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Citation for published version:

Deng, Q, Luz, S & Garcia, SDF 2023 'Hierarchical attention interpretation: an interpretable speech-level transformer for bi-modal depression detection'. <https://doi.org/10.48550/arXiv.2309.13476>

Digital Object Identifier (DOI):

[10.48550/arXiv.2309.13476](https://doi.org/10.48550/arXiv.2309.13476)

Link:

[Link to publication record in Edinburgh Research Explorer](#)

Document Version:

Early version, also known as pre-print

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HIERARCHICAL ATTENTION INTERPRETATION: AN INTERPRETABLE SPEECH-LEVEL TRANSFORMER FOR BI-MODAL DEPRESSION DETECTION

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ABSTRACT

Depression is a common mental disorder. Automatic depression detection tools using speech, enabled by machine learning, help early screening of depression. This paper addresses two limitations that may hinder the clinical implementations of such tools: noise resulting from segment-level labelling and a lack of model interpretability. We propose a bi-modal speech-level transformer to avoid segment-level labelling and introduce a hierarchical interpretation approach to provide both speech-level and sentence-level interpretations, based on gradient-weighted attention maps derived from all attention layers to track interactions between input features. We show that the proposed model outperforms a model that learns at a segment level ($p=0.854$, $r=0.947$, $F1=0.947$ compared to $p=0.732$, $r=0.808$, $F1=0.768$). For model interpretation, using one true positive sample, we show which sentences within a given speech are most relevant to depression detection; and which text tokens and Mel-spectrogram regions within these sentences are most relevant to depression detection. These interpretations allow clinicians to verify the validity of predictions made by depression detection tools, promoting their clinical implementations.

Index Terms— depression detection, speech-level transformer, hierarchical attention interpretation

1. INTRODUCTION

Depression is a common mental disorder, characterised by prolonged low mood, and loss of interest in activities, with an estimated 5% of adults suffering from it globally [1]. Recently, more research attention has been placed on developing automatic depression screening tools, using deep neural networks (DNNs) to analyse patients' speech. These tools have the potential to monitor individuals' risk of depression at early stages and assist clinicians in providing rapid interventions.

This paper addresses two limitations that may hinder the clinical implementation of early screening tools for depression: noise resulting from a segment-level labelling approach and a lack of model interpretability.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

First, segmentation of data sequences for model training is a common approach to avoid processing long sequences. For instance, [2] and [3] segmented audio data sequences along the temporal dimension, each labelled according to the participant's overall label. This segment-level labelling, however, may add noise to model training because some data segments from depressed participants may not contain depression-relevant information. To avoid labelling noise, [4] applied a post-level encoder to first encode social media posts from the same user into fixed-size embeddings. The sequence of embeddings from each user is then fed to a user-level encoder for the final depression classification given a single label. Inspired by [4] on social media analysis, the current work performs a sentence-level segmentation for speech analysis, whereby a given speech is first segmented into natural sentences. We then apply sentence-level encoders, together with a cross-attention module, to fuse audio and text segments from the same individual into a sequence of embeddings, which can then be processed by a speech-level encoder to make a single prediction, dispensing with the need for segment-level labelling. We also compare the model's performance to a model that learns at a segment level.

Second, predictions made by DNNs are hardly interpretable. The lack of interpretability can significantly delay the clinical applications of DNNs-based depression detection tools in practice [5, 6]. Attention scores have been suggested as a means of model interpretation because they provide understandable weight distributions over input features [7]. In their design of a Hierarchical Attention Network (HAN), [8] acquired attention scores from attention layers to infer the importance of tokens in social media tweets for depression detection. Intuitively, input tokens at the sequence positions with high attention scores contribute more to depression detection. However, this attention-based interpretation approach is insufficient because it ignores the computations that happened before the attention layers [9]. Specifically, in [8], before attention operations, each token has already been contextualised by every other token by a bidirectional Gated Recurrent Unit (biGRU). Therefore, representations produced from the biGRU at each input position capture not only the information of the token itself but also the context of the whole tweet. Consequently, the attention scores at later layers do

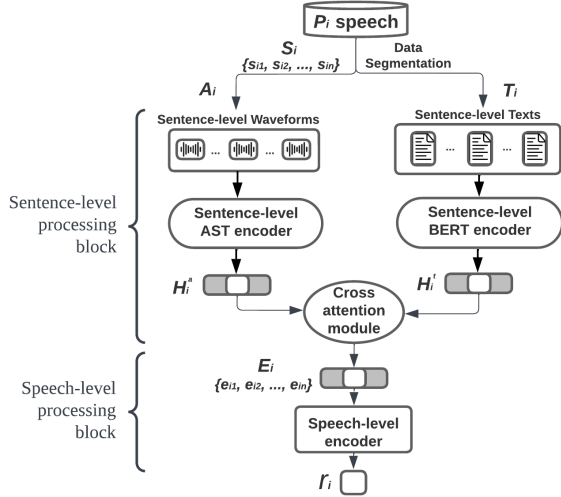


Fig. 1. Proposed speech-level transformer.

not map directly onto the input tokens, but rather onto their context-enriched representations, making it insufficient to interpret the attention scores as representing the importance of individual tokens. To address this insufficiency, we design the proposed model to be based entirely on the attention mechanism so that we can apply the method introduced in [9] to track interactions between input features at every attention layer using gradient-weighted attention maps. Based on this method, we introduce a hierarchical interpretation approach to provide both a speech-level and a sentence-level interpretation. We also highlight Mel-spectrogram regions relevant to depression detection which could potentially be used for audio interpretation for speech-based depression detection.

2. METHOD

2.1. Data pre-processing

In the current work, we used the D-vlog dataset [10]. To obtain text data, we applied the open-sourced Whisper model from OpenAI [11] to transcribe the waveforms into texts with word-level time stamps. We then designed a sentence-level data segmentation approach to obtain text segments consisting of natural sentences, each with a number of words generally longer than seven.

Each text segment has word-level timestamps in millisecond units, indicating the start and end times of each sentence. These timestamps are utilised to retrieve the relative sentence-level waveforms to constitute the audio segments, with temporal lengths averaging approximately 4.9 seconds. Each waveform is then converted to a Mel-spectrogram (a sequence of 128-dimensional log Mel filterbank features).

2.2. Model architecture

The proposed model is based entirely on the attention mechanism [12]. A visualisation of the overall model architecture can be seen in Figure 1. First, the model consists of a sentence-level processing block, which uses a pre-trained Audio Spectrogram Transformer (AST) [13] and Bidirectional Encoder Representations from Transformer (BERT) [14] to encode sentence-level audio and text data, respectively. To achieve bi-modal learning, inspired by [15], we deploy the transformer decoder as the cross-attention module (eight consecutive attention blocks), using its cross-attention layers to fuse the encoded text representations with the encoded audio representations. After the processing, the [cls] token from the text data sequence then represents the sentence-level data, incorporating information from both audio and text modalities. Second, the model consists of a speech-level processing block which is a transformer encoder (six consecutive attention layers) that operates at the speech level. It receives the sequence of sentence representations produced from the sentence-level processing block for each participant and injects positional embeddings to consider the sequence order of each sentence. A speech-level [cls] token is prepended to the sequence to aggregate the sequence into a single representation which will be mapped onto a 2-dimensional space for the final binary classification.

Consider a given speech $S_i = \{s_{i1}, s_{i2}, \dots, s_{in}\}$ from a participant P_i , where $s_{ij} = (a_{ij}, t_{ij})$ consists of both audio and text modalities of the j^{th} sentence in the speech of participant P_i . The speech $S_i = (A_i, T_i)$ is passed through the sentence-level processing block to be processed by the sentence-level encoders into two sequences of hidden representations H_i^a and H_i^t for audio and text modality, respectively. Thereby, a cross-attention module fuses H_i^a and H_i^t into a sequence of embeddings $E_i = \{e_{i1}, e_{i2}, \dots, e_{in}\}$, representing each sentence in the speech of participant P_i . The sequence E_i is then encoded by the speech-level processing block into a single representation r_i for binary classification.

2.3. Hierarchical attention interpretation

Since our model has two processing blocks (i.e., sentence-level and speech-level), we introduce a hierarchical interpretation approach to first provide a speech-level interpretation, addressing the question “Which sentences within a given speech are most relevant to depression detection?”, and then a sentence-level interpretation, addressing the question: “Within the relevant sentences, which Mel-spectrogram regions and text tokens are most relevant to depression detection?”.

For the speech-level interpretation, we derive attention scores from within the speech-level processing block. For each attention layer, we apply the approach introduced in [9] to weigh the relative importance of attention scores across attention heads to obtain a gradient-weighted attention map \bar{A} ,

achieved by equation 1. $\nabla A := \frac{\partial y_d}{\partial A}$ represents the gradients of the output for the depression class d with respect to the attention scores A . The Hadamard product \odot accounts for the relative importance of attention scores. We take the mean \mathbf{E}_h across heads, with negative contributions removed.

$$\bar{A} = \mathbf{E}_h((\nabla A \odot A)^+) \quad (1)$$

We initialise a relevancy map with the identity matrix for the speech-level processing block as $R^{ss} = \mathbf{I}^{s \times s}$, considering each sentence representation and the speech-level [cls] token as initially “self-relevant”. Then, we apply equation 2 (note that XX can represent either ss , tt , or aa) to update R^{ss} with a forward pass across every self-attention layer within the block. This provides a mechanism for continuously tracking relevancy between representations at deeper layers while updating the relevancy map.

$$R^{XX} \leftarrow R^{XX} + \bar{A} \cdot R^{XX} \quad (2)$$

After updating, we take the first row of the matrix R^{ss} , corresponding to the position of the [cls] token, which contains a relevancy score for each sentence representation. We interpret the sentences at the positions with the highest relevancy scores as most relevant to depression detection.

We then perform the sentence-level interpretation for the most relevant sentence representations. We first derive the attention scores with respect to these representations from within the sentence-level processing block. Next, we follow the same procedure as above to obtain a gradient-weighted attention map \bar{A} from each attention layer.

We initialise three relevancy maps $R^{tt} = \mathbf{I}^{t \times t}$, $R^{aa} = \mathbf{I}^{a \times a}$, and $R^{ta} = \mathbf{0}^{t \times a}$ to account for the self-attention interactions within the text modality, audio modality, and cross-modal attention interaction between the two modalities, respectively. R^{ta} is initialised to zeros because there is no interaction between modalities before cross-attention operations.

We apply equation 2 to separately update R^{tt} and R^{aa} . Specifically, R^{tt} is updated with a forward pass across the self-attention layers that consider the text inputs as the source modality. And R^{aa} is updated across the layers that consider the audio inputs as the source modality.

We update R^{ta} with a forward pass across the self-attention layers that take the text inputs as the source modality as well as all the cross-attention layers. For each of the self-attention layers, we apply equation 3.

$$R^{ta} \leftarrow R^{ta} + \bar{A} \cdot R^{ta} \quad (3)$$

For each cross-attention layer, we first normalise R^{aa} . Specifically, since R^{aa} is initialised with the identity matrix, we consider R^{aa} as consisting of two parts: $R^{aa} = \mathbf{I}^{a \times a} + \hat{R}^{aa}$. We normalise the aggregation of self-attention interactions \hat{R}^{aa} as in equations 4 and 5 so that each row of the matrix is summed to one. we then apply equation 6 to update R^{ta} .

$$\forall m, n \in a : \hat{S}_{m,n}^{aa} = \sum_{l=1}^{|a|} \hat{R}_{m,l}^{aa} \quad (4)$$

$$\bar{R}^{aa} = \hat{R}^{aa} / \hat{S}^{aa} + \mathbf{I}^{a \times a} \quad (5)$$

$$R^{ta} \leftarrow R^{ta} + \bar{A} \cdot \bar{R}^{aa} \quad (6)$$

After updating, we extract the first row from each of the relevancy maps R^{ta} and R^{tt} , corresponding to the position of the sentence-level [cls] token. The row from R^{ta} contains a relevancy score for every Mel-spectrogram patch and the row from R^{tt} contains a relevancy score for every text token. We then use these relevancy scores to highlight the patches and tokens that are most relevant to depression detection.

3. EXPERIMENTAL SETUP

3.1. Data

In the current work, we used the D-Vlog dataset [10]. The D-Vlog dataset consists of 961 YouTube video vlogs (about 160 hours) labelled by trained annotators as either “depressed” or “normal”. The authors shared the YouTube video keys which were used to download the audio waveforms for our research purposes. However, some videos were made unavailable by their authors. Also, we did not consider the videos that are longer than 15 minutes. In total, we downloaded 637 waveforms, with 52.7% labelled as “depressed”. Because some waveforms were from the same YouTube account, we stratified the train/test data splitting based on unique YouTube accounts to prevent data leaks between train/test sets. We also stratified based on class, as shown in Table 1.

Table 1. Number of Depression and Normal instances per set

	Depression	Normal
Train	299	268
Test	37	32

3.2. Implementation details

We trained the model using the first 42 sentences from each participant’s speech to fit the Graphics Processing Unit (GPU) available memory. The sentence-level audio and text data from each participant were separately batched for the sentence-level processing block to process, which outputs one sequence of embeddings, with a batch size of 1, for the speech-level processing block to process. To avoid unstable gradients, we applied gradient accumulation, whereby gradients are accumulated for 72 training steps before each parameter update to simulate a batch size of 72. We trained the model with a learning rate of 3×10^{-5} for 20 epochs.

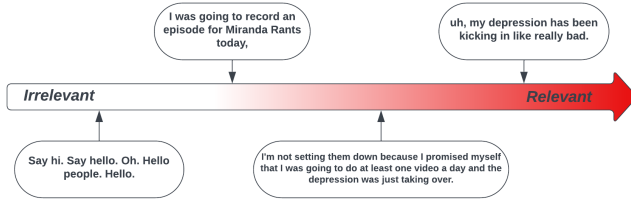


Fig. 2. The order of the sentences is relatively ranked in terms of their relevancy scores to depression classification from lowest (left) to highest (right).

3.3. Baseline model

We trained a baseline model that mirrors the architecture of the proposed model, with the exception that it lacks the speech-level processing block. For model training, we also used the first 42 sentences from each participant’s speech, each labelled as either “depressed” or “normal” according to the participant’s overall label. To aggregate sentence-level predictions for each participant, we implemented a majority voting mechanism, whereby a participant is classified as “depressed” if more than half (i.e., more than 21) of his or her speech sentences are predicted to be “depressed”. We trained the baseline model with a batch size of 128, with the same learning rate and number of epochs as the proposed model.

4. RESULTS AND DISCUSSION

4.1. Model performance

Table 2 presents the evaluation scores for both models on the test set. We observe that the proposed model outperforms the baseline model. The comparatively low performance of the baseline model might have been caused by noise introduced by segment-level labelling.

Table 2. Evaluation metrics for both models

Model	Precision	Recall	F1
Proposed Model	0.854	0.947	0.897
Baseline Model	0.732	0.808	0.768

4.2. Model interpretability

We demonstrate the interpretability of the proposed model using one true positive sample randomly selected from the test set. For speech-level interpretation, Figure 2 presents the two least and two most relevant sentences for depression detection. We note that the most relevant sentences are directly related to depression, as they include explicit mentions of depression-related utterances (e.g. “depression has been kicking in”).

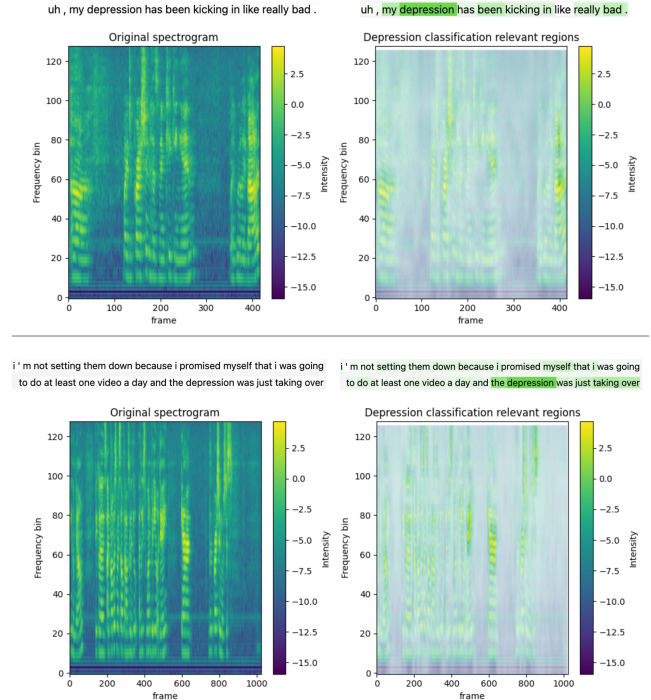


Fig. 3. For text, tokens are highlighted in proportion to their relevancy scores; the higher the score, the brighter the highlight. To highlight Mel-spectrogram regions, we map relevancy scores to their corresponding patches on the spectrogram as an alpha channel. The lower the relevancy score, the more transparent the region is.

Figure 3 presents the sentence-level interpretation for the two most relevant sentences. For text, tokens “depression”, “taking”, “over”, “I”, “myself” and “bad” are relevant to depression detection. For audio, Mel-spectrogram regions that correspond to the harmonics with high intensity are relevant to depression detection.

5. FUTURE WORKS

The highlighted Mel-spectrogram regions in this work could potentially be used for audio interpretation for speech-based depression detection. Future work may investigate what specific acoustic features are present in these regions and whether they are associated with depression, such as reduced pitch [16]. Moreover, we note that these highlighted regions are mostly indicative of articulated speech (i.e., harmonics). This might have been influenced by the application of the cross-attention module which learns interactions between spectral features and speech content (i.e., text). Future work may explore training an audio-only model to investigate if acoustic features unrelated to speech content, such as pause time [16], would be highlighted.

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