# SELF-SUPERVISED REPRESENTATIONS IN SPEECH-BASED DEPRESSION DETECTION

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## ABSTRACT

This paper proposes handling training data sparsity in speech-based automatic depression detection (SDD) using foundation models pre-trained with self-supervised learning (SSL). An analysis of SSL representations derived from different layers of pre-trained foundation models is first presented for SDD, which provides insight to suitable indicator for depression detection. Knowledge transfer is then performed from automatic speech recognition (ASR) and emotion recognition to SDD by fine-tuning the foundation models. Results show that the uses of oracle and ASR transcriptions yield similar SDD performance when the hidden representations of the ASR model is incorporated along with the ASR textual information. By integrating representations from multiple foundation models, state-of-the-art SDD results based on real ASR were achieved on the DAIC-WOZ dataset.

*Index Terms*— Speech-based depression detection, self-supervised learning, foundation model

### 1. INTRODUCTION

Depression is a serious mood disorder affecting about 280 million people in the world [1], and at present there is no objective measure for depression detection with clinical utility [2]. In order to develop a fully automatic depression detection system, a growing body of research has demonstrated that correlations of depression are detectable in spontaneous speech [3–7]. Despite encouraging progress, speech-based depression detection (SDD) is still challenging due to the variability in depression manifestations and lack of training data.

Foundation models refer to single universal models trained on broad data at scale that can be used in a variety of related downstream tasks and domains [8]. Recently, foundation models have sparked a research paradigm shift in many fields of artificial intelligence. Self-supervised learning (SSL) is a prevalent approach to pre-train a foundation model, in which the training labels are extracted from the input features themselves thus enabling the use of a large amount of unlabelled training data. It has been shown that SSL representations, the intermediate layer output of an SSL pretrained foundation model, are often useful for many downstream tasks [9]. In particular, speech foundation models, such as wav2vec 2.0 (W2V2) [10], HuBERT [11], and WavLM [12], are attracting increasing attention and have achieved state-of-the-art (SOTA) results in many speech processing tasks, including automatic speech recognition (ASR) and automatic emotion recognition (AER) [13,14], *etc.* Despite this great success, SSL representations have not been extensively studied for SDD.

This paper studies the use of SSL-pretrained speech foundation models to handle the challenges in SDD. This allows the data sparsity issue to be handled via large amount of unlabelled data used for SSL pre-training. Such unlabelled data can be produced by many speakers that cover much speaker variability and hence can help to model speaker-dependent depression manifestation variability. A block-wise analysis was first performed to compare the SSL representations from different layers of different foundation models and to understand what type of information is more effective in SDD. Next, the foundation models were fine-tuned for ASR and AER tasks separately, to investigate the knowledge transfer from ASR and AER to SDD and the effect of fine-tuning on the intermediate layers. Three different speech foundation models, W2V2, HuBERT and WavLM, were compared. ASR transcriptions were encoded by RoBERTa [15], a text foundation model, and incorporated. The ensemble with multiple foundation models gives SOTA results on the benchmark DAIC-WOZ dataset [16].

The rest of the paper is organised as follows. Section 2 introduces the proposed method and the experimental setup. Sections 3 and 4 present the block-wise analysis of speech foundation models and the use of ASR transcriptions in depression detection respectively. The foundation models are combined in Section 5, followed by conclusions.

#### 2. PROPOSED MODEL

#### 2.1. Model structure

In this paper, SDD is formulated as a binary classification task that determines whether the speaker is depressed or not. The model structure is illustrated in Fig. 1(a) which contains a foundation model followed by a depression detection block. The SDD system takes a dialogue  $\mathbf{X}$  (*i.e.* a clinical interview) as input, which consists of a sequence of sentences  $\mathbf{X} = {\mathbf{x}_1, ..., \mathbf{x}_T}$  where *T* is the number of utterances in the dialogue. The foundation model takes an utterance  $\mathbf{S}_t$  as the input and produces a vector of size  $(\tau_t, D)$  where  $\tau_t$  is the number of frames in  $\mathbf{x}_t$  and *D* is the feature dimension. Temporal pooling (average pooling was used in this paper) is then applied to the output of the foundation model, producing a *D* dimensional (-dim) vector for each utterance. The depression detection block then takes a dialogue consisting of *T*-length sequence with *D*-dim vectors as its to perform the diagnosis.

Three pre-trained foundation models were used in this paper:

Wen Wu is supported by a Cambridge International Scholarship from the Cambridge Trust. This work has been performed using resources provided by the Cambridge Tier-2 system operated by the University of Cambridge Research Computing Service (www.hpc.cam.ac.uk) funded by EP-SRC Tier-2 capital grant EP/T022159/1. The MSP-Podcast data was provided by The University of Texas at Dallas through the Multimodal Signal Processing Lab. This material is based upon work supported by the National Science Foundation under Grants No. IIS-1453781 and CNS-1823166. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation or The University of Texas at Dallas.



Fig. 1. (a) Model structure. (b) The block-wise analysis framework.

wav2vec 2.0<sup>1</sup> (W2V2), HuBERT<sup>2</sup>, and WavLM<sup>3</sup>. The base versions were used for all three foundation models which contain twelve 768dim Transformer encoder blocks and about 95M parameters. The depression detection block consists of two 128-dim Transformer encoder blocks with four attention heads each, followed by a fullyconnected (FC) output layer. Transformer structure was chosen as it's the de facto standard model in sequence modelling tasks. The depression detection block has 0.3M parameters.

## 2.2. Dataset

DAIC-WOZ [16], a benchmark dataset for depression detection, consists of 189 clinical interviews between an interviewer and a patient. 30 out of 107 interviews within the training set and 12 out of 35 interviews within the development set are classified as depressed. Classification performance is evaluated by the F1 score. Following prior work [7, 17–20], results on the development subset are reported. The model was initialised and trained for 20 different random seeds and both the highest (F1-max) and the average (F1-avg) value are reported, along with the standard deviation (F1-std) across seeds.

## 2.3. Data augmentation

Depression is usually assessed by clinical interview and labelled at the session-level, which results in one label per interview. Given a certain amount of data, the number of samples in an SDD dataset is usually much smaller than the number of utterances and frames often used in other speech tasks (*e.g.* speech and speaker recognition), which makes SDD a very data sparse scenario. For instance, DAIC-WOZ consists of 50+ hours of speech recordings that correspond to merely 189 samples. Privacy concerns and labelling difficulty further increase the data sparsity issue in SDD. Furthermore, data imbalance is another severe issue since the positive cases are much fewer than negative cases (28% vs. 72% in training). Therefore, it is crucial to use data augmentation to alleviate both data scarcity and imbalance issues for SDD.

Algorithm 1 Sub-dialogue shuffling
1: $N^+ \leftarrow$ Number of positive samples in the training set
2: $N^- \leftarrow$ Number of negative samples in the training set
3: Set number of sub-dialogues for each positive sample $M^+$
4: $M^- \leftarrow N^+ \times M^+ / N^-$
5: Set $\epsilon_l, \epsilon_h$ satisfying $0 < \epsilon_l < \epsilon_h <= 1$
6: for Dialogue $\mathbf{X}^{(n)}, n = 1, 2, \dots, N$ do
7: $T \leftarrow \operatorname{len}(\mathbf{X}^{(n)})$
8: <b>if</b> $\mathbf{X}^{(n)}$ is positive <b>then</b> $M \leftarrow M^+$
9: else $M \leftarrow M^-$
10: <b>end if</b>
11: <b>for</b> Sub-dialogue $\mathbf{X}^{(n)m}, m = 1, 2, \dots, M$ do
12: Sample $\epsilon$ uniformly from $[\epsilon_l, \epsilon_h)$
13: $d \leftarrow \epsilon T - 1$
14: Sample <i>s</i> randomly from range $[0, T - d]$
15: $e \leftarrow s + d$
16: $\mathbf{X}^{(n)_m} \leftarrow \mathbf{X}^{(n)}_{s:e}$
17: end for
18: end for

In this paper, the training set was augmented using sub-dialogue shuffling, which samples a sub-dialogue  $\mathbf{x}_{s:e}$  from each complete dialogue  $\mathbf{x}_{1:T}$ , where s and e are the randomly selected start and end utterance indexes. The details are given in Algorithm 1. Firstly, the number of positive and negative samples in the training set are counted and  $M^+$  is set which is the desired number of sub-dialogues for each positive dialogue (line 1-3 of Algorithm 1). To augment while balancing the training samples,  $M^-$  is computed based on  $N^+, N^-$ , and  $M^+$  (line 4). Then,  $M^+$  and  $M^-$  sub-dialogues are generated for each complete dialogue belonging to the positive and negative classes respectively (line 8-10 of Algorithm 1).  $\epsilon_l$  and  $\epsilon_h$  are two variables that determine the length range of the subdialogues. When generating a sub-dialogue, its length d is first defined by a coefficient randomly drawn from  $[\epsilon_l, \epsilon_h)$  (line 12-13). The start index s is then randomly chosen from its available range and the end index is then determined (line 14-16).

### 3. BLOCK-WISE SSL REPRESENTATION ANALYSIS

It has been previously found that the output of different encoder blocks of a speech foundation model contains different levels of information [21, 22]. The block-wise evolution of the representations follows an acoustic-linguistic hierarchy, where the shallowest layers encode acoustic features, followed by the word meaning information, and phonetic and word identities. The analysis of the intermediate block representations can provide insights to better understand the information relevant to SDD. In this section, we perform such an analysis for the first time for SDD. The model structure used for block-wise analysis is shown in Fig. 1(b). Each time output from one intermediate Transformer block from the foundation model was used for downstream SDD.

#### 3.1. Effect of data augmentation

The effect of data augmentation was first investigated using the output of the last (12th) Transformer block of the pre-trained WavLM model (WavLM<sub>12</sub><sup>PT</sup>). Augmenting data trades off between generating more data and matching the true data distribution. As shown in Table 2, the F1 score increases and standard deviation decreases as the number of sub-dialogues for each positive sample  $M^+$  increases

<sup>&</sup>lt;sup>1</sup>Available at https://huggingface.co/facebook/wav2vec2-base

<sup>&</sup>lt;sup>2</sup>Available at https://huggingface.co/facebook/hubert-base-ls960

<sup>&</sup>lt;sup>3</sup>Available at https://huggingface.co/microsoft/wavlm-base-plus

W2V2 <sup>PT</sup>			HuBERT <sup>PT</sup>			WavLM <sup>PT</sup>					
Block	F1-avg	F1-max	F1-std	Block	F1-avg	F1-max	F1-std	Block	F1-avg	F1-max	F1-std
2	0.531	0.615	0.044	2	0.557	0.615	0.033	2	0.545	0.636	0.033
4	0.549	0.667	0.055	4	0.582	0.621	0.020	4	0.571	0.629	0.029
6	0.597	0.700	0.056	6	0.606	0.667	0.046	6	0.630	0.692	0.034
8	0.627	0.667	0.043	8	0.628	0.714	0.049	8	0.700	0.750	0.024
10	0.536	0.667	0.060	10	0.667	0.762	0.052	10	0.685	0.720	0.031
12	0.519	0.636	0.066	12	0.610	0.696	0.034	12	0.647	0.714	0.033
W2V2 <sup>ASR</sup>			W2V2 <sup>AER</sup>			WavLM <sup>AER</sup>					
Block	F1-avg	F1-max	F1-std	Block	F1-avg	F1-max	F1-std	Block	F1-avg	F1-max	F1-std
2	0.556	0.696	0.051	2	0.541	0.615	0.050	2	0.537	0.600	0.022
4	0.598	0.700	0.052	4	0.579	0.643	0.043	4	0.627	0.690	0.027
6	0.639	0.690	0.045	6	0.605	0.737	0.041	6	0.638	0.667	0.027
8	0.615	0.649	0.025	8	0.640	0.688	0.036	8	0.707	0.786	0.032
10	0.558	0.645	0.040	10	0.608	0.696	0.058	10	0.720	0.769	0.036
12	0.531	0.615	0.054	12	0.558	0.667	0.045	12	0.684	0.750	0.032

 Table 1. DAIC-WOZ SDD results using the outputs from different intermediate blocks of different foundation models. Highest F1 value in each column shown in bold.

$M^+$	100	200	500	1000	1500
F1-avg	0.451	0.583	0.647	0.679	0.669
F1-max	0.640	0.700	0.714	0.762	0.727
F1-std	0.131	0.082	0.033	0.027	0.031

**Table 2.** DAIC-WOZ SDD results with increased number of augmented utterances. WavL $M_{L12}^{PT}$  used as input.  $M^+$  is the number of sub-dialogues for each positive sample.

up until 1000, then F1 decreases and standard deviation increases. The model runs the risk of overfitting the training data if each original sequence is replicated too many times.  $M^+ = 500$  is used in following experiments, weighing performance and training time.

## 3.2. Pre-trained SSL representations

The parameters of the three pre-trained foundation models (W2V2<sup>PT</sup>, HuBERT<sup>PT</sup>, WavLM<sup>PT</sup>) were frozen and the SDD results using different intermediate blocks of the models are shown in Table 1. F1-avg of the intermediate blocks of three models are plotted in Fig. 2(a). For all three models, F1 first improves as the layer number increases and then F1 decreases. Overall WavLMPT produces a F1 score higher than the other two models. Features extracted from the 10th-block give the highest F1 for HuBERTPT while features extracted from the 8th-block have the overall best performance for  $W2V2^{PT}$  and  $WavLM^{PT}$ . It has been found [21] that the first a few W2V2 Transformer blocks show increased similarity with Mel filter bank (FBank) features, indicating that shallow layers encode acoustic information much like FBank. Word meaning information is mainly encoded in middle blocks, especially around the 8th-block [21]. Hence it can be inferred that features contain word meaning information are useful for SDD.

## 3.3. ASR and AER fine-tuned representations

This section investigates how fine-tuning changes the findings in Section 3.2. It has been implied in Section 3.2 that intermediate layer containing information correlated with word meaning is effective to SDD. And it has been found [20] that emotion information is also useful to SDD. Thus, our foundation models are fine-tuned based on ASR and AER tasks. Three fine-tuned systems are investigated in this paper: W2V2 base model fine-tuned for ASR on the 960 hours of Librispeech  $(W2V2^{ASR})^4$ , W2V2 base model fine-tuned on 110



**Fig. 2.** Trends of DIAC-WOZ F1-avg values at different blocks for the foundation models.

<sup>&</sup>lt;sup>4</sup>Available at https://huggingface.co/facebook/wav2vec2-base-960h

System	F1-avg	F1-max	F1-std
RoBERTa <sup>Hyp</sup>	0.599 0.635	0.667 0.667	0.042
Cat{RoBERTa <sup>Hyp</sup> ,W2V2 <sub>6</sub> <sup>ASR</sup> }	0.635	0.007	0.029

**Table 3**. Comparison of using reference and ASR transcriptions for SDD, where  $Cat\{\cdot, \cdot\}$  refers to a concatenation.

hours of MSP-Podcast dataset [23] for AER by adding two extra FC layers at the end (W2V2<sup>AER</sup>), and WavLM base model fine-tuned in the same way as W2V2<sup>AER</sup> for AER (WavLM<sup>AER</sup>). The concordance correlation coefficients for valence, activation, and dominance are 0.418, 0.658, 0.562 for W2V2<sup>AER</sup>, and 0.445, 0.667, 0.597 for WavLM<sup>AER</sup>. The model parameters were frozen after fine-tuning.

SDD results of the fine-tuned models are shown in the bottom half of Table 1. Comparing the results of W2V2<sup>ASR</sup> and W2V2<sup>AER</sup> with W2V2<sup>PT</sup>, as shown in Fig. 2(b), the peak of W2V2<sup>ASR</sup> is more towards earlier blocks while the peak of W2V2<sup>AER</sup> is towards later blocks. As shown by Fig. 2(c), the performance of WavLM<sup>AER</sup> also improves over WavLM<sup>PT</sup> on later layers. The fine-tuned foundation models presumably learn more task-specific information. For a W2V2 model fine-tuned with character-level connectionist temporal classification loss [24], the output of the last few layers are more directly related to the word identities. Fine-tuning the foundation model for AER improves the overall performance, indicating that emotion and depression share some para-linguistic indicators encoded by the fine-tuned models.

## 4. THE USE OF ASR TRANSCRIPTIONS

It has been shown that text information is effective for SDD [6, 25]. However, reference transcriptions are usually not available in practice. This section uses an ASR system to transcribe the depression detection interview and investigates the performance of using erroneous transcriptions in SDD. Transcriptions were obtained from the final output of the W2V2<sup>ASR</sup> model which has a word error rate (WER) of 3.4% on LibriSpeech test-clean and 8.6% on test-other while 40.9% on DAIC-WOZ. The ASR and reference transcripts were encoded by a text foundation model, the RoBERTa base model<sup>5</sup> [15], and fed into the depression detection block. The SDD results with ASR generated hypotheses and reference transcriptions are compared in Table 3 (RoBERTa<sup>Hyp</sup>, RoBERTa<sup>Ref</sup>). Replacing the reference transcriptions with ASR generated hypotheses leads to a decrease of 0.36 in average F1 score and also a larger standard deviation.

Utterance-level representations derived from RoBERTa<sup>Hyp</sup> were combined with those derived from the 6th-block representations of the ASR-fine-tined W2V2 model (W2V2 $_{6}^{SR}$ ) by concatenation.

System	F1-avg	F1-max	F1-std
<b>RoBERTa</b> <sup>Hyp</sup>	0.599	0.667	0.042
$WavLM_8^{PT}$	0.700	0.750	0.024
WavLM <sup>AER</sup>	0.720	0.769	0.036
$Cat{WavLM_8^{PT}, RoBERTa^{Hyp}}$	0.725	0.759	0.021
$Cat{WavLM_{10}^{AER}, RoBERTa^{Hyp}}$	0.756	0.800	0.023

**Table 4.** Results of combining different speech and text foundation models, where  $Cat\{\cdot, \cdot\}$  refers to a concatenation.

<sup>5</sup>Available at https://huggingface.co/roberta-base

System	Ensemble 1	Ensemble 2
		/
$WavLM_{10}^{AER}$ $WavLM_{10}^{AER}$ $Cat{WavLM_{10}^{AER}, RoBERTa^{Hyp}}$	V	$\sqrt[n]{\sqrt{1}}$
F1-avg	0.800	0.829
F1-max	0.857	0.886

**Table 5**. Ensemble of foundation models. Cat $\{\cdot, \cdot\}$  refers to a concatenation.

Paper	[19]	[18]	[7]	[17]	[20]	ours
F1-avg	0.69	-	-	-	-	0.83
F1-max	-	0.70	0.77	0.85	0.87	0.89

Table 6. Cross comparison on DAIC-WOZ development subset.

From Table 3, this combination produced better SDD results than using the reference transcriptions alone.

## 5. COMBINATIONS OF FOUNDATION MODELS

This section studies further combinations of SSL representations derived from both speech and text foundation models. Similar to the experiments in Table 3, speech SSL representations were combined with the ASR transcriptions by a concatenation, and the results are shown in Table 4. Combining speech and ASR-hypothesis-based text representations can improve F1-avg and F1-max as well as reduce F1-std, which improves both SDD classification performance and stability.

Finally we investigated the use of a system ensemble by voting. Two ensembles were investigated: (i) The ensemble of systems based on three speech foundation models:  $W2V2_{8}^{PT}$ , HuBERT<sub>10</sub><sup>PT</sup>, WavLM<sub>8</sub><sup>PT</sup>; (ii) The ensemble of systems from three modalities: WavLM<sub>8</sub><sup>PT</sup> (audio modality), Cat{WavLM<sub>10</sub><sup>AER</sup> (emotion modality).

The results of using ensembles are shown in Table 5. Reference transcriptions were not used in these ensembles and our bestperforming depression detection systems require only the speech input. Table 6 cross compares our results with those published in literature. Paper [19] used W2V2 and reported the average result across five models. Reference transcriptions were used by papers [7, 17, 18, 20]. The comparison shows that the ensemble of foundation models produced competitive performance for depression detection based on speech input only.

## 6. CONCLUSION

This paper studies the use of SSL representations in speech-based depression detection. Block-wise analysis of the foundation models implies that word meaning information is helpful in SDD. Fine-tuning pre-trained speech foundation models for AER improves SDD performance, indicating that some indicators are shared between AER and SDD. SDD performance when using ASR transcriptions matches that of using reference transcriptions when combined with the hidden representations derived from an ASR-fine-tuned foundation model. The ensemble of speech and text foundation models produced the SOTA F1 score of 0.89 on DAIC-WOZ dataset without using the reference transcriptions.

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