 – Score:**

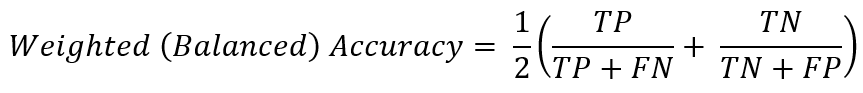
Text

Description automatically generated

**Figure 4. 4:** Formula for F1-Score

The F1-Score measure takes both recall and precision into account and is thus the “harmonic mean” of the two [61]. As the CMU-MOSEI dataset is imbalanced, the F1-Score is one of the most critical measures for our project. Since F1-Score is a combination of precision and recall, it considers how the data is distributed, making it ideal for imbalanced data.

**Weighted (Balanced) Accuracy:**

****

**Figure 4. 5:** Formula for Weighted Accuracy

The Balanced Accuracy is the average between the recall and the specificity of a given model. As we are dealing with an imbalanced dataset, another important metric is the Balanced Accuracy. Unlike the regular accuracy, it doesn’t inflate its values for the majority class [63]. Both the positive and negative classes are taken into equal account while computing the balanced accuracy.

**Confusion Matrix:**

A picture containing chart

Description automatically generated

**Figure 4. 6:** Confusion Matrix

The confusion matrix describes the model’s performance in the form of a matrix. The image above shows two classes – Positive (1) and Negative (0). In our problem, the existence of an emotion is the positive (1) class, while no presence of that emotion is the negative (0) class. True Positives (TP) indicate the number of emotions correctly predicted or classified as the positive class, whereas True Negatives (TN) display the number of cases correctly classified as the negative class. False Positives (FP) refers to the number of cases incorrectly classified as positive but actually belong to the negative class. False Negatives (FN) denote the number of instances that were wrongly classified as the negative class, when they belong to the positive class [61].

In addition to calculating the above metrics, we will be comparing our results with the ones obtained by two previously implemented models (discussed in 2.6 and results shown in B.2).

4.2 Testing

Our classification problem was **“Given a fused feature, predict whether the emotion is present (label = 1) or not (label = 0)”**. The model was trained and evaluated separately for each emotion class. For testing the performance of our model, we used the test set provided by CMU-MOSEI. This set had 4832 values and was “unseen” by the model while training. The predicted labels that were generated while testing, were compared to the actual labels (provided in separate .csv files for each class) so that we could calculate the various metrics explained in 4.1.

4.3 Results analysis and comparisons with other MER models

4.3.1 Weighted (Balanced) Accuracy

The bar chart and table below present our results and the ones obtained by the Multi-task Gated Contextual Cross-Modal Attention (MGCCMA) and the Graph-MFN models.

Chart, bar chart

Description automatically generated

**Figure 4. 7:** Comparison of Weighted (Balanced) Accuracies

Table

Description automatically generated

**Figure 4. 8:** Weighted (Balanced) Accuracies for each model

As observed from the results, our model couldn’t outperform the MGCCMA and the Graph-MFN models in terms of the weighted accuracies. However, for the “Happy” emotion class, the Feed-Forward NN produced a weighted accuracy 2% higher than the one calculated by the MGCCMA model. The plausible reason our model wasn’t able to surpass the weighted accuracy scores of the two models was that it was likely prone to some overfitting. We arrived at this conclusion because while fitting the NN, we had achieved high training accuracies, but as shown in Table 2.1, the final testing accuracy (weighted accuracy) was lower than the MGCCMA and the Graph-MFN models. However, due to the presence of the dropout layer, the overfitting is minimized. A possible solution to this problem could be to carefully modify the NN model, such as eliminating some layers but not too many, which can lead to underfitting.

A key observation to note here is that even while the Feed-Forward NN’s weighted accuracies didn’t exceed the other two models, it attained values comparable to them despite having a simple architecture. This possibly could be that we generated our sentence embeddings using BERT, which produces feature vectors for each word depending on the context it is used in. The GloVe method was used to create the embeddings for the MGCCMA and Graph-MFN models. GloVe does not construct feature vectors based on context; instead, each word in its lexicon has one unique embedding, even if it has several meanings.

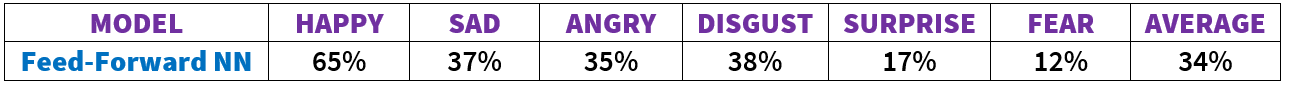
4.3.2 Precision

As shown from Table 4.10 and Figure 4.9, the “Happy” emotion class has the highest precision score. This might be due to the reason that the “Happy” class serves as the majority class (see Figure 2.5) in the CMU-MOSEI dataset.

Chart, bar chart

Description automatically generated

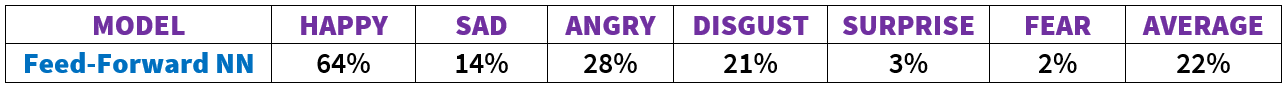
**Figure 4. 9:** The precision scores – Graph format



**Figure 4. 10:** Precision scores calculated for each emotion class

In comparison to the “Sad” and “Angry” classes, which have a higher number of samples, the “Disgust” class achieved a higher precision score (second highest). From this, we can conclude that the model did a better job in predicting the “Disgust” class when compared to the “Sad” and “Angry” classes. The “Fear” class had the lowest score compared to the other classes. One reason for this could be because Sadness and Anger can cause Fear in some people. Consider the 2020 presidential election between Trump and Biden. Many Republican Party supporters opted to vote for Joe Biden instead of Donald Trump. Citizens were disappointed and angered with Trump’s handling of the COVID-19 situation, which had a negative impact on the country’s economy and resulted in a significant increase in the number of cases in 2020. Republican supporters switched sides after being impressed with Biden’s handling of vaccines and COVID. This was primarily due to fears about the spread of COVID-19 and the economy [64]. It can be deduced from this example that Anger and Sadness can sometimes lead to Fear. Hence, the “Fear” class’s precision is low since it can be misinterpreted as “Anger” or “Sadness”.

4.3.3 Recall



**Figure 4. 11:** Recall scores for each class

As seen from the results obtained, our model did not perform well while trying the identify some classes such as “Surprise”, “Fear”, “Sad”, etc. The “Happy” and “Angry” classes, on the other hand, had the highest recall scores. We can deduce that whether people are happy or angry, they are more likely to convey their feelings. As a result, the recall scores are high. In the case of the emotion “Fear”, our dataset consists of instances obtained from online videos. These videos cover a wide range of topics, such as reviews, arguments, ads, etc. [30]. YouTubers or video content creators rarely make videos in which they appear or speak about anything they are terrified of, unless they’re discussing a current political issue affecting them or a terrible incident that happened to them. Even when people are surprised by something, they are expressive about it. On the other hand, our model produced a low recall score for the “Surprise” class. This is most likely due to the lack of data instances for classes like “Surprise” and “Fear”. Oversampling or undersampling could be used to balance out the classes and so improve the low scores. Lower recall and higher precision scores from our results indicate the model could not identify the classes correctly but could be reliable while trying to predict a class.

4.3.4 F1-Score

Chapter 5 – Conclusion and Future Work

5.1 Challenges faced in each stage

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Appendix A - Requirements Analysis

The several kinds of functional and non-functional requirements of the system to be implemented are described in this section. We will use the MoSCoW technique to prioritize our requirements as it will help us examine and organize our project in a systematic manner. Each priority letter and its associated color code are included in the table below.

|  |  |  |
| --- | --- | --- |
| **Priority** | **Full Form** | **Color Code** |
| **M** | **Must-Have -** It is crucial to achieve these set of requirements in this project |  |
| **S** | **Should Have –** It is important to achieve these set of requirements, but can be opted out |  |
| **C** | **Could Have –** These set of requirements are optional. |  |
| **W** | **Would Have –** These set of requirements are related to the future work of this project |  |

A.1 Functional Requirements

The functional requirements go into extensive detail about the project’s objectives and components. Additionally, it also emphasizes on the various functionalities of the system. The below table describes the multiple functional requirements of our system.

|  |  |  |
| --- | --- | --- |
| **Functional Requirements** | | |
| **S.No.** | **Description** | **Priority** |
| FR-1  **DONE** | **Getting the Natural Dataset**  Examine the benefits and drawbacks of the many datasets available and select a natural dataset. | **M** |
| FR-2  **DONE** | **Choosing the suitable Neural Network Models**  Learn about the different types of Neural Network models that are available. Choose the models that are appropriate for facial features, audio, and textual input. | **M** |
| FR-3  **DONE** | **Selecting the ML Classifier Model**  Examine some of the ML classifiers for emotion recognition and select one to utilize in the project. | **M** |
| FR-4  **DONE** | **Selecting a Pre-Processing method**  Examine some of the various pre-processing methods available for each of the three modalities: audio, text, and visual features, and choose one to use for each in our project. | **M** |
| FR-5  **DONE** | **Selecting a Feature Extraction Method**  Investigate some of the available feature extraction methods for each modality (audio, text, and visual) and choose the three most suitable ones for the project. | **M** |
| FR-6  **DONE** | **Selecting a Feature Fusion Method**  Examine some of the Feature Fusion methods used in Deep Learning and choose one that is appropriate for our model. | **M** |
| FR-7  **DONE** | **Selecting the most suitable features**  Use the chosen feature extraction methods to extract the relevant features for each modality from the input data provided. | **M** |
| FR-8  **DONE** | **Fusion of the features**  After pre-processing and extracting the features, fuse all of them using the selected method | **M** |
| FR-9  **DONE** | **Training the Neural Network model**  Train the Neural Network model to recognize and classify Ekman’s basic emotions (Happy, Sad, Anger, Fear, Disgust, Surprise) | **M** |
| FR-10  **DONE** | **Testing the proposed architecture**  Calculate the metrics – Accuracy, Precision, Recall, F1-Score, True Positive Rate, and False Positive Rate | **M** |
| FR-11 | **Performing a Comparative Analysis between the model and previous works**  Compare the model’s accuracy, precision, recall, F1-Score, true-positive rate, and false-positive rate with the previous similar works. | **M** |
| FR-12  **NOT DONE** | **Getting the Acted Dataset**  Review the advantages and disadvantages of various datasets and finalize upon an acted dataset. | **S** |
| FR-13  **NOT DONE** | **Testing the model on the Acted Dataset**  Alongside recognizing emotions, train the model to recognize the textual input data’s sentiments (positive/negative/neutral). | **S** |
| FR-14  **NOT DONE** | **Comparative Analysis between Acted Dataset and Natural Dataset**  Compare the model’s accuracy, precision, recall, F1-Score, true-positive rate, and false-positive rate with the previous similar works, when it is trained with the Acted dataset and when it is trained with the Natural Dataset. | **S** |
| FR-15  **NOT DONE** | **Try different Neural Network Models & ML Classifiers**  Try different types of Neural Networks and ML Classifiers and see if it improves the performance of the model. | **C** |
| FR-16  **NOT DONE** | **Try to classify emotions based on Plutchik’s Wheel of Emotions**  Based on Plutchik’s Wheel of Emotions, train the model to classify emotions and their intensity levels. | **C** |
| FR-17  **NOT DONE** | **Classify emotions based on the Geneva Emotion Wheel**  Based on Geneva Emotion Wheel, train the model to classify emotions and their intensity levels. | **W** |
| FR-18  **NOT DONE** | **Making the model suitable for Sentiment Analysis**  Alongside recognizing emotions, train the model to recognize the textual input data’s sentiments (positive/negative/neutral). | **W** |

A.2 Non-Functional Requirements

The non-functional requirements define the set of requirements that the program must meet and adhere to, such as accessibility, flexibility, and readability. Given below is the table of non-functional requirements that our program must meet.

|  |  |  |
| --- | --- | --- |
| **Non-Functional Requirements** | | |
| **S.No.** | **Description** | **Priority** |
| NFR-1 | **GDPR Requirements**  The model must follow the GDPR guidelines. | **M** |
| NFR-2 | **Version Control**  To maintain track of the changes, the code must be committed to the GitHub repository on a regular basis. The code will be backed up regularly as a result of committing regularly. | **M** |
| NFR-3 | **Readability**  The code must be thoroughly commented and organized in such a way that anyone with a great interest in the subject can fully comprehend it. | **M** |
| NFR-4 | **Accessibility and Reusability**  The code must be made publicly available on GitHub, and it can be reused for other projects in the future. | **M** |
| NFR-5 | **Package Selection**  The code should make use of Python packages that are also available in other IDEs. | **M** |
| NFR-6 | **Scalability and Flexibility**  Even when trained with different types of datasets, the model should give the desired results, and the code should allow for adjustments. | **S** |

Appendix B - Project Implementation and

Analysis

B.1 Project Implementation

In our research, we noticed that when compared to the IEMOCAP and MELD datasets (discussed in [2.4.2](#avail_DS)), the CMU-MOSEI dataset produced high accuracies for the previously implemented MER models, as shown in [[6](#ref_6)], [27], [29], and [30]. Due to its success shown in the previously implemented MER models (described in [[6](#ref_6)], [27], [29], and [30]), we have chosen CMU-MOSEI as our primary dataset for this project. As mentioned in our aim, we will be using three modalities: audio, textual, and visual features while implementing the MER model. Incorporating these three modalities will allow us to look at all possible sorts of modalities involved in ER. FACS will be used for extracting the facial features and inspired by [25] and [30], we plan to use FaceNet for embedding the extracted FACS features. In the case of the audio modality, we will be extracting MFCCs using COVAREP, like in [30]. Due to its success in [[6](#ref_6)] and in various NLP projects, BERT will be used for embedding the raw textual data. Feature fusion methods will be researched more. For the classification of emotions, inspired by [29], we will be using an LSTM as our DL classifier.

However, since ML/DL projects are unpredictable due to the algorithm behavior, involvement of large amount of data and the occurrence of potential risks/issues, a lot of trial and error is involved during the implementation of the model. Hence, our above discussed methodology is subject to change. Additionally, the project will be primarily developed using Python. Research will be conducted to decide which ML framework, TensorFlow or PyTorch, will be used.

B.2 Evaluation Strategy

For the evaluation of our results, we will be using the key metrics that are normally used for evaluating any ML project. The metrics are described in detail below.

* **Accuracy:**



**Figure B. 1:** The formula of Accuracy

In ML, the accuracy is calculated as the ratio of the number of correct predictions to the total number of predictions made.

* **Precision:**

**Text

Description automatically generated with medium confidence**

**Figure B. 2:** The formula of Precision

The precision is defined as the proportion of the correctly identified emotions to all positive predictions.

* **Recall:**

Text

Description automatically generated

**Figure B. 3:** The formula of Recall

Recall indicates how many emotions the model correctly identified out of all the positively identified emotions.

* **F1 – Score:**

Text

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**Figure B. 4:** The formula of F1-Score

The F1-Score measure takes both recall and precision into account and is thus the harmonic mean of the two. As the CMU-MOSEI dataset is an imbalanced dataset, the F1-Score is one of the most important measures for our project. This is because, since F1-Score is a combination of precision and recall, it considers how the data is distributed, making it ideal for imbalanced data.

* **Confusion Matrix:**

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**Figure B. 5:** Confusion Matrix

The confusion matrix describes the performance of the model in the form of a matrix. The image above shows two classes – Positive (1) and Negative (0). In our problem, the existence of an emotion is the positive (1) class while no presence of that emotion is the negative (0) class. True Positives (TP) indicate the number of emotions that were correctly predicted or classified as the positive class, whereas True Negatives (TN) display the number of cases correctly classified as the negative class. False Positives (FP) refers to the number of cases that were incorrectly classified as positive but actually belong to the negative class. False Negatives (FN) denotes the number of instances that were wrongly classified as the negative class, when they belong to the positive class.

Besides using the above evaluation metrics, we also plan to compare our results against the results produced by the following models (discussed in [2.6](#relatedWork_lit_review)).

* **The Deep-HOSeq Model:**

The accuracy of proposed multimodal model ([Deep-HOSeq](#Deep_HOSeq_relWork)) [29] for seven emotions is as shown below.

**Table

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**Figure B. 6:** The Deep-HOSeq results [29]

* **The Multi-task Gated Contextual Cross-Modal Attention Model:**

Below given are the proposed model’s ([Multi-task Gated Contextual Cross-Modal Attention](#Multi_task_gated_relWork)) [27] F1-Scores and the weighted Accuracies of each emotion.

Table

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**Figure B. 7:** The [Multi-task Gated Contextual Cross-Modal Attention](#Multi_task_gated_relWork) results [27]

* **The Graph-MFN Model:**

In addition to the above-mentioned models, we also plan to evaluate our results with the ones presented by the creators of the CMU-MOSEI dataset [30]. The creators used a “Graph-MFN” architecture for their model. The weighted accuracies and F1-Scores of each emotion is as shown below.

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**Figure B. 8:** The Graph-MFN results [30]

Our model will be fine-tuned and continuously evaluated using the validation sets provided by CMU-MOSEI. For the final evaluation of our model, we will be using CMU-MOSEI’s testing sets. We plan to compare our model’s F1-Scores and accuracies to the results produced by the three models above.

Appendix C – Project Management

This section discusses the software development methodology used, the project plan, the potential risks we might encounter while implementing the project, and a brief discussion about the professional, legal, ethical, and social issues the project faces.

C.1 Project Plan

The figure below illustrates the Gantt Chart, which describes all the tasks and their respective deadlines. As seen in the chart, there are eight major tasks, each of which has been broken down into subtasks. The Gantt chart will help us systematically track our progress to ensure the tasks are being met on time.

![Timeline

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generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEAlgCWAAD/4Tn4RXhpZgAATU0AKgAAAAgABgALAAIAAAAmAAAIYgESAAMAAAABAAEAAAExAAIAAAAmAAAIiAEyAAIAAAAUAAAIrodpAAQAAAABAAAIwuocAAcAAAgMAAAAVgAAEUYc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFdpbmRvd3MgUGhvdG8gRWRpdG9yIDEwLjAuMTAwMTEuMTYzODQAV2luZG93cyBQaG90byBFZGl0b3IgMTAuMC4xMDAxMS4xNjM4NAAyMDIyOjAxOjIwIDA5OjQ3OjAyAAAGkAMAAgAAABQAABEckAQAAgAAABQAABEwkpEAAgAAAAMwMAAAkpIAAgAAAAMwMAAAoAEAAwAAAAEAAQAA6hwABwAACAwAAAkQAAAAABzqAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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**Figure C. 1**: Gantt Chart

As issues can arise while implementing an ML project due to enormous volumes of data, out-of-date Python libraries, or a specific framework not being suitable for the project, we have allocated a gap of 2-3 days between a few major tasks in case there is a delay in completing some tasks.

C.2 Development Methodology

We will be following the Agile-based **SCRUM** software development methodology for this project. SCRUM follows an iterative and incremental method of delivering the final product in a series of tasks called “Sprints” [46]. Weekly sprint retrospective meetings with the SCRUM Master, i.e., our project supervisor, will be held to ensure that the project is implemented functionally and productively. During the sprint retrospective meetings, we will be discussing our progress and the issues that arose in the project. The SCRUM Master will then provide their feedback or recommendations for the project. The SCRUM methodology allows us to be more flexible and incorporate any changes to the project or the requirements.

Diagram

Description automatically generated

**Figure C. 2**: The Scrum Methodology Model

C.3 Risk Management

Several risks are likely to occur throughout the implementation of a project; therefore, it is critical to identify them and devise strategies to mitigate their impact. Identifying and managing these risks can assist us in meeting the deadlines of the tasks and delivering the final project on time. The table below identifies the possible risks we might encounter while implementing our project. Alongside the risk, their type, probability of their occurrence, and impact on the project have been specified. The table also mentions the possible signs associated with the risks and ways to avoid them in the future. The minimization strategies and contingency plans of the risks have also been documented.

|  |  |  |
| --- | --- | --- |
| **Risk Management** | | |
|  | **Planning and Monitoring** | |
| **Risk** | **Monitoring & Avoidance** | **Contingency & Minimization** |
| **Data Loss**  Type- Tools  Likely – Low  Impact - High | **Monitoring:** The code was not saved correctly, or an issue occurred while saving. | **Contingency:** Start the project all over again. |
| **Avoidance:** Regularly backing up the code to GitHub. | **Minimization:** Use the documentation consisting of the steps involved in implementing the software. |
| **Runtime taking a long time**  Type- Tools  Likely – High  Impact - Medium | **Monitoring:** Due to the large dataset or some functions implemented, the project takes quite some time to run. | **Contingency:** Unable to achieve some of the tasks on time. |
| **Avoidance:** Use external resources such as Paperspace to access higher RAM and GPU, which can help accelerate the runtime. | **Minimization:** Try to implement most of the tasks beforehand. |
| **Model producing inaccurate results**  Type- Requirements  Likely – High  Impact - Medium | **Monitoring:** Due to some errors in the code or logic, the model produces undesired results. | **Contingency:** Implement some of the functions again. |
| **Avoidance:** Keep testing the code regularly to check if any errors are there. | **Minimization:** Test the code with different kinds of input values. |
| **Selected libraries giving issues**  Type- Tools  Likely – Medium  Impact - High | **Monitoring:** The chosen library might not be suitable for some functions implemented. | **Contingency:** Change of tools can affect the project plan deadlines and result in a lag. |
| **Avoidance:** After implementing the functions, keep testing them regularly. | **Minimization:** Keep testing out the code regularly. |
| **Dataset Issues**  Type- Requirements  Likely – Medium  Impact - High | **Monitoring:** The original planned dataset is not suitable for our system and causes serious issues. | **Contingency:** Select an alternative dataset and modify the code according to the dataset contents. |
| **Avoidance:** Find alternative similar datasets that have been used in ER. | **Minimization:** Download the new dataset. |
| **Feature Extraction not implemented properly**  Type- Requirements  Likely – Medium  Impact - High | **Monitoring:** Selected feature extraction method does not produce desired results during the results evaluation stage. | **Contingency:** Use a new method for extracting the features. |
| **Avoidance:** Research other popularly used methods for feature extraction | **Minimization:** Implement the newly chosen technique and modify the program accordingly. |
| **Implementation of new features – Causing the system to break**  Type - Tools  Likely – Medium  Impact - High | **Monitoring:** When implementing new features or functions, the program may crash or enter an infinite loop caused due to a bug in the code. | **Contingency:** Re-implement some of the features or functions again in a different method. |
| **Avoidance:** Before trying out a new feature or function on a data structure (sets/lists/arrays) containing many elements, try it on a smaller data structure with few elements. | **Minimization:** Regularly test out the newly implemented features or functions. |

C.4 Professional, Legal, Ethical, and Social Issues

C.4.1 Professional and Legal Issues

The articles, book chapters, research papers, conference papers, and journal papers that have been used in this dissertation report have all been appropriately cited and referenced. If any code snippet has been taken from another source, it will be referenced. The program will be published under the GNU General Public License. (*See the GNU General Public License Version 3 for more details* – [41])

C.4.2 Ethical and Social Issues

This project does not involve human subjects, and no personal or confidential data will be collected. The dataset we will be using is open-sourced [42], and the data present in the dataset has been taken from various publicly available YouTube videos. The project is in accordance with the GDPR (*General Data Protection Regulation*) rules.