THE IMPORTANCE OF SPEECH STIMULI FOR PATHOLOGIC SPEECH CLASSIFICATION

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ABSTRACT

Current findings show that pre-trained wav2vec 2.0 models can be successfully used as feature extractors to discriminate on speaker-based tasks. We demonstrate that latent representations extracted at different layers of a pre-trained wav2vec 2.0 system can be effectively used for binary classification of various types of pathologic speech. We examine the pathologies laryngectomy, oral squamous cell carcinoma, parkinson’s disease and cleft lip and palate for this purpose. The results show that a distinction between pathological and healthy voices, especially with latent representations from the lower layers, performs well with the lowest accuracy from 77.2% for parkinson’s disease to 100% for laryngectomy classification. However, cross-pathology and cross-healthy tests show that the trained classifiers seem to be biased. The recognition rates vary considerably if there is a mismatch between training and out-of-domain test data, e.g., in age, spoken content or acoustic conditions.

Index Terms— pathologic voices, laryngectomy, oral squamous cell carcinoma, cleft lip and palate, parkinson’s disease

1. INTRODUCTION

Speech pathologies have been studied using a wide variety of approaches. Latent features such as GMM-Supervectors [1], i-vectors [2] and x-vectors [3] have been found useful for the analysis of pathologies from speech samples. Bocklet et al. use GMM-Supervectors to assess various speech pathologies [4], to evaluate the intelligibility of laryngeal cancer patients [5] and to rate Parkinson’s patients [6]. X-vectors [7] are used to classify between patients with Parkinson’s disease and a healthy control group. More recent research employed latent representations obtained from wav2vec 2.0 [8] (W2V2) models in phoneme recognition, vocal fatigue detection, speech emotion recognition, and dysfluency detection [8][9][10][11]. Furthermore, latent W2V2 representations have been successfully used for the distinction between speakers and languages [12]. These works demonstrate that W2V2 embeddings are well suited to encode speaker and language characteristics. The extent to which these embeddings are capable of capturing the characteristics of voice pathology is still being explored.

In this paper, we utilize wav2vec 2.0 (W2V2) to extract latent speech representations and explore their suitability for the detection of various types of pathologic voices. We employ a pre-trained W2V2 encoder for feature extraction and train binary classifiers for each of the pathological datasets, using large margin classifiers, tree-based methods, and neural networks. Finally, we perform cross-corpus tests and investigate which classifiers are able to predict other pathological and healthy data. We show the importance of selecting control or training data and the influence of factors such as age, utterance content, and acoustic conditions.

2. DATA

We use four pathological speech corpora to train binary classifiers on features extracted using a pre-trained W2V2 model. The pathologies investigated are recordings of tracheoesophageal speakers after a laryngectomy, oral squamous cell carcinoma speakers, parkinson’s disease speakers and cleft lip and palate speakers. All training corpora contain speech from native German speakers. Some subjects exhibit strong forms of local dialects. Each pathological corpus is briefly described in Section 2.1. Four additional corpora consisting of healthy speech are used to cross-test the trained binary pathology classifiers. These are briefly described in Section 2.2.3.

2.1. Pathological Speech Corpora

Laryng41: The tracheoesophageal (TE) substitute voice is a common treatment to restore the patient’s ability to speak after laryngectomy, i.e., the removal of the entire larynx. The Laryng41 (LAR) corpus is a collection of tracheoesophageal speakers, reading the German version of the “The North Wind and the Sun” (NWS) text passage [13]. The corpus contains 41 laryngectomees ($\mu = 62.0 \pm 7.7$ years old, 2 female and 39 male) with TE substitute voice.

Oral Squamous Cell Carcinoma: Oral squamous cell carcinoma (OSCC) and its treatment impair speech intelligibility by alteration of the vocal tract. The OSCC dataset is comprised of 71 patients ($\mu = 59.9 \pm 10.1$ years old, 16 female and 55 male) with OSCC in various stages. The patients were recorded reading the German version of the NWS text passage.

Parkinson’s Disease: Parkinson’s disease (PD) is a degenerative disorder of the central nervous system that mainly affects the motor system. The full PD corpus contains 88 native German speakers diagnosed with PD ($\mu = 66.6 \pm 9.0$ years old, 44 female and 44 male) and a healthy control group comprised of another 88 speakers ($\mu = 58.1 \pm 14.2$ years old 43 female, 45 male) [6]. The dataset contains speech of different tasks, we selected the task of reading a phonetically rich text for the experiments in this work.

Erlangen-CLP: The Erlangen-CLP corpus [15] is a speech database of 818 children ($\mu = 8.7 \pm 13.3$ years old, 355 female and 463 male) with Cleft Lip and Palate (CLP) and 380 age-matched control speakers ($\mu = 7.8 \pm 10.4$, 185 female and 195 male) who spoke the PLAKSS test. The PLAKSS test consists of words with all German phonemes in different positions and is used by speech therapists in German-speaking countries. We use a subset consisting of 598 CLP speakers.

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2.2. Healthy Control Corpora

The healthy control groups for our training comprises the respective control groups from the CLP and PD corpora. Since LAR and OSCC have no matching controls, we use a collection of 110 elderly ($\mu = 75.7 \pm 9.6$ years old, 79 female and 31 male) native German speakers reading the NWS text passage. We call this corpus AgedVoices110 (AV). The conditions in AgedVoices110 are similar to those in the LAR and OSCC corpora in several ways: the participants read the same phonetically rich text, belong to a similar age cohort (> 60 years old), the same recording equipment was used, and the recordings were performed in the same hospital. Furthermore, the participants live in the same region of Germany and speak the same local dialect.

2.3. Additional Corpora

Tuda-De100: The Tuda-De100 (TUDA) data comprises 100 utterances from the Tuda distant speech corpus [15], in the age range of 21 to 30. We randomly selected a small subset of utterances from 10 speakers (5 female, 5 male) recorded with the Yamaha PSG-015 microphone. Each speaker reads 10 sentences from the German Wikipedia.

MLS100: The Multilingual LibriSpeech (MLS) dataset [17] is a large multilingual speech corpus of read audiobooks from LibriVox. Similar to the Tuda-De100 data, we randomly selected a subset of 100 utterances from 10 German speakers (5 female, 5 male), each reading 10 sentences.

PhattSessionz100: The goal of the PhattSessionz (PSZ) project [18] was the creation of a regionally balanced speech database of German adolescent speakers in the age range of 12 to 20. We randomly selected 100 utterances from the “reading phonetically rich sentences” task for 10 speakers (5 female, 5 male) for our experiments.

NWS Reading: NWS Reading (NWSR) is a small corpus that consists of 8 native German speakers (1 female and 7 male) reading the NWS text passage multiple times throughout a period of approximately one year. Six speakers were more than 50 years old at the time of recording and two speakers were 12 and 23 years old.

### 3. METHOD

We use a pre-trained W2V2 model and extract embeddings for each utterance of the individual datasets from each of the 12 transformer blocks over the entire length. The dimensionality of the resulting features extracted with W2V2 is 768. The respective training datasets were aggregated by speaker using the mean of all utterance embeddings from a speaker to get more robust features for pathological speech distinction.

We evaluate three different classes of models; large margin classifiers, tree-based methods, and neural networks. We choose Support Vector Machine (SVMs), XGBoost (XGB), and a feedforward neural network with fully connected layers (Multilayer Perceptron, short MLP) for the task. The optimal hyperparameters for each estimator are determined in a 5-fold cross-validation on the training set using the grid search method.

SVMs are trained using radial basis function (RBF) kernels. The kernel parameter $\gamma$ is selected from $\gamma \in \{10^{-k} | k = 5, \ldots, 1\} \subset \mathbb{R}_{> 0}$, and the penalty parameter of the error term $C$ is selected from $C \in \{5, 10, 20, 50\} \subset \mathbb{N}_{> 0}$.

XGB models are trained using a tree booster as the underlying learner. The maximum tree depth parameter $d$ is chosen from $d \in \{2^k | k = 1, \ldots, 4\} \subset \mathbb{N}_{> 0}$. The learning rate $\eta$ is chosen from the set $\eta \in \{\frac{1}{10^k} | k = 1, \ldots, 5\} \subset \mathbb{R}_{> 0}$ and and the minimum sum of an instance weight $w$ is chosen from $w \in \{2^k | k = 0, \ldots, 3\} \subset \mathbb{N}_{> 0}$.

The MLP employs the Adam [19] optimizer with exponential decay rates of $\beta_1 = 0.9$, $\beta_2 = 0.999$ and a $L_2$ regularization term of $10^{-4}$. The MLP learning rate $\alpha$ is chosen from $\alpha \in \{10^{-k} | k = 1, \ldots, 4\} \subset \mathbb{R}_{> 0}$. The activation function is either Tanh or ReLU, the number of hidden layers is either 2 or 3, and the number of hidden units varies between 32 and 128.

We summarize the results of the models trained on W2V2 features from the lower-layers (LL), middle-layers (ML) and higher-layers (HL) results. LL corresponds to the embeddings of layers 1 to 3, ML to layers 4 to 9, and HL to layers 10 to 12. We first calculate the mean across the layers, and afterwards the mean across the different types of classifiers, resulting in one accuracy score across the three model classes.

### 4. EXPERIMENTS

#### 4.1. Closed set pathology classification

We first train binary classifiers (SVM, XGB and MLP) for each of the four pathologies CLP, LAR, OSCC, and PD aggregated by train features from lower-, middle-, and high-layers.

|          | LL | ML | HL |
|----------|----|----|----|
| CLP      | 99.5 | 97.8 | 92.9 |
| LAR      | 100 | 99.6 | 99.3 |
| OSCC     | 98.7 | 98.8 | 93.6 |
| PD       | 77.2 | 79.6 | 72.5 |

Table 1. Classification accuracy results of binary classifiers for CLP, LAR, OSCC, and PD aggregated by train features from lower-, middle-, and high-layers.

The MLP employs the Adam [19] optimizer with exponential decay rates of $\beta_1 = 0.9$, $\beta_2 = 0.999$ and a $L_2$ regularization term of $10^{-4}$. The MLP learning rate $\alpha$ is chosen from $\alpha \in \{10^{-k} | k = 1, \ldots, 4\} \subset \mathbb{R}_{> 0}$. The activation function is either Tanh or ReLU, the number of hidden layers is either 2 or 3, and the number of hidden units varies between 32 and 128.

We summarize the results of the models trained on W2V2 features from the lower-layers (LL), middle-layers (ML) and higher-layers (HL) results. LL corresponds to the embeddings of layers 1 to 3, ML to layers 4 to 9, and HL to layers 10 to 12. We first calculate the mean across the layers, and afterwards the mean across the different types of classifiers, resulting in one accuracy score across the three model classes.

#### 4.1. Closed set pathology classification

We first train binary classifiers (SVM, XGB and MLP) for each of the four pathologies CLP, LAR, OSCC and PD, on each of the 12 W2V2 transformer block outputs. As a result, we get 36 models for each pathology.

Table 1 shows the results for our four pathologies aggregated by LL, ML and HL. These indicate that the lower-layer embeddings, except for PD, are best suited for the classification of the specific pathology, resulting in accuracy scores from 98.7% to 100%. PD classification works best with latent features from the sixth layer across all classifiers, resulting in a mean accuracy of 79.6%. Since PD is a long-term degenerative disorder and the dataset also contains early stage impairments, it is possible that the motor system is still affected to a degree that is too low for a precise classification. LAR on the other side is the simplest classification task involving a surgical procedure, the removal of the larynx, resulting in the most significant change in acoustics. This is the reason why we get results from 99.3% to 100% accuracy from lower- to higher-layer features. The CLP and OSCC classifiers yield similar results on lower-layer and middle-layer features, while resulting in an around 5% relative accuracy drop on high-layer features. The results indicate that important pathological voice information can be represented by W2V2 embeddings, especially in the lower and middle layers. It is consistent with the results from [12], where the authors found that the lower-layer representations are best suited for speaker- and language-based distinction tasks.
4.2. Cross-pathology tests

Since the binary classifiers yield near perfect results on the particular pathologies, we try to investigate what exactly was learned and how the models trained on one pathology deal with other pathological and healthy data. We pick the classifiers of a particular pathology and test each of the remaining three pathological datasets to see how these handle unseen pathologies. We assign pathological test data the label for pathological. The evaluations are listed in Table 2.

CLP: The CLP models classify all three pathologies as pathological with a minimum accuracy of 93.1% for LAR, trained on the lower-layer embeddings. Middle-layer embeddings result in an uncertainty for LAR (58.7%) and PD (44.9%) whereas OSCC is classified 76.6% as pathological. High-layer embeddings mostly classify LAR and OSCC as pathological, while PD remains at 46.5% pathological. It is not clear why the CLP classifiers classify all other pathologies as pathological or CLP on lower-layer features. This could be due to the significant age difference or acoustic differences between the corpora, which leads to the classification of all non-training data into the pathological class. Moreover, the spoken content also differs between the corpora. Whereas in CLP single words are uttered, in LAR and OSCC the NWS text is read, and in PD a completely different text is read.

LAR: The LAR models trained on lower-layer features classify almost the complete OSCC and PD data as healthy, CLP as 78% healthy. OSCC and PD predominantly remain healthy for middle- and high-layer LAR classifier, while CLP data is classified 79.3% as pathologic on high-layer embeddings. Since the LAR pathology offers the easiest distinction due to the enormous change in acoustics, probably because of this the other pathological data are not classified as pathological or as LAR. The difference from CLP to OSCC and PD could possibly arise from the acoustic mismatch, between child and adult data.

OSCC: The OSCC models mostly predict CLP as pathologic across all layer embeddings, starting on lower-layers with 87.9%, middle-layers 92.7% and completely pathologic on high-layer features. On LAR data the lower- and middle-layer features yield in uncertain classification from 50.8% to 59.2%, on high-layer features as pathologic for 72.1%. Uncertainty also prevails for PD on lower-layer features with 43.8% pathologic, while predominantly classified as healthy on middle- and high-layer features. The high assignment of CLP to OSCC pathology may result from anatomic similarity between the two pathologies. However, the age factor could also play a role in this case. Regarding PD, the similar age of the two pathologies might explain the better assignment to the non-pathologic class.

PD: PD models classify on lower-layer features CLP and LAR mostly as healthy, only 13.7% and 26.4% pathologic. On CLP data, an uncertainty arises on middle- and high-layer features, with 40.7% and 48.4% pathologic. LAR data is classified mostly as pathologic on middle- and high-layer features around 75%. OSCC pathologic data is classified as pathologic across all layer features, starting with 73.7% on lower-layer features and 93.4% on high-layer features, possibly because of the same effects on the speech system.

4.3. Cross-healthy tests

Similar to cross-pathology tests, we conduct tests on healthy out-of-domain data. Additional to the training controls data, we evaluate the pathology classifiers on the NWSR, MLS, TUDA and PSZ corpora. We assign healthy test data the label, which is equivalent to the healthy control groups in training. The results are listed in Table 3.

We use corpora with different spoken content in our experiments; read sentences (MLS, TUDA, PSZ), NWS reading (NWSR, AV, LAR, OSCC), text reading (PD), phoneme rich words (CLP). To match the MLS100, Tuda-De100, and Phattsessionz100 datasets with the lengths of the remaining corpora, we merged utterances of at least 50 seconds and extracted features based on these. The results show that the length of the utterances has a significant influence on the classification. An increase in accuracy is evident for PSZ across all models and feature-layers, especially for the CLP classifier, with over 60% relative accuracy boost using lower-layer features. This is probably due to the lower variability in the data as a result of the long utterances. In Figure 1 it is visible that in comparison to STC, smaller clusters and thus less variability is evident for STC_L, SCT (short sentences) and STC_L (long sentences) contain the three datasets with read sentences.

Table 2. Cross-corpora classification results for pathological data aggregated on embeddings’ origin. Columns represent the cross-pathology data, rows represent the trained classifiers for the named pathology.

|            | CLP | LAR | OSCC | PD |
|------------|-----|-----|------|----|
| CLP        | LL  | 93.1| 98.5 | 96.8|
|            | ML  | 58.7| 76.6 | 44.9|
|            | HL  | 68.5| 60.7 | 46.5|
| LAR        | LL  | 22.0| 1.3  | 0.3 |
|            | ML  | 40.3| 13.6 | 5.2 |
|            | HL  | 79.3| 27.4 | 12.8|
| OSCC       | LL  | 87.9| 50.8 | 43.8|
|            | ML  | 92.7| 59.2 | 31.6|
|            | HL  | 100 | 72.1 | 31.1|
| PD         | LL  | 13.7| 26.4 | 73.7|
|            | ML  | 40.7| 75.5 | 89.7|
|            | HL  | 48.4| 74.2 | 93.4|

Fig. 1. 2-dimensional t-SNE projection of latent features extracted at W2V2 layer 3 for control datasets aggregated by speech content type (perplexity = 30).

CLP: CLP models classify PD controls, MLS and TUDA mostly as pathologic using lower-layer features. AV and NWSR corpora are classified as healthy or uncertain at 66.1% and 56.4%. Classification with features from the higher-layers is more reliable for the healthy corpora and shows less variance in metrics across datasets. The classification works best for PSZ, which could be attributed to a more similar age range compared to the other corpora. The highest age mismatch is for PD, AV, and NWSR, which also
Table 3. Cross-corpora classification results for healthy data aggregated on embeddings’ origin.

|        | CLP | PD  | AV  | NWSR | MLS | TUDA | PSZ |
|--------|-----|-----|-----|------|-----|------|-----|
|        | LL  | -   | 11.7| 66.1 | 56.4| 23.7 | 20.9| 72.2|
| CLP    | ML  | -   | 69.1| 70.3 | 69.3| 74.2 | 62.4| 93.1|
|        | HL  | -   | 56.7| 79.1 | 61.5| 89.4 | 48.8| 99.4|
| LAR    | LL  | 94.0| 99.2| -    | 96.1| 100  | 93.8| 100 |
|        | ML  | 81.6| 96.7| -    | 98.0| 99.5 | 95.5| 92.2|
|        | HL  | 39.2| 88.1| -    | 86.3| 99.6 | 77.9| 75.0|
| OSCC   | LL  | 45.5| 77.7| -    | 92.6| 75.8 | 41.5| 29.4|
|        | ML  | 19.1| 86.6| -    | 84.0| 88.1 | 20.1| 7.8 |
|        | HL  | 0.0 | 79.4| -    | 37.6| 82.2 | 25.2| 6.7 |
| PD     | LL  | 91.0| 93.8| -    | 78.4| 80.2 | 59.0| 76.7|
|        | ML  | 71.6| 65.2| -    | 49.9| 58.8 | 32.5| 61.4|
|        | HL  | 57.9| 27.3| -    | 17.8| 29.4 | 16.1| 17.8|

LAR: Features from the lower-layers enable an unambiguous assignment to the healthy class across all healthy corpora and controls. The results decrease slightly with the use of middle-layer features, and the same applies to the high-layer features. Among the high-layer features, the CLP controls are the only ones to be classified as healthy, at only 39.2%. This might again be due to the significantly different age ranges of the corpora.

OSCC: The CLP, PSZ and TUDA corpora, which are mostly classified as pathological across all feature layers, are notable. MLS is classified as non-pathologic across all feature layers, with at least 75.8%. The classification for NWSR works probably best because of the same task recorded, and for PD probably because of the similar age range. The OSCC classifier trained on lower-layer has particular problems in classifying children’s and young people’s speech.

PD: The PD models on lower-layer features yield results of at least 76.7% assignment to the healthy class in PSZ. The only exception is TUDA with 59.0%. High-layer features cause classification to pathologic class, with a maximum of 29.4% healthy on MLS. Only exception is CLP with 57.9% healthy.

In general, it is observable that with features from the lower layers, the LAR, OSCC and PD classifiers provide a better categorization to the associated class. For high-layer features, there is more variation in accuracy across corpora.

5. DISCUSSION

At first glance, W2V2 embeddings, especially from the lower-layers, seem to be well suited for binary distinction of pathologies. However, both the cross-pathology and cross-healthy tests show that the trained classifiers can not always handle unseen out-of-domain data well. A wide variety of factors can influence classification scores: acoustic conditions at the time of recording, age differences of the speakers, the spoken content and the length of the utterances.

We have seen that in both cross-pathological tests and cross-healthy tests, the results vary greatly compared with the other corpora when there are significant age differences. CLP classifiers assign all other pathology data to the pathological class. Conversely, the LAR classifier also classifies the pathologic CLP data as pathologic especially for high-layer features, but not for the other pathologies. Among healthy corpora, the OSCC classifier has difficulties with CLP, PSZ, and TUDA, which correspond to corpora with the youngest speakers compared to PD, AV, and NWSR. Look-

ing at the Figure[1] an arrangement by age emerges. CLP represents the youngest speakers, the cluster above for STC and STC_L represents the TUDA dataset, the red upper cluster corresponds to the AV dataset.

In cross-healthy tests, it is noticeable that OSCC classifier performs particularly well with NWSR, which might be due to the same spoken content. In cross-pathology tests, the effect is the other way around. The OSCC classifiers on PD are not consistent with the other corpora, especially on the high-layer features.

It is also noteworthy that LAR classifiers generally classify both cross-pathological data and healthy data as healthy. We cannot be certain that this is because all data unseen in training is classified as healthy based on only acoustical conditions. In Figure[1] we can clearly see that each dataset is represented in its own cluster. Furthermore, CLP is divided into three clusters, and after examining those, we found that one of the small clusters (on the left) is noisy data, and the other reflects the oldest children. The MLS data is further remarkable for being grouped by speaker on the t-SNE plot. All the data was collected using different recording setups as volunteers recorded themselves reading.

Overall, no consistent trend emerges, which argues for good binary classifiers of pathological speech. Further investigation is needed and corpora are required to find the exact causes of the mismatches. A consistent result would require data from all age groups, recording conditions, and spoken content.

6. CONCLUSION

We have shown that latent representations extracted using a pre-trained W2V2 model include characteristics that are necessary for pathological speech distinction. We found that especially the features extracted from the low layers exhibit the strongest distinction required for pathological speech detection. The accuracy of the best classifiers trained on lower-layer features is 99.5% for CLP, 100% for LAR, 98.7% for OSCC, and 77.2% for PD. However, based on the cross-corpora tests, we find that the selection of matched control groups is important for robust classification, especially for binary classification. The trained pathology classifiers often can not handle unseen or mismatching data. Our findings support the concerns in [20], however in further investigation on the same pathologies in a multi-class scenario [21] we found that classifiers trained on different pathologies provide more robust results, have a regularizing effect and mitigate the concerns. Future work will need to examine what classifiers predict on data with the same content across different age structures, for example, for children who read the NWS passage.
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