Automated Speech-based Depression Severity Assessment Using ResNet-101 and ALMD

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BSc (Hons.) Computer Science
Deliverable 1: Final Year Dissertation

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November 2024

Declaration

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Abstract

Depression is considered the largest cause of disability in the world, seriously affecting the well-being of an individual emotionally, physically, and socially. Unfortunately, early detection and treatment are considerably difficult to carry out. Therefore, there is an immediate need for scalable and accessible diagnostic approaches. In the recent years, automated depression severity assessment has shown impressive enhancements. Although speech is a rich medium capturing subtle changes and varied vocal patterns that often reflect the state of the mind and emotions, we see that speech-based automated depression severity estimation is less common and achieves lower performance when compared to video and multi-modal approaches.

This dissertation proposes a new framework for speech-based depression severity assessment by capturing the progression of features across frames more effectively. This is achieved by extracting features through Adaptive Local Motion Descriptor (ALMD) and ResNet-101, performing both dynamic and static feature extractions from audio spectrograms. Further, the extracted features are then fused and processed by a pre-trained Transformer model predicting the depression severity score (BDI-II). This study aims to improve the performance and robustness of speech-based depression assessment by capturing subtle indicators of emotional and psychological states, providing a foundation for scalable diagnostic tools and improving early detection accessibility.

Keywords:

Depression detection, Speech-based Depression Severity Estimation, ALMD, Adaptive Local Motion Descriptor, ResNet-101, Transformer, BDI-II, dynamic texture descriptors, hand-crafted dynamic descriptors

Acknowledgements

First and foremost, I am truly grateful for my supervisor, Dr. MD. Azher Uddin for guiding and monitoring my work closely to provide meaningful feedback. This project would not have been possible without his guidance.

I would also like to thank my beloved family and close friends for their invaluable time and constant support.

Table of Contents

List of Figures

List of Tables

Abbrevations

ADTP Audio Delta Ternary Patterns. 6
AI Artificial Intelligence. 1, 32
ALMD Adaptive Local Motion Descriptor. iii, vii, ix, xi, xiii, xv, 0–3, 5, 7, 9, 11–17, 19–21, 23, 25, 27, 29, 31, 33
AVEC Audio-Visual Emotion Challenge and Workshop. 7, 18
AVEC-2013 3rd Audio-Visual Emotion recognition Challenge. 3–5, 8, 9, 18
AVEC-2014 4th Audio-Visual Emotion recognition Challenge. xi, 2, 3, 5, 6, 8, 9, 11, 18, 20, 25, 30, 32
AWS Amazon Web Services. 30

BCS British Computing Society. 32
BDI Beck Depression Inventory. 1
BDI-II Beck Depression Inventory-II. iii, 1–3, 5, 9, 12, 18, 19, 25
Bi-LSTM Bi-Long Short-Term Memory. 8, 9, 15

CNN Convolutional Neural Network. 5, 7–10
CPU Processor. 17

DCNN Deep Convolutional Neural Network. 4, 5, 7
DCNN-LSTM Deep Convolutional Neural Network with Long Short-Term Memory. 6
DNN Deep Neural Network. 5
DSC Depression Recognition Sub-Challenge. 18
DSM-IV Diagnostic and Statistical manual of Mental disorders. 1

FDHH Feature Dynamic History Histograms. 7, 9
FFT Fast Fourier Transform. 6
FVCM Feature Variation Coordination Measurement. 6

G-SR Gaussian Staircase Regression. 3, 4
GDPR General Data Protection Regulation. 32
GFN Graph Fusion Networks. 9
GPU Graphics Card. 17
GRU Gated Recurrent Unit. 15

HAM-D Hamilton Rating Scale for Depression. 1

HMHN Hybrid Multi-Head Cross Attention Network. 7

LASSO Least Absolute Shrinkage and Selection Operator. 5
LLDs low-level descriptors. 3–5
LPQ Local Phase Quantization. 7
LSCAformer Long and Short-term Cross-Attention-aware transFormer. 8
LSTM Long Short-Term Memory. 5, 6, 9, 10

MADRS Montgomery–Åsberg Depression Rating Scale. 1
MAE Mean Absolute Error. vii, 6, 16, 18–20
MAFF Multi-modal Attention Feature Fusion. 9
MFCCs Mel-frequency Cepstral Coefficients. 3, 5, 6, 13
MFM-Att Multi-level Attention mechanism. 9
MHH Motion History Histograms. 7, 9
ML Machine Learning. 1
MRELBP Median Robust Extended Local Binary Patterns. 4
MRLBP-TOP Median Robust Local Binary Patterns from Three Orthogonal Planes. 7
MSN Multi-scale Spatio0temporal Network. 7

parallel-CNN Parallel-Convolutional Neural Network. 7
PHQ Patient Health Questionnaire. 1
PLS Partial Least Squares. 7, 9
PRA-Net Part-and-Relation Attention Network. 7

RAM Memory. 17
RMSE Root Mean Square Error. vii, 3, 4, 6, 16, 18–20
RNN Recurrent Neural Network. 7, 10, 15
rPPG Remote Photoplethysmographic. 9
RVM Relevance Vector Machine. 3
RVM-SR Relevance Vector Machine Staircase Regression. 3, 4

SAN Self-Attention Networks. 5
SER Speech Emotion Recognition. 5, 6
SM-RR Speaker Marginalization Rank Regression. 3, 4
SR Speaker Recognition. 5, 6
STA Spatio-Temporal Attention. 9
SVR Support Vector Regressor. 3, 5

TAP Temporal Attentive Pooling. 9
TMFE Transformer-based Multi-modal Feature Enhancement network. 9

VLDN Volume Local Directional Number. 8

VLDSP Volume Local Directional Structural Pattern. 8

WG-SR Weighted Gaussian Staircase Regression. 3, 4
WHO World Health Organisation. 1

1 Introduction

Depression, regarded as the single largest contributor to global disability [WHO 2020] is a highly common mental health disorder. Affecting millions globally, it causes significant negative consequences for individuals, and society as a whole. It often results in constant sadness, a loss of interest in activities, loneliness, disturbances during sleep, and impaired concentration. Depression has in some cases also led to several severe physical conditions, including heart disease, Parkinson's, cancer, diabetes, and more [Aswal et al. 2018]. The World Health Organisation (WHO) reported a 25% increase of anxiety and depression was seen globally since COVID-19 [WHO 2022], with depression affecting approximately 280 million people. Not surprisingly, depression happens to be the most common cause of suicide [Nz 2014], tragically claiming over 700,000 lives each year as reported by WHO [2020, 2023]. Despite known effective treatment for mental disorders, only a small percentage of affected individuals receive the needed care [WHO 2020, 2023]. The percentage of those who receive this care is unfortunately fewer than 10% in many countries [Aswal et al. 2018; WHO 2020]. This, along with the rising prevalence of depression, raises a desperate need for innovative approaches to detect and intervene depression during the early stages. Fortunately, the evolution in Artificial Intelligence (AI) and Machine Learning (ML), has unfolded several new approaches for automated depression detection that could complement traditional diagnostic methods.

There have been multiple approaches to detect and estimate the severity of depression. Score prediction, a subset of severity estimation has emerged to be one of the most effective and reliable methods for the same by assigning a continuous value that reflects the severity of symptoms. This is highly encouraged in clinical settings, where distinguishing between the intensity and severity of depression can significantly influence what treatment the patient should receive. Several such rating scales used in depression research are Hamilton Rating Scale for Depression (HAM-D), Montgomery–Åsberg Depression Rating Scale (MADRS) and Beck Depression Inventory (BDI), Patient Health Questionnaire (PHQ) [Beck et al. 1996, 1961; Demyttenaere and De Fruyt 2003; Hamilton 1959; Maust et al. 2012; Montgomery and Åsberg 1979; Spitzer et al. 1999; Svanborg and Åsberg 2001]. One of the most widely used and reliable [Faraci and Tirrito 2013; Ginting et al. 2013; Gottfried et al. 2024; Hailu Gebrie 2018; McElroy et al. 2018] self-report scale to evaluate the severity of depressive symptoms is Beck Depression Inventory-II (BDI-II) (a revised version of BDI corresponding with the updated Diagnostic and Statistical manual of Mental disorders (DSM-IV) [Association et al. 2000] criteria for depression) [Demyttenaere and De Fruyt 2003]. This would be used to predict the depression score for the following dissertation. These scores are a categorization of depression into distinct levels as shown in Table 1.

Despite recent advances in AI, research has focused mainly on Multi-modal and Video-based depression severity assessment. Comparatively, speech-based depression severity assessment

Level	Score Range
Minimal depression	0–13
Mild depression	14–19
Moderate depression	20–28
Severe depression	29–63

Table 1. Depression Severity Levels

is less common although indicative states of depression such as the subtle changes in speech patterns and vocal characteristics can be found.

The existing work in speech-based depression severity assessment mostly tend to achieve a higher error rate when compared to those in video as well as multi-modal based. They also focuses on deep networks that are stacked, which can affect the model's performance to handle variations in audio quality [Yin et al. 2023]. Furthermore, to the best of our belief, the studies on speech-based automated depression severity assessment have not explored the use of applied dynamic texture descriptors in speech-based depression detection. Addressing these gaps, a novel hybrid architecture that integrates advanced feature extraction methods such as Adaptive Local Motion Descriptor (ALMD) [Uddin et al. 2017] and ResNet-101 [He et al. 2015] is proposed, capturing both static and dynamic elements within the audio. These features are fused and evaluated using a Transformer model architecture [Vaswani 2017] to measure the BDI-II score. The 4^{th} Audio-Visual Emotion recognition Challenge (AVEC-2014) [Valstar et al. 2014] would be used for the training and evaluation of the model.

1.1 Aim

The aim of the dissertation is to improve speech-based depression detection through a framework applying advanced feature extraction methods ensuring both static and dynamic elements are taken into consideration, a machine learning model, and evaluation.

1.2 Objectives

To achieve this aim, the specific objectives include:

- Develop an end-to-end framework to assess severity of speech-based depression.
- Segment the audio into spectrograms.
- Extract spatial features from spectrograms.
- Capture dynamic information from spectrograms.
- Implement a pre-trained model to predict depression severity score.
- Train and evaluate the proposed framework.
- Evaluate the proposed model's performance using prediction accuracy metrics.
- Compare the model's error rate against the state-of-art models.

2 Literature Review

This chapter looks into the different approaches and models used in the automated severity assessment of depression. The most widely researched modalities are Speech-based, Video-based and Multi-modal based in no specific order. We shall look into the previous research done in these areas in the sub-sections below. Speech-based automated depression severity assessment in Section 2.1 will be examined in detail as it directly aligns with our proposed idea. This will be followed with a critical analysis in Section 2.4 as well as a comparison of related work in Section 2.5.

2.1 Speech-based Automated Depression Severity Assessment

In the 3rd Audio-Visual Emotion recognition Challenge (AVEC-2013), Valstar et al. [2013] utilized crucial audio features from 3-second short segments using the openEAR toolkit [Eyben et al. 2009]. These features such as energy and spectral related low-level descriptors (LLDs), assisted in predicting continuous values for valence and arousal using Support Vector Regressor (SVR). This research was framed as the baseline and deemed depression severity assessment as a regression problem. In the proceeding challenge, 4th Audio-Visual Emotion recognition Challenge (AVEC-2014), Valstar et al. [2014] utilized audio and video features to predict depression severity, with audio features comprising LLDs as done in [Valstar et al. 2013] as well as MFCCs. The focus was on capturing the rhythm and acoustic patterns from tasks such as reading and free-form speech. This challenge established a benchmark for RMSE in predicting BDI-II scores, facilitating comparative research.

Building upon the foundation laid by AVEC-2013 and AVEC-2014 challenge, [Cummins et al. 2015b] considered Relevance Vector Machine (RVM)[1], selected because of their potential advantages over SVR as mentioned in [Tipping 2001] and [Tipping 2003]. In the context of speech depression severity assessment, datasets are often limited in number of speakers and duration. RVMs are well suited to shorten this gap as it performs dimensionality reduction and feature selection on the dataset. Features were extracted through a brute-force approach outputting a wide range of speech features such as pitch variability, formant frequencies, sub-band energy variability and other paralinguistic cues. This was tested on both AVEC-2013 and AVEC-2014, where the results of AVEC-2013 outperformed the other.

Cummins et al. [2017] continued to build upon his previous work, using just AVEC-2013. The authors compared various regression approaches to address the irregularities between the features of audio and the stages of depression. The variations included Gaussian Staircase Regression (G-SR), Weighted Gaussian Staircase Regression (WG-SR), Relevance Vector Machine Staircase Regression (RVM-SR), and Speaker Marginalization Rank Regression (SM-RR)

[1] a Bayesian regression approach that has become widely popular for various speech-based regression tasks

[Cummins et al. 2015a; Kaya et al. 2014; Valstar et al. 2013; Williamson et al. 2013], where each was designed to address distinct feature spaces and specific conditional ranking functions. The authors have also tested out 3 combinations as shown in Table 2, out of which the fusion of G-SR, WG-SR and SM-RR gave an RMSE of 8.16 which was the lowest known RMSE for the dataset AVEC-2013.

System	**RMSE**
Baseline [Valstar et al. 2013]	14.12
Brute-Force & Decision-tree [Kaya et al. 2014]	9.78
G-SR [Williamson et al. 2013]	8.50
WG-SR [Cummins et al. 2015a]	9.75
RVM-SR [Cummins et al. 2017]	9.86
SM-RR [Cummins et al. 2017]	9.64

(a) Results compared in [Cummins et al. 2017]

Fused Systems	**RMSE**
WG-SR + RVM-SR + SM-RR	9.26
WG-SR + RVM-SR + SM-RR + G-SR	8.27
WG-SR + SM-RR + G-SR	8.16

(b) Results achieved by fused systems Cummins et al. [2017]

Table 2. Comparison of systems and fused systems for depression detection

Deep-learned features derived from neural networks outperform hand-crafted features across various domains. This was proven by He and Cao [2018] who proposed a novel approach combining the two features to predict depression severity from speech signals. Over 2 thousand baseline audio features were extracted, Median Robust Extended Local Binary Patterns (MRELBP) was applied to spectrograms generated for each audio clip. Deep-learned features were extracted from two Deep Convolutional Neural Network (DCNN), one taking the raw speech as input and the other using spectrograms. 20 seconds was found to be the optimal length for the LLDs. The two DCNNs were then joined to boost performance. Among hand-crafted features and deep-learned features, the later achieved better results. This showed that deep learned model can help predict depression better and the spectrogram DCNN represents the characteristics of depression well.

Niu et al. [2019] introduced a hybrid network, extracting MFCCs segments of speech through Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) and Deep Neural Network (DNN). This combination captured depression-related information in various representations including spatial and temporal changes as well as a discriminative representation. Using p-norm pooling combined with Least Absolute Shrinkage and Selection Operator (LASSO), utterance-level features are created from segment-level features. Classification is done using SVR, to predict the BDI-II scores. Results had outperformed previous approaches, largely due to the optimization of the pooling parameter and the effectively captured high-level features relating to depression.

Integrating Self-Attention Networks (SAN) with DCNN, Zhao et al. [2020] proposed Figure 1, a hybrid feature extraction model for depression severity assessment from audio data. The hybrid network made use of LLDs and 3D log-Mel spectrograms to capture long-term dependencies and local temporal structures respectively through SAN and DCNN. Segment-level complementary features are formed by combining the outputs from the independently trained models. These features are then fed into a SVR for BDI-II score prediction. On both datasets, AVEC-2013 and AVEC-2014, results outperformed baselines and other models.

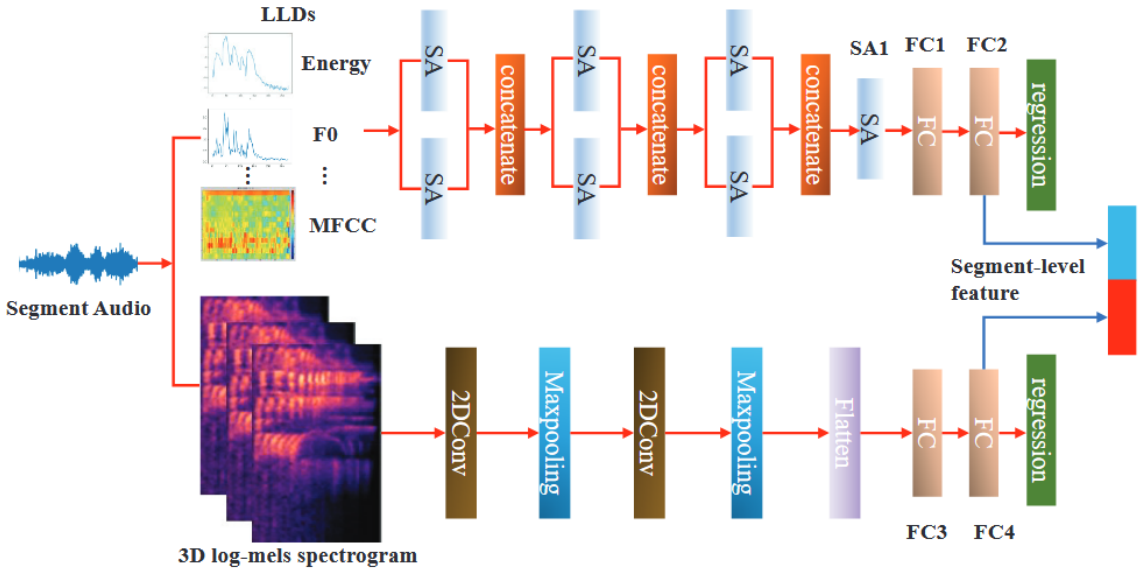

Fig. 1. Hybrid Network for extracting segment-level complementary features [Zhao et al. 2020]

A hierarchical model introduced by Dong and Yang [2021], integrates deep Speaker Recognition (SR) and Speech Emotion Recognition (SER) features to identify vocal and emotional cues

in speech. Features are extracted by extracting SR and SER features from spectrograms using a pre-trained ResNet-50. A Feature Variation Coordination Measurement (FVCM) is used to further analyze temporal patterns and correlations on the obtained feature matrices. The first layer of the hierarchical model, predicts the depression severity regression interval for the recordings determined by training many fuzzy classifiers. In the second layer, a regressor is trained using the deep speech coordination features that was learned from the first layer's classifiers. The approach achieved RMSE value of 8.82 on and MAE value of 6.79, surpassing other speech-based models that existed. These results were also quite competitive to video and multi-modal systems.

Fu et al. [2022] used the AVEC-2014 dataset to focus on spectral and temporal dynamics. Traditional audio features (extracted using MFCCs and Fast Fourier Transform (FFT) spectrograms) along with Audio Delta Ternary Patterns (ADTP), proposed by the author, captures temporal movements in speech frequencies. The MFCCs and FFTs images, are then provided to a Deep Convolutional Neural Network with Long Short-Term Memory (DCNN-LSTM), extracting high-level features, comprising two LSTMs layers and three fully connected layers in a joint tuning configuration to integrate ADTP, MFCCs, and FFT deep features. This model is depicted in Figure 2.

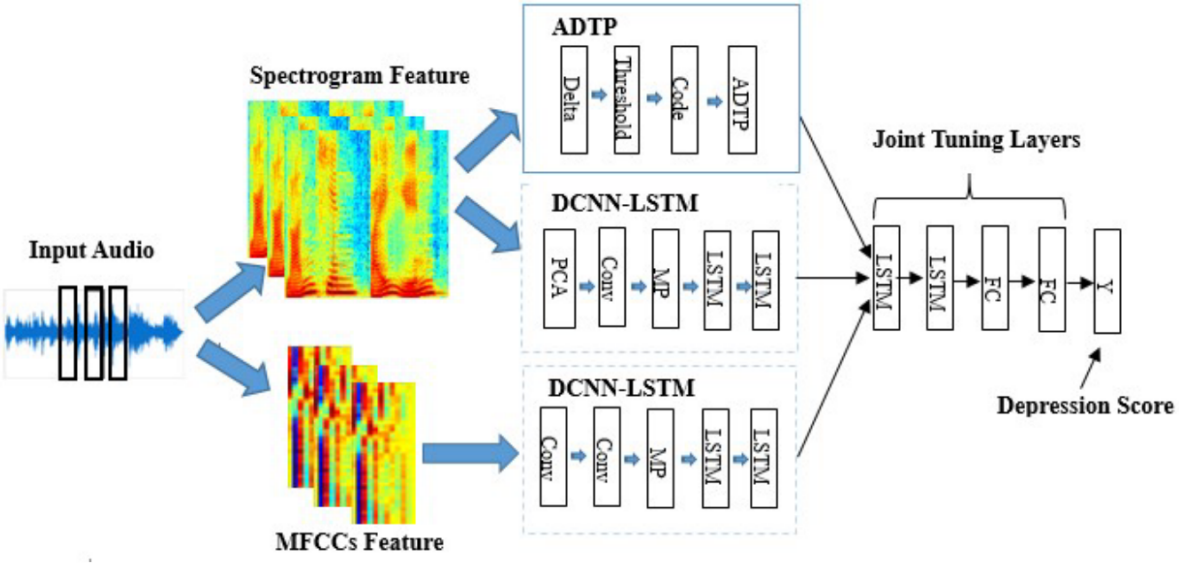

Fig. 2. Model proposed by Fu et al. [2022] to capture temporal motion features of depression

Yin et al. [2023] addresses limitations in traditional deep learning methods, which rely on single-stream stacked networks. In this case, capturing the entire range of depression indicators in audio data might not be possible. To overcome this limitation, they integrate a Parallel-Convolutional Neural Network (parallel-CNN) with a transformer to capture both local and temporal features in speech.

2.2 Video-based automated depression severity assessment

Here, we see the evolution from simple CNNs to complex architectures that integrate spatial and temporal features together with attention mechanisms. Early models like the ones implemented by Meng et al. [2013] and Valstar et al. [2013] focused on hand-crafted features, such as Motion History Histograms (MHH) and Local Phase Quantization (LPQ), applying Partial Least Squares (PLS) regression on the AVEC datasets.

With the adoption of CNNs, Zhu et al. [2017] introduced a two-stream CNN architecture capturing both facial appearance and motion, and applying the appearance and dynamics DCNN, while Jan et al. [2017] combined CNNs with their model, Feature Dynamic History Histograms (FDHH) to enhance temporal feature extraction. Building on CNNs, He et al. [2018] proposed Median Robust Local Binary Patterns from Three Orthogonal Planes (MRLBP-TOP), a novel dynamic feature descriptor extracting dynamic features from face.

The recent emergence of advanced architectures, utilizes both spatial and temporal dimensions of facial data. Researchers, Al Jazaery and Guo [2018]; Zhou et al. [2020] used 3D-CNNs and Recurrent Neural Network (RNN)s to improve spatio-temporal feature extraction. Addressing the limited dynamic encoding of traditional 2D CNNs and the dependence of 3D CNNs on temporal information from a single range, De Melo et al. [2020] introduced a 3D Multi-scale Spatio0temporal Network (MSN), combining 3D CNNs for capturing facial dynamics in depression with an exploration of different temporal ranges. This outperformed simpler CNNs in depression detection.

Recent works have explored attention mechanisms extensively. While researches like He et al. [2021]; Jianwen and Xiao [2023] incorporated attention mechanism to improve spatial focus and emphasize on local and global relevant facial areas, Li et al. [2023] developed a Hybrid Multi-Head Cross Attention Network (HMHN) capturing complex relationships among depression-related features from various key facial areas, reducing the error rate of depression assessment. Liu et al. [2023] proposed Part-and-Relation Attention Network (PRA-Net) enhancing depression features by separating feature maps into different parts of representations while applying self-attention and relation attention mechanisms. This approach strengthens the model's ability to identify specific facial regions which display the most depressive symptoms, allowing the model achieve state-of-the-art performance.

Advanced frameworks using Bi-LSTM and Transformer models have further improved temporal analysis. This is seen from Uddin et al. [2022], who introduced Volume Local Directional Structural Pattern (VLDSP), addressing limitations in extracting finer facial motion details in Volume Local Directional Number (VLDN) [Uddin et al. 2020], while mentioning the importance of facial dynamics [He et al. 2021], and reducing the computational complexity observed in previous methods such as [De Melo et al. 2020]. They also utilized the Inception-ResNet-v2 network [Szegedy et al. 2016], extracting visual spatial features. These extracted features were then fed into a CNN and a Bi-LSTM model for temporal analysis as depicted in Figure 3.

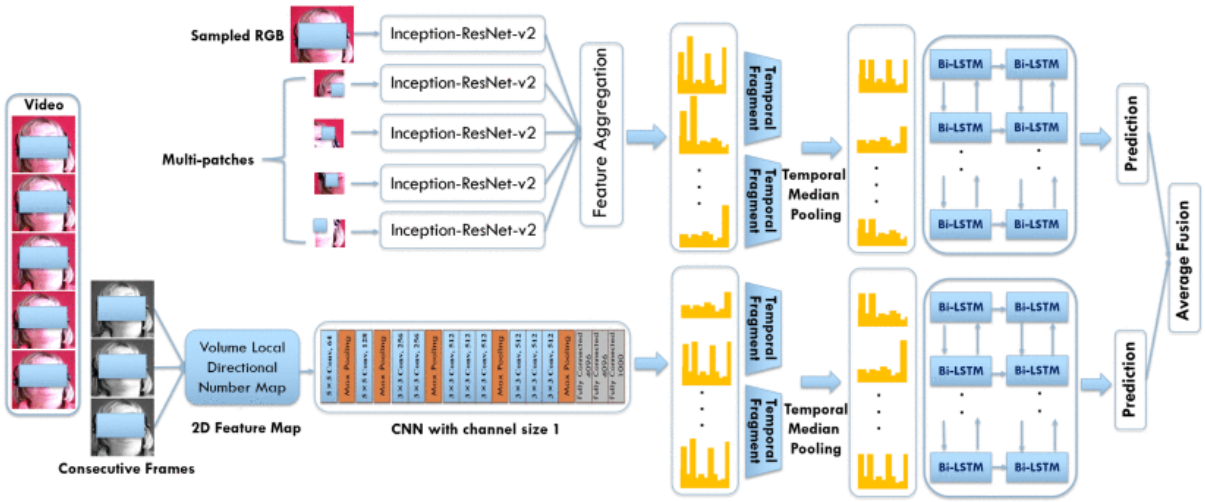

Fig. 3. The model proposed by Uddin et al. [2022] involving advanced frameworks

He et al. [2024] used Long and Short-term Cross-Attention-aware transFormer (LSCAformer), employing a dual-branch system capturing long and short term temporal features and combined them using cross-attention mechanisms. This structure helped capture the full range of depressive facial cues.

Finally, Lage Cañellas et al. [2023] proved the importance of pre-processing and scheduling techniques by using ResNet-50 with optimized pre-processing and achieving comparable results to more complex architectures on both AVEC-2013 and AVEC-2014 datasets.

2.3 Multi-modal automated depression severity assessment

As seen in Section 2.2, Meng et al. [2013] extracted dynamic features basing on MHH and applied PLS regression to capture the relationship between the depression label and the feature for facial features. This was also applied on a combination of features of changing facial and vocal expressions, tested upon using AVEC-2013. The model was among the first ones that used both facial and vocal expressions in a dynamic context. Jan et al. [2017] extracted features from visual as spoken in the previous sub-section which was then fused with CNN for facial feature extraction and FDHH for audio processing. Their model achieved a good performance on the AVEC-2014 dataset.

Focusing on facial expressions for recognizing depression, Niu et al. [2020] employed a STA network in combination with Multi-modal Attention Feature Fusion (MAFF). Audio and video frames were segmented to extract relevant features using MAFF. This approach is applied to both spatial and temporal data to improve depression predictions.

Uddin et al. [2022] developed a comprehensive multi-modal framework using both audio and video data, applying MAFF pooling along with spatio-temporal networks and Temporal Attentive Pooling (TAP). TAP focused on segment level as well as temporal features achieving a reliable estimation of the BDI-II depression scores.

Fang et al. [2023] proposed a multi-modal Fusion model with a Multi-level Attention mechanism (MFM-Att) depicted in Figure 4. This was designed to capture intra-modal and inter-modal attention using LSTMs, Bi-LSTM and attention mechanisms across audio, visual, and text data. The model utilized various features from various modalities to enhance performance. This was followed by Fan et al. [2024], who introduced a Transformer-based Multi-modal Feature Enhancement network (TMFE) combining visuals, speech, and Remote Photoplethysmographic (rPPG) signals. They also integrated inter-modal and intra-modal Transformers to improve feature extraction. Further, Graph Fusion Networks (GFN) was employed and deep CNNs were then applied to extract the audio and video abstract features. State-of-art results was achieved on both AVEC-2013 and AVEC-2014.

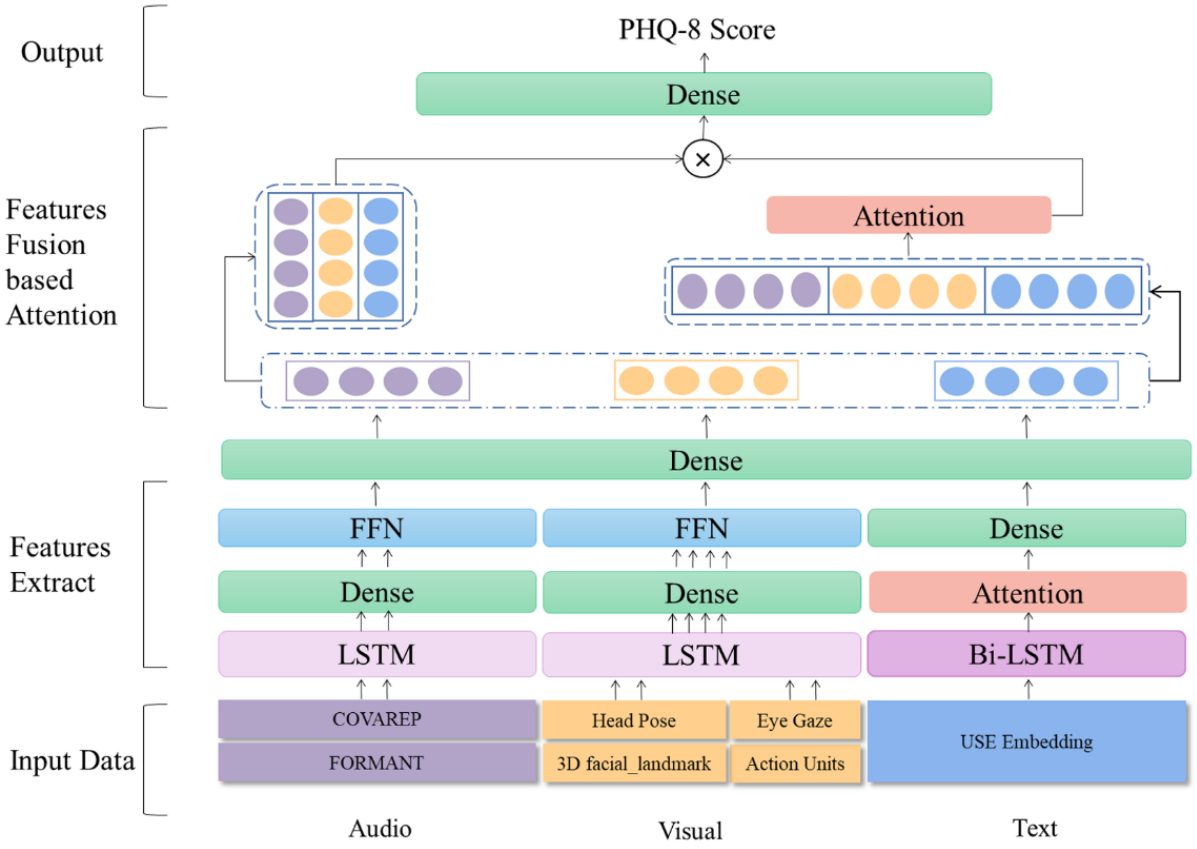

Fig. 4. A tri-modal method proposed by Fang et al. [2023] capturing Audio, Visual and Text based features

2.4 Critical Analysis on Related Work

With the recent advancements in depression detection models, there has been a large shift to deep learning-based models. While speech-based methods have good potential, they result in a higher error rate when compared to video-based or multi-modal approaches. Nevertheless, audio remains a promising modality if the features were considered in detail, capturing small fluctuations and hesitations in speech.

Most speech-based models use conventional deep learning models like CNNs and LSTMs for feature extraction and classification [Cummins et al. 2017; He and Cao 2018; Niu et al. 2019; Yin et al. 2023]. These models, although standardized, they might miss subtle, unique audio features that could enhance the depression detection prediction. Uddin et al. [2022]; Zhao et al. [2020] relied on RNNs but found it difficult to capture long-range dependencies in audio data. This in turn, limited their effectiveness for lengthy recordings. He and Cao [2018];

Niu et al. [2019] applied hand-crafted static feature extraction approaches but this requires domain expertise, making the approach less adaptable and more labor-intensive compared to automated deep learned features. Furthermore, only a limited number of studies incorporate hand-crafted dynamic descriptors such as Fu et al. [2022] who employed hand-crafted dynamic descriptors to extract temporal features from spectrograms. Those spectrograms were then used as input for 3D convolutional models but failed to sufficiently integrate complementary temporal descriptors, critical for capturing the progression of temporal patterns in acoustic features.

Till current date, no research in speech-based depression has implemented dynamic texture descriptors to capture the missing variations of vocal characteristics in spectrograms. These gaps underscore the need for models using both dynamic texture descriptors along with hand-crafted dynamic descriptors, motivating the idea of our proposed method in Section 3.

2.5 Comparison of Related Work

As discussed earlier, video-based and multi-modal models currently surpass audio-only methods in terms of performance. Hence, there exists a scope for improvement in speech-based depression detection. Table 3 compares the various automated speech-based depression approaches that use the AVEC-2014 seen in Section 2.1.

Study	**RMSE (Test)**	**MAE (Test)**
Baseline [Valstar et al. 2014]	12.57	10.03
Cummins et al. [2015b]	10.99	N/A
He and Cao [2018]	9.99	8.19
Niu et al. [2019]	9.66	8.02
Zhao et al. [2020]	9.57	7.94
Dong and Yang [2021]	8.82	6.79
Fu et al. [2022]	9.27	7.26
Niu et al. [2020]	8.31	6.73
Uddin et al. [2022]	6.95	8.46

Table 3. Comparison of various speech-based depression studies tested on the AVEC-2014

In Section 3 we shall take a detailed look into our methodology which will be followed by the requirements necessary for the project in Section 4.

3 Methodology

As shown in Figure 5, the proposed model is an end-to-end framework for automated depression severity assessment. The processing starts with the segmentation of audio into equal segments from each raw audio. Each audio segment is then transformed into a spectrogram to visualize the audio, to extract the frequency and intensity over time. ResNet-101 [He et al. 2015] will be utilized to extract the spatial features from the spectrograms, whereas the Adaptive Local Motion Descriptor (ALMD)[2] [Uddin et al. 2017] would be utilized to capture the dynamic and temporal aspects. These spatial and temporal features will be used to predict the depression severity scores using BDI-II scores through a Transformer [Vaswani 2017].

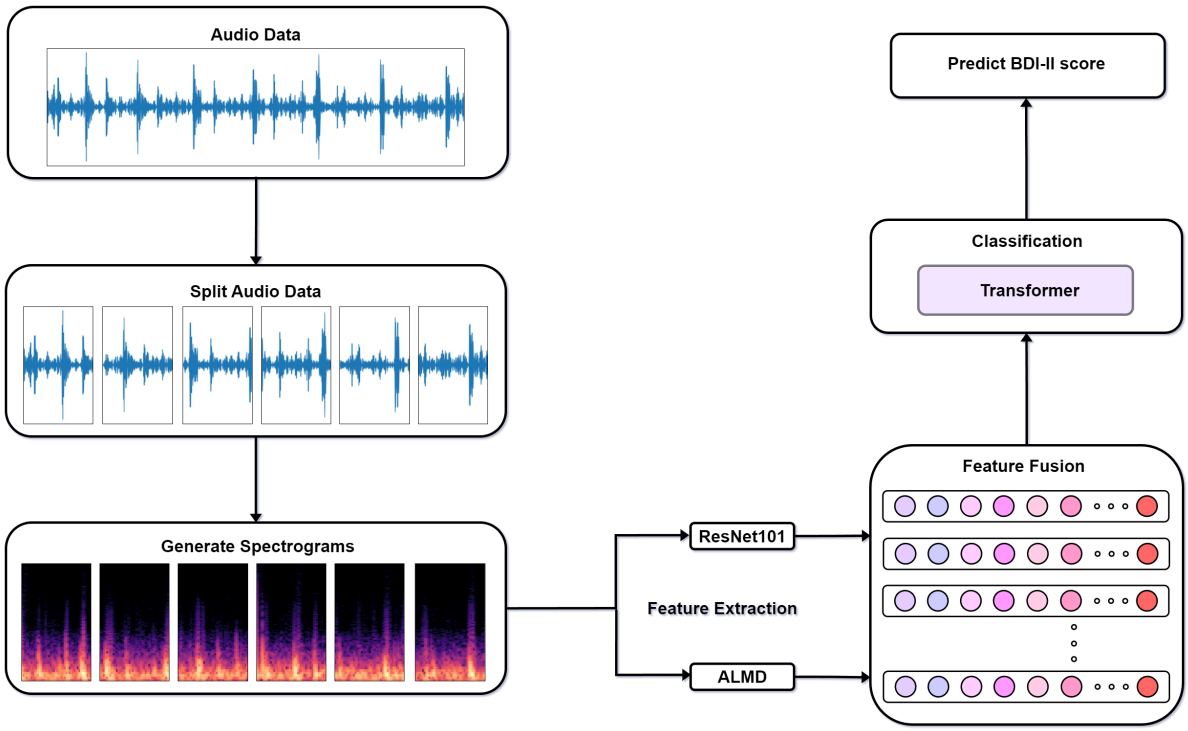

Fig. 5. Our proposed method

[2]ALMD was inspired by Histogram of Optical flow [Perš et al. 2010] and Local Ternary Pattern [Tan and Triggs 2010]

Below we shall see a more descriptive reasoning of why the specific architecture was chosen:

3.1 ALMD

As discussed in Section 2.4, most of the works have ignored the importance of hand-crafted dynamic descriptors. The integration of ALMD could address this limitation as it provides long-term and consistent patterns against fluctuations as proved in the study done by Uddin et al. [2017].

ALMD compares two back-to-back spectrograms to capture dynamic transitions (see Figure 6). This allows depression related vocal variations, missed by static descriptors like MFCCs [Fu et al. 2022; Niu et al. 2019] to be captured.

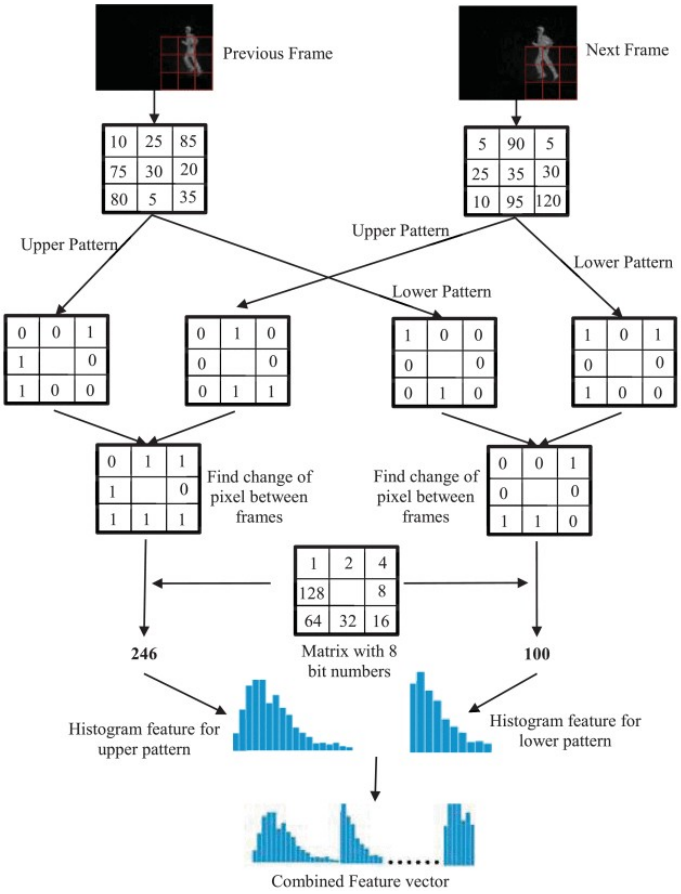

Fig. 6. An example of the Adaptive Local Motion Descriptor (ALMD) performed on image frames as shown in [Uddin et al. 2017]

3.2 ResNet-101

ResNet-101 is a 101-layer network, hence it can learn much deeper representations without losing performance. It also handles complex data like spectrograms in speech-based depression detection by learning features from low-level patterns to high-level representations.

While ALMD compares two spectrograms, ResNet relies on single spectrogram. This could potentially outperform traditional single-frame-focused networks capturing both the static and dynamic aspects of speech.

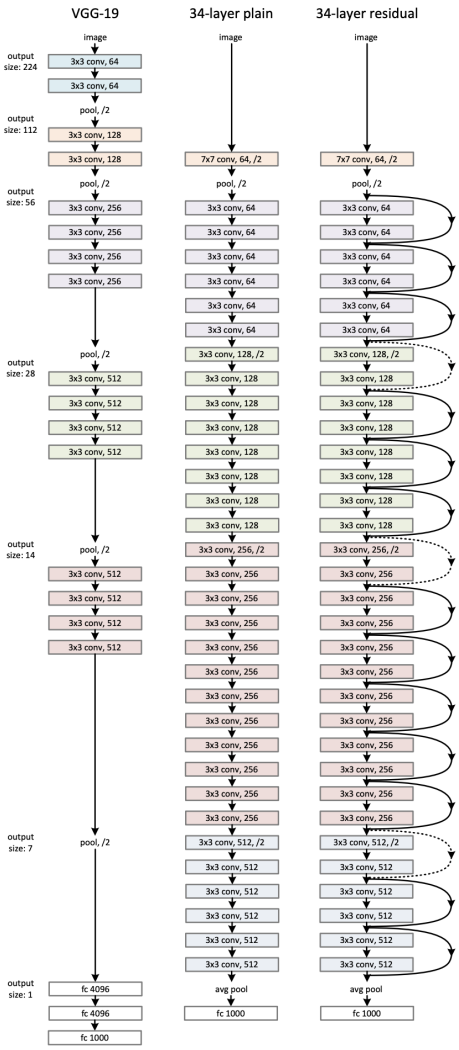

Fig. 7. ResNet-101 as depicted by He et al. [2015]

3.3 Transformer

As proved by Yin et al. [2023], transformers are effective in capturing long-term audio dependencies. There has been other studies involving transformers in depression detection such as [Rodrigues Makiuchi et al. 2019; Yang et al. 2017; Zhao et al. 2018]. Combined with ALMD, the proposed method can effectively encode both local and global temporal dynamics.

As shown in Figure 8, Transformers, unlike RNN models (such as Gated Recurrent Unit (GRU) and Bi-LSTM) can handle variable-length sequences. Their self-attention mechanism, allows it to dynamically prioritize certain parts of the data without losing any information. This has presented us with an opportunity for a closer look at the most relevant vocal features of the speakers which may carry depression-related characteristics.

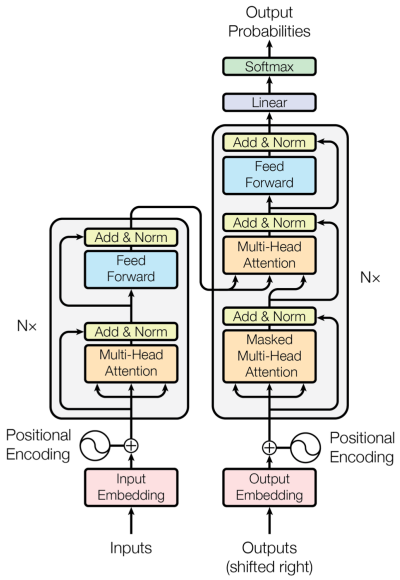

Fig. 8. Transformer model architecture as shown in Vaswani [2017]

This combination of ALMD, ResNet-101, and a pre-trained Transformer model is ideal due to their complementary strengths ensuring a robust representation of both static and dynamic aspects of depression-related audio features, enhancing accuracy and reliability.

4 Project Requirements

This section provides a structured and comprehensive overview of the different requirements needed for the success of the project.

4.1 Functional Requirements

Table 4 below displays the functional requirements needed for the implementation of the model.

ID	Requirement Description	Priority
FR1	Generate spectrograms for different audio segments	MUST
FR2	Split the raw audio into different segment counts (e.g., 5, 10, 15)	MUST
FR3	Organize the generated spectrograms into separate folders for each segment count	MUST
FR4	Store the pre-processed data in the same folder to reduce redundant processing	SHOULD
FR5	Extract spatial features from each spectrograms using ResNet-101	MUST
FR6	Extract dynamic and temporal features from each spectrograms using ALMD	MUST
FR7	Perform feature fusion to combine the features extracted from the spectrograms	MUST
FR8	Feed the fused features into the Transformer model	MUST
FR9	Validate the model on the test split	MUST
FR10	Evaluate the model's error rate using RMSE and MAE	MUST
FR11	Experiment with the hyper-parameters for optimal performance	MUST
FR12	Determine the best-performing model and hyper-parameter settings	MUST
FR13	Save the trained model features for reuse	SHOULD
FR14	Provide a configuration file for optimal parameters	COULD
FR15	Create a script to run the model with customizable parameters	WOULD

Table 4. Functional Requirements

4.2 Non-Functional Requirements

In this model, the non-functional requirements necessary are outlined by Table 5.

ID	Requirement Description	Priority
NFR1	Store data securely, ensuring no personal identification from audio data	MUST
NFR2	Maintain stability and consistency in model outputs across runs	SHOULD
NFR3	Ensure localized data processing to prevent data loss	MUST
NFR4	Aim for superior performance compared to benchmark models	SHOULD
NFR5	Well documented code-base and models for ease of functionality extension	SHOULD

Table 5. Non-Functional Requirements

4.3 Hardware & Software Requirements

Minimum requirements necessary for the working and testing of the model is given below in Table 6

ID	Component	Requirement Description
HR1	Processor (CPU)	Intel i7 or AMD Ryzen 7 and above
HR2	Graphics Card (GPU)	NVIDIA GPU with CUDA support
HR3	Memory (RAM)	16GB - Recommended
HR4	Storage	512GB SSD - Recommended for faster data processing
SR1	Software/Tools	• TensorFlow, • Keras, • OpenCV, • Scikit-learn, and others

Table 6. Hardware & Software Requirements

In Section 5, we shall take a look into the evaluation aspect of the model.

5 Evaluation

In this section, we shall take a look into the dataset being used to evaluated the proposed model (Figure 5) as well as the evaluation metrics that shall be used to test the performance and error rates of the model.

5.1 Dataset

The AVEC-2014 dataset is widely preferred for depression severity assessment, due to its multi-modal data (audio and video) enabling standardized comparisons using metrics like RMSE and MAE while promoting advancements in audio-based, video-based and multi-modal approaches. As for speech-related research, AVEC-2014 provides diverse low-level and dynamic features, making it particularly effective for research.

In this study, we utilize a smaller part of the AVEC-2013 audio-visual depression corpus [Valstar et al. 2013], the AVEC-2014[3] dataset [Valstar et al. 2014] which was developed as part of the Audio-Visual Emotion Challenge and Workshop (AVEC) series. This challenge has two sub-challenges, we shall be looking at the **Depression Recognition Sub-Challenge (DSC)** which requires to predict the level of self-reported depression. AVEC-2014 is well used and recognized, designed for research in affective computing and mental health analysis, supporting both emotion recognition and depression severity estimation tasks.

The dataset contains a total of 300 audio-visual recordings of 84 German-speaking participants, each engaging in two tasks:

(1) **Northwind Task:** The participants read aloud an excerpt from the German fable "The North Wind and the Sun".
(2) **Freeform Task:** The participants answer to one open-ended personal questions about topics such as childhood memories, favorite dish, or best gift.

The audio for each recording was resampled to a uniform bitrate of 128kbps, while the video was standardized to a resolution of 640 x 480 pixels with a frame rate of 30 fps.

The tasks discussed above were then split into three equal segments (50 recordings each of the Northwind task and the Freeform task in each of the 3 segments), while ensuring there is a balanced distribution in terms of age, gender, and depression levels. The labels are present for the Training and the Development set.

The depression score for each recording session is predicted using the BDI-II scores which serve as the ground truth for model evaluation, representing various levels of depression severity [Beck et al. 1996]. (Refer to Table 1) These scores are used to assess the model's capability to estimate depression severity. The models are trained and tested on BDI-II scores which are seen as the target labels. The evaluation metrics used for the models shall be further discussed in Section 5.2.

[3]Only audio files of the dataset would be leveraged for this study

5.2 Evaluation Metrics

The model's error rate is tested using the two extensively used prediction accuracy metrics used for regression, namely Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) and shall be further discussed below. Here, errors are the differences between the BDI-II score predicted by the regression model and the actual BDI-II values.

5.2.1 Root Mean Square Error (RMSE)

RMSE is a standard metric to evaluate the accuracy of predictions. It measures the average magnitude of prediction errors, giving more weight to large errors. RMSE is given by the formula:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

where y_i and $\hat{y}_i$ represents the actual and predicted BDI-II scores, respectively.

Higher model performance is achieved by lower RMSE values, indicating that there are fewer large errors in the model's predictions. As RMSE is the sum of the squared errors, it could be highly affected by outliers. This could lead to a worst overall RMSE just with a few wrong predictions [Campana and Delmastro 2017].

5.2.2 Mean Absolute Error (MAE)

MAE calculates the average absolute difference between model's predicted BDI-II score and the actual BDI-II scores. Unlike RMSE, MAE treats all of the errors equally, providing a simpler measure of model performance. It is given by the formula:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

where y_i and $\hat{y}_i$ represents the actual and predicted BDI-II scores, respectively.

Here, better model performance is achieved by lower MAE, indicating that there errors and significantly minimized.

These metrics aim to provide reliable predictions to develop the models aligning with clinical standards, ensuring a reliable assessment of our model's performance in estimating speech-based depression severity.

6 Conclusion

This study presents the proposal of an end-to-end framework for automated speech-based depression severity assessment, that uses advanced feature extraction and deep learning techniques. The model integrates ALMD and ResNet-101 for feature extraction, followed by a Transformer model for predicting the depression score.

The process began with an extensive literature review, examining the benchmarks, the state-of-the-arts and the variety of possible models in audio, video, and multi-modal automated depression detection approaches. This review informed the choice of techniques and highlighted the limitations of existing speech-based models. The methodology was then selected and defined to address fluctuations and variations in speech. This architecture involves splitting raw audio into segments, and converting each segmented audio into spectrograms to transform temporal audio data into spatial representations. Features shall then be extracted from these spectrograms through two models: ALMD, which extracts temporal motion patterns, and ResNet-101 which captures detailed spatial information. The fused features will then be processed by a pre-trained Transformer model, which can learn the long-term dependencies and complex patterns that are indicative of depression severity. After the implementation of the model, it shall be trained and tested on the AVEC-2014 dataset, evaluated by using metrics such as RMSE and MAE.

Our future work will include the implementation and the evaluation of the proposed model (Refer to Section 3). The model shall also be compared with the current state-of-arts and possible improvements shall be considered to be implemented in the future. The ultimate aim is to ensure the system is well created with minimal limitations to aim for a model that can be employed for clinical deployment, ensuring it is reliable, accessible and scalable for real-world applications.

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A Project Management

Organization and planning are important aspects for the management of a project to stay on track with its goals and tasks, to avoid the risk of straying off of deadlines, leading to an incomplete or rushed project. The following section will cover the scope and plan of the project along with the milestones that would guide the project's execution, followed by a set of possible risks that could occur during the making of this project as well as the mitigating strategies related to the risks. It also defines the scope, objectives, and milestones that guide the project's execution.

A.1 Project Scope

The research aims to address current gaps in speech-based depression detection, particularly the limited use of dynamic texture descriptors along with hand-crafted dynamic descriptors. This shall be achieved by creating an end-to-end novel framework that integrates advanced feature extraction methods such as Adaptive Local Motion Descriptor (ALMD) and ResNet-101. These extracted features shall be fused and evaluated through a Transformer model architecture to measure the BDI-II score using the AVEC-2014 dataset.

Key tasks with the project scope would include:

- Developing a pipeline to segment, pre-process, and analyze audio data.
- Applying the feature extraction methods, specifically ALMD and ResNet-101.
- Employing a Transformer model to predict the BDI-II score.
- Evaluating the model's performance using RMSE and MAE metrics.
- Comparing the model against existing models, benchmark models, and state-of-the-art models.
- Exploring the professional, legal, ethical, and social considerations in the use of sensitive data.

A.2 Project Deliverables

The project is divided into 4 crucial parts with definite deadlines:

A.2.1 Deliverable 1 Report

The first deliverable contains a brief overview of the study. This includes:

(1) Deciding a topic.
(2) Researching on the selected topic.
(3) Selecting a dataset to work with.
(4) Creating a detailed literature review.
(5) Finding the gaps in the literature.
(6) Proposing a model that could address the gap(s) found.
(7) Understanding the model and its requirements.
(8) Selecting evaluation strategies to test the performance of the model.
(9) Understanding the professional, legal, ethical and social considerations.
(10) Creating a project plan for the remaining deliverables.
(11) Document all the above into a brief report.

A.2.2 Final Dissertation Report

This deliverable is an expansion and implementation of the initial report which would include the following:

(1) Understand the model chosen more in-depth.
(2) Begin implementing the model.
(3) Create the hyper-parameters.
(4) Use the required pre-trained models.
(5) Build the remaining models if necessary.
(6) Train the dataset on the model created.
(7) Test the dataset using the evaluation metrics.
(8) Find the best hyper-parameters.
(9) Conclude the result by comparing it with existing models.
(10) Document all findings and processes into a comprehensive report.
(11) Find the possible improvements that could be implemented in the future to complement the model.

A.2.3 Code Submission

Once the implementation is completed, the code for the end-to-end framework is required to be submitted along with all its dependencies. This could also include instructions to replicate for future work.

A.2.4 Poster and Mini-Viva

Once the final dissertation has been submitted, summarize the research findings and framework architecture implemented through an oral presentation. Ensure that the aims, objectives as well as the results and conclusion is effectively addressed.

A.3 Project Plan

The project timeline is structured using a Gantt chart to track progress and ensure timely completion of tasks as milestones. The plan is divided into a span of 2 semesters:

(1) Semester 1 which includes Deliverable 1 Report (Appendix A.2.1)
(2) Semester 2 which includes the remaining deliverables consisting of Final Dissertation Report (Appendix A.2.2), Code Submission (Appendix A.2.3) followed by the Poster and Mini-Viva (Appendix A.2.4).

Detailed Gantt charts outlining the progression of this project as described above are outlined is shown below in Figure 9 and Figure 10. This provides a visual representation of the tasks and milestones achieved and to be achieved, ensuring a structured approach to the fulfillment of the project aims and objectives.

Following the gantt charts, we shall look into the possible risks our project could face in Appendix A.4.

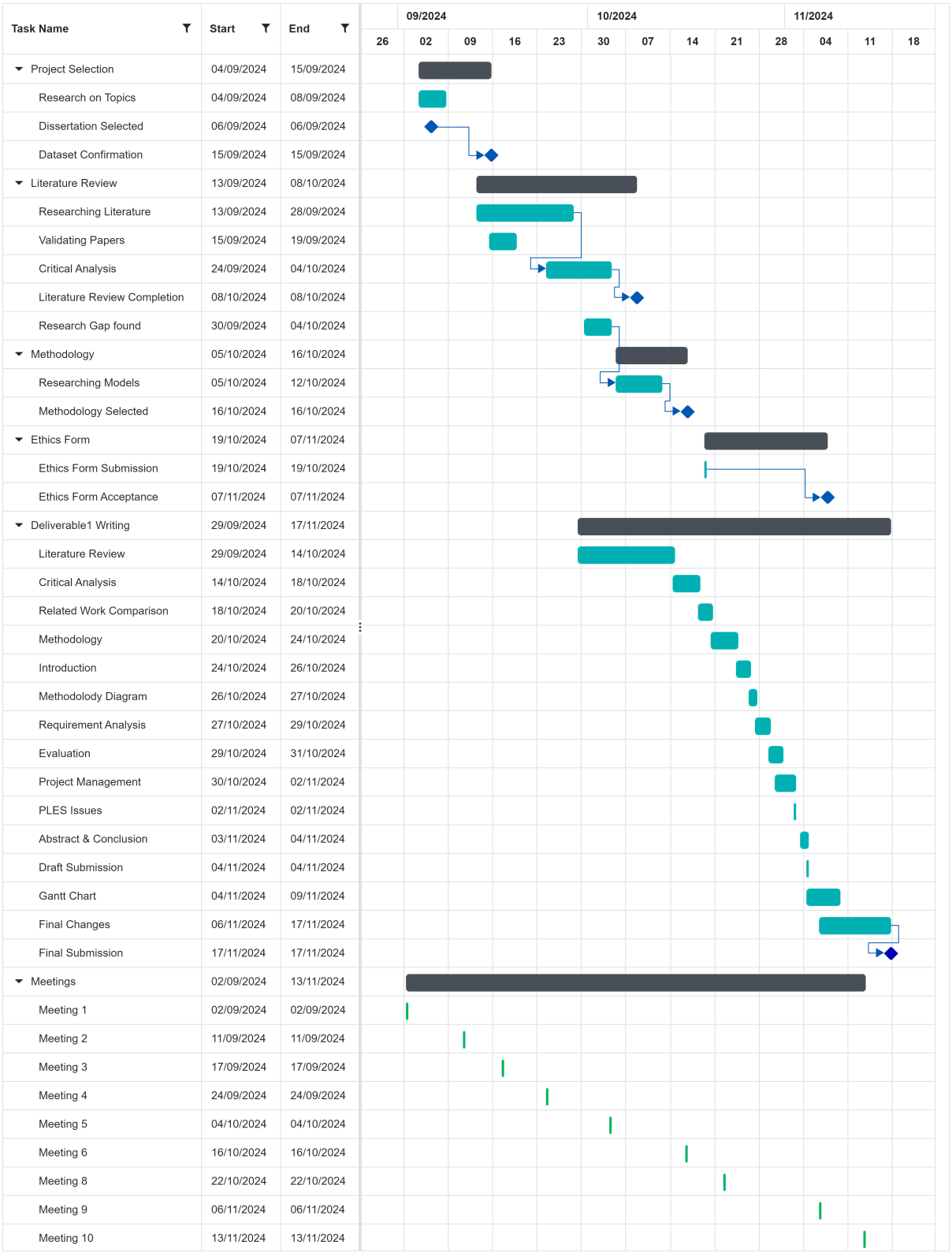
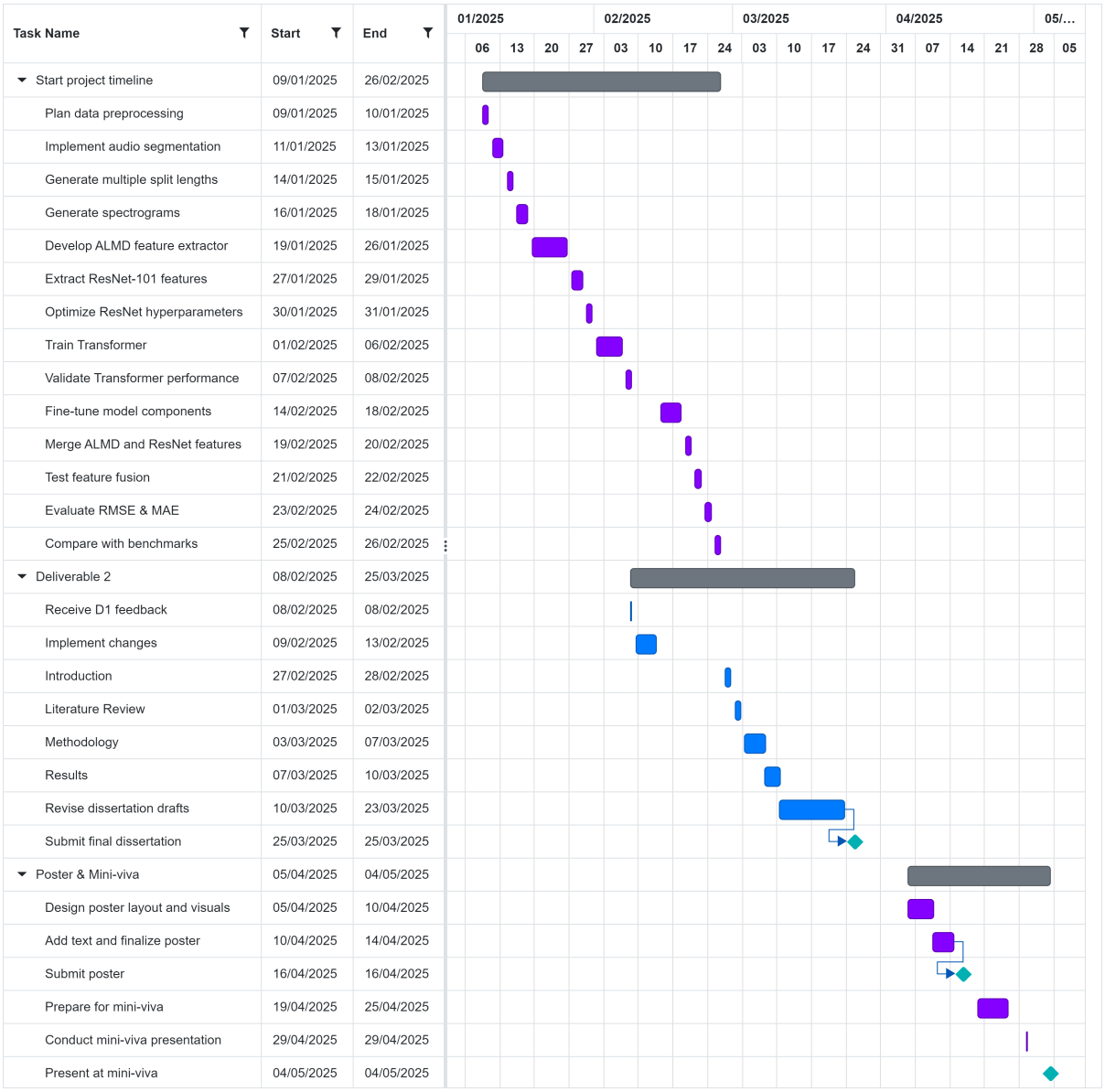


Fig. 9. Timeline for Semester 1



Task Name	Start	End
Start project timeline	09/01/2025	26/02/2025
Plan data preprocessing	09/01/2025	10/01/2025
Implement audio segmentation	11/01/2025	13/01/2025
Generate multiple split lengths	14/01/2025	15/01/2025
Generate spectrograms	16/01/2025	18/01/2025
Develop ALMD feature extractor	19/01/2025	26/01/2025
Extract ResNet-101 features	27/01/2025	29/01/2025
Optimize ResNet hyperparameters	30/01/2025	31/01/2025
Train Transformer	01/02/2025	06/02/2025
Validate Transformer performance	07/02/2025	08/02/2025
Fine-tune model components	14/02/2025	18/02/2025
Merge ALMD and ResNet features	19/02/2025	20/02/2025
Test feature fusion	21/02/2025	22/02/2025
Evaluate RMSE & MAE	23/02/2025	24/02/2025
Compare with benchmarks	25/02/2025	26/02/2025
Deliverable 2	08/02/2025	25/03/2025
Receive D1 feedback	08/02/2025	08/02/2025
Implement changes	09/02/2025	13/02/2025
Introduction	27/02/2025	28/02/2025
Literature Review	01/03/2025	02/03/2025
Methodology	03/03/2025	07/03/2025
Results	07/03/2025	10/03/2025
Revise dissertation drafts	10/03/2025	23/03/2025
Submit final dissertation	25/03/2025	25/03/2025
Poster & Mini-viva	05/04/2025	04/05/2025
Design poster layout and visuals	05/04/2025	10/04/2025
Add text and finalize poster	10/04/2025	14/04/2025
Submit poster	16/04/2025	16/04/2025
Prepare for mini-viva	19/04/2025	25/04/2025
Conduct mini-viva presentation	29/04/2025	29/04/2025
Present at mini-viva	04/05/2025	04/05/2025

Fig. 10. Timeline for Semester 2

A.4 Risk Analysis

This sub-section talks about the possible risks that could be faced during the project. The risks, along with their level of occurrence as well as the level of negative impact it would cause are mentioned below in the following table Table 7. This is followed by mitigating strategies that could be followed to avoid or overcome the possible risks.

ID	Risk	Likelihood Level	Impact Level
1	Dataset Inadequacy	Low	Medium
2	Model Overfitting	Medium	High
3	Insufficient Computational Resources	Low	High
4	Ethics Form Rejection	Medium	High
5	Difficulty Implementing Transformer	Medium	Medium
6	Data Pre-processing Errors	High	Medium
7	High Memory Usage with Transformers	Medium	High
8	Poor Model Performance	Medium	High
9	Software Bugs	High	Medium
10	Time Management Issues	Medium	High

Table 7. Risk Assessment

A.4.1 Risk Mitigating Strategies

The strategies given below can be directly linked to the risks provided in Table 7.

(1) **Dataset Inadequacy:** If the AVEC-2014 dataset proves to be insufficient, apply audio data augmentation to increase the number of samples to be tested and trained on. Ensure proper data cleaning and pre-processing is done to maximize the dataset's utility.
(2) **Model Overfitting:** Implement techniques like dropout, early stopping, and data augmentation. Ensure that the model is using the provided test set for a balanced distribution of the data (refer to Section 5.1), ensuring no bias.
(3) **Insufficient Computational Resources:** To avoid leakage of data, using cloud computing services like Google Colab (Pro version), Amazon Web Services (AWS), etc, shall not be used. Instead other computational intensive processes shall be looked into. For

example, results of the pre-processed data shall be saved to the disk for reuse, reducing intensive repetitive computation.

(4) **Ethics Form Rejection:** Follow up with the ethics committee to understand the reasons of rejection, talk to the supervisor to confirm no ethical rules are broken.
(5) **Difficulty Implementing Transformer:** Divide the Transformer implementation into steps, such as pre-training, fine-tuning, and evaluation. .
(6) **Data Pre-processing Errors:** Validating pre-processing results by visualizing intermediate outputs such as spectrograms generated could reduce pre-processing errors.
(7) **High Memory Usage with Transformers:** Techniques like gradient check-pointing could be implemented to save memory during back-propagation. Reducing the model size or experimenting with different hyper-parameters during training could reduce memory usage accordingly.
(8) **Poor Model Performance:** Test the model's performance with smaller configurations before scaling. Use thorough hyper-parameter.
(9) **Software Bugs:** Develop in modular increments and use version controls such as GitHub to track code changes and resolve issues efficiently.
(10) **Time Management Issues:** Allocate buffer time in the gantt charts for unexpected delays and prioritize high-impact tasks early on.

B Professional, Legal, Ethical, and Social Considerations

This study adheres to principles outlined by the institution and governing research bodies ensuring integrity and value to society. The following subsections addresses the professional, legal, ethical, and social considerations in the methodology and execution of this project.

B.1 Professional Considerations

The research maintains strong professional standards for data collection, analysis, and reporting, ensuring transparency. Models and methodologies are aligned with current state-of-arts in AI and mental health research. The development of these methodologies and models rely on open-source software and libraries such as python, Keras, TensorFlow, OpenCV, Scikit-Learn and others. Any utilized software libraries are referenced and rightly licensed within their terms of use. All of these ensure that the project shall be well in line with standards set by the British Computing Society (BCS) code of conduct for professional integrity in software utilization, code development, and documentation.

B.2 Legal Considerations

The research complies with legal requirements, including data protection laws under the regulations of the United Arab Emirates and General Data Protection Regulation (GDPR). The dataset AVEC-2014, while restricted in access, is used solely for academic and research purposes under the guidance of the supervising professor. These procedures ensure compliance with national and international regulations governing sensitive health data in research.

B.3 Ethical Considerations

From an ethical perspective, the research ensures the handling of data AVEC-2014, is in no way traceable to any participant or their personal information. The participants are also well informed that this data collected in AVEC-2014 shall be used for research purposes. An elaborate of the data collection is mentioned in Section 5.1. The model shall be well-trained and tested, while also ensuring no leakage. The research is done in data compliance with the standards and data-sharing agreements of the Ethics Committee in Heriot-Watt University.

B.4 Social Considerations

This project's objective is to build an automated speech-based depression severity estimation system, with a purely technical focus that does not involve the processing of controversial data. This is ensured as the AVEC-2014 is widely used and recognized in the line of research. The system shall be designed to contribute positively to early detection in mental health without introducing any social or ethical concerns. Each segment of the recording shall be treated without any bias. Throughout the study, the project avoids any activities that could lead to any ethical dilemmas or social implications, ensuring a responsible approach to depression

assessment. The study does not involve external human participation as the performance and accuracy of the model(s) is solely based on the regression based evaluation metrics.