INTERSPEECH 2023
20-24 August 2023, Dublin, Ireland

Transforming the Embeddings: A Lightweight Technique for Speech Emotion Recognition Tasks

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Abstract

Speech emotion recognition (SER) is a field that has drawn a lot of attention due to its applications in diverse fields. A current trend in methods used for SER is to leverage embeddings from pre-trained models (PTMs) as input features to downstream models. However, the use of embeddings from speaker recognition PTMs hasn't garnered much focus in comparison to other PTM embeddings. To fill this gap and in order to understand the efficacy of speaker recognition PTM embeddings, we perform a comparative analysis of five PTM embeddings. Among all, x-vector embeddings performed the best possibly due to its training for speaker recognition leading to capturing various components of speech such as tone, pitch, etc. Our modeling approach which utilizes x-vector embeddings and mel-frequency cepstral coefficients (MFCC) as input features is the most lightweight approach while achieving comparable accuracy to previous state-of-the-art (SOTA) methods in the CREMA-D benchmark.

Index Terms: Speech Emotion Recognition, Speaker Recognition, Convolutional Neural Networks (CNN)

1. Introduction

Human beings express different emotions under different circumstances. Emotions serve as routes of communication between humans. Emotional connection helps humans to communicate more effectively and as social beings, helps humans understand each other in a better way, celebrate joyful moments together, and be a supporting shoulder during tough times. Understanding each other's emotions is natural for humans, however, that's an arduous task for machines. This is essentially important when machines are often used for anticipating emotions nowadays and have become a crucial problem for machines for effective human-machine interaction.

Emotions can be detected in various ways such as through facial features, behavior, body gestures, physiological signals, and speech. In this work, we focus on Speech emotion recognition (SER), the method of understanding emotions in human speech in particular, which has received attention due to its potential applications in a broad range of diverse areas, including psychology, healthcare, etc. Various methods have been applied for SER, such as Hidden Markov Model (HMM) [1], classical machine learning [2], deep neural network-based approaches [3]. Recent works on SER have also used embeddings from various speech (wav2vec, wav2vec 2.0) and audio (YAMNet, VGGish) pre-trained models (PTMs) as input features for downstream models [4]. PTMs can be of varied types, for example, CNN-based (YAMNet, VGGish) and transformer-based (wav2vec, wav2vec 2.0) architectures. They are trained on enormous amounts of data, either in a supervised or self-supervised manner. Self-supervised Learning (SSL) speech PTM embeddings have proven to be state-of-the-art (SOTA) in comparison to other PTM embeddings [5] across various speech-related tasks such as SER, speaker count estimation, etc. The wide availability of embeddings from PTMs has made a significant contribution to the progress of SER.

However, much focus on speaker recognition PTM embeddings for SER hasn't been given in contrast to speech SSL PTM embeddings such as wav2vec2.0 [6], Unispeech-SAT [7]. Pappagari et al. [8] showed the association between speaker and emotion recognition; focusing on the usefulness of speaker recognition PTM embeddings for SER. Nevertheless, for understanding the effectiveness of speaker recognition PTM embeddings for SER, a comparison with other PTM embeddings is required that has been missing in the literature. So, we tackle this research gap by performing a comparative analysis of various PTM embeddings. To summarize, the main contributions of our work are as follows:

- Comparative analysis of different PTM embeddings (x-vector, ECAPA, wav2vec 2.0, wavLM, Unispeech-SAT) on CREMA-D benchmark. The top performance is achieved by x-vector embeddings among all the other embeddings.
- Our hypothesis for the performance of x-vector embeddings is that the model learned numerous components of speech such as tone, pitch, and so on as a result of speaker recognition training. Further refinement of these embeddings with Convolutional Neural Network (CNN) resulted in contributing towards the same, capturing more important representations.
- Our approach which uses x-vector embeddings and mel-frequency cepstral coefficients (MFCC) as input features to a downstream CNN model achieves comparable performance in terms of accuracy with SOTA works on CREMA-D while being the most lightweight method in terms of the number of parameters involved. See Section 4.4.

This paper is divided into five sections. Section 2 walks through past literature on approaches carried out for SER followed by Section 3 which discusses the PTM embeddings considered for our analysis. In Section 4, we provide brief information on the speech emotion corpus considered for our analysis, downstream classifier, training details, and experimental results. Lastly, Section 5 summarizes the work presented.

2. Related work

Studies have shed light on SER from the beginning of the 21st century [9, 10]. Initial research involved the usage of Hidden Markov Models (HMMs) [11] and followed by the usage of classical machine learning algorithms with handcrafted fea-

10.21437/Interspeech.2023-2561

tures [12]. CNN has been applied to SER [13] after AlexNet gained popularity in the ImageNet challenge. Huang et al. [13] work comprised two phases with CNN: unsupervised learning followed by semi-supervised learning. HMMs were again brought to the limelight by Mao et al. [14] with certain modifications. They experimented with three different HMM-based architectures, namely, Gaussian Mixture-based HMMs, Subspace Gaussian Mixture-based HMMs, and deep learning-based HMMs. Various CNN architectures such as AlexNet, ResNet, Xception, and different variants of VGG and DenseNet pre-trained on ImageNet for image recognition tasks were leveraged for SER [15]. Zhang et al. [16] used AlexNet in conjunction with Bidirectional LSTM and attention mechanism. Fusion of MFCC and features retrieved from pre-trained CNN as input features to LSTM model was put to use by Arano et al. [17]. Although CNNs were considered to be most suitable for SER, with time, transformers have also earned a spot [18, 19]. A model architecture with multiple transformer layers stacked on top of one other was proposed by Wang et al. [20]. Heracleous et al. [21] was the first to use ViT for the purpose of emotion recognition.

In recent times, the usage of embeddings from various PTMs like YAMNet, wav2vec, etc., as input features to classifiers for SER [4] can be seen. This approach of using embeddings extracted from PTMs has become a widely used method due to the various benefits associated with it, such as saving time and cost involved with training a model from scratch and also boosts in performance as these models are trained on diverse large-scale data and learn nuanced representations of the input data. Speech SSL PTM embeddings have shown superior performance in comparison to embeddings from other PTMs such as YAMnet, VGGish, etc for SER [4]. Atmaja et al. [22] gave a comparison of various SOTA speech SSL PTM embeddings by training and evaluating a fully connected network on top of the extracted embeddings.

However, research into speaker recognition PTM embeddings hasn't received much attention in comparison to their counterparts for SER, so we work in this direction by comparing different PTM embeddings to evaluate their effectiveness. We hypothesize that PTM initially trained for speaker recognition can be more effective for SER as knowledge gained for speaker recognition such as learning tone, pitch, etc. from speech can be beneficial.

3. Pre-trained Model Embeddings

For our analysis, we consider five PTM embeddings: x-vector, ECAPA, wav2vec 2.0, wavLM, and Unispeech-SAT. x-vector [23] and its modified version Emphasized Channel Attention, Propagation, and Aggregation (ECAPA) [24] are speaker recognition PTMs. x-vector is a state-of-the-art speaker recognition system and it is a time delay neural network (TDNN) trained end-to-end in a supervised fashion without any handcrafted features for identifying speakers. After the training is completed, it is used for obtaining speaker embeddings from variable-length utterances. x-vector outperforms i-vector, prior speaker recognition system. ECAPA approach made numerous enhancements in the frame and pooling level to the original x-vector model architecture by rectifying its limitations. We use readily available x-vector[1] and ECAPA[2] models from *HuggingFace*. Combination of voxceleb 1 and voxceleb 2 were used as pre-training data for both the models with the input speech signals sampled as 16KHz single-channel [25]. We extract embeddings of 512 and 192-dimension from x-vector and ECAPA respectively with the help of *Speechbrain* [25] library.

We follow Speech processing Universal PERformance Benchmark (SUPERB) [26] during consideration of speech SSL PTMs (wav2vec 2.0, wavLM, Unispeech-SAT). SUPERB evaluates features from SSL PTMs across a wide range of tasks, such as speaker identification, SER, speech recognition, voice separation, and so on. WavLM [27] outperformed all its competitors except Unispeech-SAT. It is proposed as a generalized model for solving various posterior speech-related tasks. During pre-training, wavLM learns both speech prediction and denoising in conjunction which aids in understanding the multi-dimensional information such as speaker identity, content, etc. embedded in speech. In contrast, pre-training for the Unispeech-SAT was done in a speaker-aware way. It is a contrastive loss based multitask learning model. For our experiments, we utilize wavLM base+[3] and UniSpeech-SAT base[4] version. WavLM base+ has 12 transformer-encoder layers and pre-training was done on 94k hours of data from several speech datasets such as LibriLight, VoxPopuli, and GigaSpeech whereas the Unispeech-SAT base version was pre-trained on 960 hours of Librispeech.

The performance of wav2vec 2.0 is not as high in comparison with wavLM and Unispeech-SAT on SUPERB. However, previous researchers have made use of its embeddings for SER [6] and has proven to be effective so we add it to our experiments. wav2vec 2.0 was pre-trained in a self-supervised manner on Librispeech. We use base[5] version that contains 12 transformer blocks. The final hidden states are retrieved from wavLM, UniSpeech-SAT, and wav2vec 2.0 and transformed to a vector of 768-dimension for each audio file to be utilized as input features for the downstream classifier using pooling average. Sampling is done at 16KHz for each audio file to be provided as input for the SSL PTMs.

4. Experiments

4.1. Benchmark Speech Emotion Corpus

We select Crowd-sourced emotional multimodal actors dataset (CREMA-D) [28] for our experiments as it provides a rich data source for SER due to the variations in ages and ethnicities across speakers. It acts as high-quality benchmark data for training and evaluating machine learning models. It is a gender-balanced database in English. It contains 7442 utterances from 91 different speakers across six emotions: Anger, Happiness, Sadness, Fear, Disgust, and Neutral. The audio clips include 48 male and 43 female artists. They spoke from a list of twelve sentences.

4.2. Downstream Model

For the first set of experiments, which involves a comparison of PTM embeddings, we use 1D-CNN on top of the embeddings from PTMs followed by a Fully Connected Network (FCN) as shown in Figure 1. *Softmax* function is used in the output layer

[1] `https://huggingface.co/speechbrain/spkrec-xvect-voxceleb`

[2] `https://huggingface.co/speechbrain/spkrec-ecapa-voxceleb`

[3] `https://huggingface.co/docs/transformers/model_doc/wavlm`

[4] `https://huggingface.co/docs/transformers/model_doc/unispeech-sat`

[5] `https://huggingface.co/facebook/wav2vec2-base`

that outputs the probabilities for different emotions. The same modeling approach is followed across all the PTM embeddings. Secondly, for double input (PTM + MFCC features), a similar modeling technique is used with 1D-CNN applied on both inputs and then concatenated together. For extracting MFCC from raw audio waveforms, we use *Librosa*[6] library. The modeling approach remains same for different variations of input. We utilize *Tensorflow* library for our experiments.

Models are trained in a 5-fold fashion, with four folds utilized for training and one fold maintained for testing. Information regarding the hyperparameters set can be found in Table 1. The hyperparameters other than those mentioned are kept as default. We also use early stopping and learning rate decay during training.

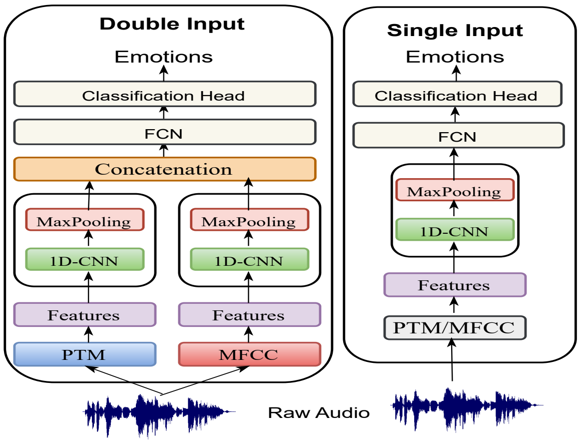


Figure 1: *Proposed Model architecture for Double Input i.e embeddings from PTM + MFCC as input features; Single input i.e embeddings from PTM/MFCC as input features*

Table 1: *Hyperparameter Details*

Number of Kernels for 1D-CNN	32
Kernel Size for 1D-CNN	3
Number of Neurons for each layer of FCN	200, 90, 56
Activation Function in Intermediate Layers	ReLU
Training epochs	50
Optimizer	Rectified Adam
Learning Rate	1e-3
Batch Size	32

4.3. Experimental Results

We compare the performance of PTM embeddings by training and evaluating them with the downstream model. The results are shown in Table 2. The performance of baseline MFCC features and wav2vec 2.0 embeddings is not significantly different which points towards wav2vec 2.0 embeddings being unable to capture important information in comparison to its other PTM counterparts. Unispeech-SAT achieves higher performance than ECAPA and other speech SSL PTM embeddings (wav2vec 2.0, wavLM). This can be resultant of its speaker-aware pre-training. However, ECAPA performs better than the other two speech SSL PTM embeddings. Out of all the PTM embeddings, the model trained on x-vector embeddings performed the best with an accuracy of 68.19%. This validates our hypothesis that models pre-trained for speaker recognition learns about tone, pitch, and other characteristics which are useful for SER. We also plot t-SNE plots of the raw embeddings retrieved from the PTMs and is shown in Figure 2. These figures follow up the results presented in Table 2, with slight cluster formation in accordance to different emotions that can be seen for x-vector embeddings in comparison to others.

We extended our experiments by combining PTM embeddings with MFCC as input features, and the results are shown in Table 3. Except for Unispeech-SAT, combining MFCC with PTM embeddings results in increased accuracy.

4.4. Comparison to State-of-the-art

Accuracy: We compare our top-performing model (x-vector + MFCC) against SOTA works presented in Table 4. As seen, our approach is able to attain comparable performance against SOTA methods.

Lightweight: We compare our model in terms of the number of parameters with representative SOTA works which have mentioned the parameters in their models. We have not compared our model to CLAP [29] as it involves additional modality i.e. descriptions of the speech emotions and we are only comparing with works that have worked only with speech as input. ViT [30] has 75.7M parameters while SepTr [31] has 9.4M parameters. SepTr + LeRaC [32] also contains a similar number of parameters as SepTr. Our model has 1.79M parameters which are far lesser parameters than the models mentioned above. During the training phase, it requires only 1 second per epoch on P100 GPU. For fusion_cat_xwc [5], it's difficult to quantify the exact number of parameters involved as it is a work carried out for HEAR [33]. It consists of an ensemble of several speech SSL PTMs with no fine-tuning followed by a downstream Multilayer Perceptron classifier.

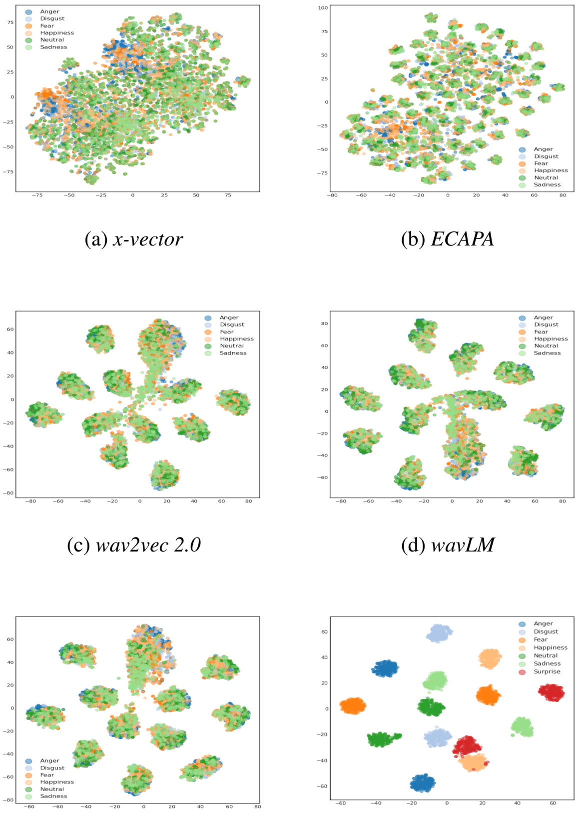
Table 2: *Performance of different PTM embeddings; MFCC are taken as baseline input features and all the scores are average of 5-folds*

Input Features	Accuracy (%)
MFCC	47.44
x-vector	**68.19**
ECAPA	58.91
wav2vec 2.0	48.12
wavLM	55.68
Unispeech-SAT	67.27

Table 3: *Performance achieved by combination of PTM embeddings + MFCC as Input Features; all the scores are average of 5-folds*

Input Features	Accuracy (%)
x-vector + MFCC	**70.53**
ECAPA + MFCC	63.02
wav2vec 2.0 + MFCC	58.13
wavLM + MFCC	57.52
Unispeech-SAT + MFCC	67.01

[6] https://librosa.org/doc/main/generated/librosa.feature.mfcc.html



(a) *x-vector* (b) *ECAPA*

(c) *wav2vec 2.0* (d) *wavLM*

(e) *Unispeech-SAT* (f) *x-vector_TESS*

Figure 2: *Figure 2a, 2b, 2c, 2d, 2e represents the t-SNE plots of PTM embeddings on CREMA-D and Figure 2f represents the t-SNE plot of x-vector embeddings on TESS*

Table 4: *Comparison of proposed approaches (CNN(x-vector), CNN(x-vector, MFCC)) with SOTA works on CREMA-D benchmark; CNN(x-vector), CNN(x-vector, MFCC) represents CNN model with x-vector embeddings and x-vector embeddings + MFCC as input features respectively*

Method	**Accuracy (%)**	**Year**
GRU [34]	55.01	2020
GAN [35]	58.71	2020
ResNet-18 [36]	65.15	2020
ViT [30]	67.81	2020
ResNet-18 ensemble [37]	68.12	2021
CNN(x-vector)	68.19	
SepTr-VH [31]	70.47	2022
CNN(x-vector, MFCC)	70.53	
SepTr + LeRaC [32]	70.95	2022
CLAP [29]	72.56	2022
fusion_cat_xwc [5]	**74.70**	2022

4.5. Additional Experiment

Furthermore, we evaluated our model (CNN(x-vector, MFCC)) on an additional speech emotion corpus i.e. Toronto Emotional Speech Set (TESS) [41] to evaluate the effectiveness of our model. TESS is an English database consisting of 2800 utterances with 2 female speakers spreading across seven emotions: Anger, Happiness, Sadness, Fear, Disgust, Neutral, and Surprise. We use the same set of hyperparameters as given in Table 1. We follow a 5-fold procedure for training our model and report the average accuracy score for 5-folds in comparison with previous works which is presented in Table 5. t-SNE plot of raw embeddings extracted from x-vector is shown in Figure 2f, with clear segregation of clusters is observed based on different emotions. These results show the effectiveness of our model for SER, especially, embeddings from x-vector as input features.

Table 5: *Performance of proposed approach (CNN(x-vector, MFCC)) and its comparison with previous methods on TESS*

Approach	**Accuracy (%)**	**Year**
CNN [38]	85	2019
CNN [39]	97.1	2022
CNN(x-vector, MFCC)	99.82	
IMEMD-CRNN [40]	**100**	2022

5. Conclusions

In this work, we perform a comprehensive comparative study of five PTMs (x-vector, ECAPA, wav2vec 2.0, wavLM, Unispeech-SAT) for analyzing their performance for SER. x-vector embeddings fared the best in comparison to the other PTM embeddings, which might be due to its training for speaker recognition, which leads to the capture of many important components of speech such as tone, pitch, and so on. x-vector embeddings and MFCC as input features based downstream CNN approach attained comparable performance in accordance with accuracy and also the most lightweight technique on CREMA-D. The results of this study can aid in selecting appropriate embeddings for tasks related to SER and serve as a baseline approach for future research in this direction.

6. References

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