DYSFLUENCIES Seldom come alone — detection as a multi-label problem

Sebastian P. Bayerl*, Dominik Wagner*, F. Höning†, T. Bocklet*, E. Nöth†, Korbinian Riedhammer*

* Technische Hochschule Nürnberg Georg Simon Ohm, Germany
†KST Institut GmbH, ‡Intel Labs
‡ Friedrich-Alexander-Universität Erlangen-Nürnberg, Germany

ABSTRACT

Specially adapted speech recognition models are necessary to handle stuttered speech. For these to be used in a targeted manner, stuttered speech must be reliably detected. Recent works have treated stuttering as a multi-class classification problem or viewed detecting each dysfluency type as an isolated task; that does not capture the nature of stuttering, where one dysfluency seldom comes alone, i.e., co-occurs with others. This work explores an approach based on a modified wav2vec 2.0 system for end-to-end stuttering detection and classification as a multi-label problem. The method is evaluated on combinations of three datasets containing English and German stuttered speech, yielding state-of-the-art results for stuttering detection on the SEP-28k-Extended dataset. Experimental results provide evidence for the transferability of features and the generalizability of the method across datasets and languages.

Index Terms— stuttering, dysfluency detection, dysfluency, cross-dataset, pathological speech

1. INTRODUCTION

Dysfluency means abnormality of fluency, which includes, but is not limited to, stuttering [11]. Stuttering is a complex fluency disorder that can be identified by its core symptoms: repetitions of words, syllables, and sounds, prolongations, and blocks while speaking [2]. Therapeutic options, including modifying one’s speech, have been proposed to alleviate the symptoms and improve fluency. Stuttering can be debilitating to a person’s ability to communicate, which also extends to voice technology, making it necessary to detect atypical speech reliably and apply custom models.

Recent work on machine learning for stuttering has concerned itself with stuttering detection [3] and stuttering classification [4, 5] and stuttering classification [6]. Grosz et al. used pre-trained German wav2vec 2.0 (W2V2) models and combined them with other classifiers in an ensemble approach [6]. The authors of [8] also used W2V2 features, treating them like low-level descriptors, and computed several functionals on the features, similarly to the openSMILE approach [10].

In [5], the authors describe an approach employing long short-term memory (LSTM) networks with a residual neural network (ResNet) backend to detect stuttering in the UCLASS corpus [11]. Lea et al. applied multi-task learning with LSTMs in their dysfluencies detection approach [12]. Dysfluency detection systems trained on one dataset generalized to another, with data quantity being the deciding factor for detection performance [12]. Recent work by [3] could show that W2V2 features can be fine-tuned for dysfluency detection using stuttering data from other datasets. The features extracted from models fine-tuned with stuttering data were transferable from English to German for all dysfluency types but word repetitions. Both works did not explore the effect of multi-dataset training on their detection systems.

The SEP-28k dataset, and the relabeled FluencyBank dataset, are fairly new resources. No suggested evaluation split makes it hard to reproduce and compare results to the baseline systems [12]. Several researchers have used it to evaluate their methods but have failed to publish their exact splits or have filtered out examples that substantially impact evaluation results. Sheikh et al. removed a class by combining word- and sound repetitions and filtered out clips with an additional non-stuttering label, e.g., natural pause or background music [12], i.e., removing difficult examples. They randomly split the remaining data into a train, development, and test set (80/10/10%), irrespective of the speakers [13]. Other work filtered out all non-unanimously labeled clips from the training and test data, aiming for easy samples [14]. The work by [15] left out the block class and did use random splitting irrespective of the speaker, which is known to lead to optimistic results, as the authors of [16] could show. Furthermore, they explored the influence of dataset partitioning, created non-speaker overlapping splits of SEP-28k and provided baseline experiments and evidence for the large variance of detection results due to dataset partitioning [16].

Apart from problems with reproducibility, most works ignore that one dysfluency seldom comes alone, i.e., dysfluency patterns co-occur. In SEP-28k-Extended (SEP-28k-E), FluencyBank, and KSoF, about 30%, 36%, and 21% of clips were labeled with more than one dysfluency type — making stuttering detection and classification multi-label problems.

This paper explores dysfluency detection and classification as a multi-label problem, contributing a new W2V2-based end-to-end (E2E) method to detect and classify stutter-
tered speech and evaluating it on three datasets, yielding state-of-the-art detection performance on the SEP-28k–E dataset split. Furthermore, we provide conclusive evidence for the generalizability of the method by exploring multi-dataset and multi-language training for dysfluency detection.

2. DATA

In our experiments, we use three corpora containing 3-second long clips with stuttered speech; SEP-28k–Extended, FluencyBank, and the Kassel State of Fluency (KSoF) dataset [16, 12, 17]. The SEP-28k–E contains English stuttered speech extracted from podcasts and is based on the SEP-28k corpus, extending it with speaker labels and a speaker-exclusive Train-Dev-Test split.

The SEP-28k corpus contains an additional 4144 English clips extracted from the interview part of the adults who stutter dataset of the FluencyBank corpus [18] that were labeled using the same protocol. For evaluation purposes, we use the split defined by [3]. All three datasets were labeled similarly with five types of dysfluencies: blocks, prolongations, sound repetitions, word repetitions, and interjections. KSoF is a German dataset whose clips were additionally labeled with speech modifications, marking a clip as containing a person using a speech technique known as fluency shaping. This is a technique persons who stutter (PWS) learn in stuttering therapy to help them overcome their stuttering [17]. The label distribution of the complete dataset and the respective test partition can be found in Table 1.

To evaluate the effect of multi-lingual and -dataset training, we define three combinations of datasets. ALL-EN is a combination of FluencyBank and SEP-28k–E, Multilingual-Small (Multi-S) is a combination of KSoF and FluencyBank, and Multilingual (Multi) consists of KSoF, FluencyBank, and SEP-28k–E. Systems training with Multi-S, Multi, and KSoF predict seven classes (Modified (Mod), Blocks (Bl), Interjections (Int), Prolongation (Pro), Sound Repetitions (Snd), Word Repetitions (Wd), No Dysfluencies (No-Df)). The FluencyBank, SEP-28k–E, and ALL-EN splits are trained to detect six classes (Bl, Int, Pro, Snd, Wd, No-Df).

3. METHOD

3.1. wav2vec 2.0

The base W2V2 model consists of a convolutional feature extractor at the beginning of the model that takes in the waveform, followed by 12 transformer encoder blocks. The model encodes 20ms of audio into 768-dimensional feature vectors after each transformer block, yielding 12 x t x 768 hidden representations [19]. W2V2 features perform well in dysfluency detection [3] and other speech tasks, such as automatic speech recognition (ASR), and mispronunciation detection [19, 20].

![Fig. 1. Schematic overview of the wav2vec 2.0 model with weighted layer sum (WLS) and modified attention-based single and multi-task (STL, MTL) classification head.](https://example.com/f1.png)

### Table 1. Label distribution in % of SEP-28k–E (28k–E), FluencyBank (FB), and KSoF. The suffix ‘-T’ indicates the test set label distribution.

| Label | 28k–E | 28k–E–T | FB | FB–T | KSoF | KSoF–T |
|-------|-------|---------|----|------|------|--------|
| Bl    | 12.0  | 12.0    | 10.3 | 8.4  | 20.7 | 18.0   |
| Int   | 21.2  | 19.5    | 27.3 | 31.0 | 13.0 | 20.2   |
| Pro   | 10.0  | 10.1    | 8.1  | 10.3 | 12.0 | 17.3   |
| Snd   | 8.3   | 6.7     | 13.3 | 11.5 | 14.8 | 11.4   |
| Wd    | 9.8   | 10.5    | 10.4 | 9.65 | 3.9  | 3.7    |
| Mod   | -     | -       | -   | -    | 24.4 | 18.1   |
| No    | 56.9  | 58.2    | 54.1 | 56.9 | 24.8 | 29.4   |
| Σ     | 28177 | 6562    | 4144 | 785  | 5597 | 1253   |

![Online: https://tinyurl.com/yck9fmfv](https://example.com/link1)

![Online: https://tinyurl.com/24vm6dec](https://example.com/link2)
class for an audio clip. All models reported have an auxiliary branch with two outputs and a softmax activation function. A schematic representation of the components and changes w.r.t. the default classification head is shown in Figure[1].

3.2. Loss

Previous studies have shown the usefulness of multi-task learning (MTL) when training dysfluency detection systems, using either an artificial ‘any’ label, indicating the presence of any dysfluency, or gender classification [12, 3, 13]. In our experiments, we use a combination of weighted Binary Cross Entropy (BCE) and Focal Loss (FL) [22]. FL is an extension of the BCE loss using the α and γ parameters to put special emphasis on minority classes to handle class imbalance (see Table [1]).

\[ FL(p_t) = -\alpha(1 - p_t)^\gamma \log(p_t). \]  

(2)

FL can be used equivalently to BCE loss for multi-label problems by calculating the loss for each class using the output of a given output neuron. The total loss is calculated by either summing up the losses for each class or using the mean value as shown in eq. (3) and used in this work.

\[ FL_{\text{multi}} = \frac{1}{n} \sum_{i=1}^{n} FL_n(p_{t_i}) \]  

(3)

As in eq. (4), the final multi-task loss is a weighted sum of \( L_{\text{main}} \) and \( L_{\text{aux}} \), combining BCE loss for the auxiliary task and FL for the main task of multi-label dysfluency detection.

\[ L_{\text{MTL}} = w_{\text{main}} L_{\text{main}} + (1 - w_{\text{main}}) L_{\text{aux}} \]  

(4)

4. EXPERIMENTS

Our experiments provide insights into dysfluency detection as a multi-label problem, the influence of training data quantity, and composition across datasets and languages. Preliminary experiments included modifying the classification head of the W2V2 model by adding an attention mechanism for pooling w.r.t. a trainable token parameter, mean-, or statistical pooling as implemented in [21], or a classification token-based mechanism as used by BERT [23], which led to slightly worse results. Using multi-task instead of single-task learning and using FL as a primary loss instead of weighted BCE loss lead to consistently better results, except for word repetitions on the KSoF dataset. The models reported here were the best w.r.t. their overall dysfluency detection performance.

All experiments were performed using the weights of pre-trained W2V2 base feature extractors. The experiments using Multi, Multi-S, FluencyBank, SEP-28k-E, and ALL-EN training data, were based on a model that was previously pre-trained on 960h of LibriSpeech [24] and fine-tuned for ASR (ASR BASE 960h (EN)) [19]. The experiments using only KSoF data for training were based on a model that was fine-tuned for German ASR using the Common Voice 9.0 dataset (ASR BASE CV-9 (DE)).

Experiments 10 – 15 utilized weights obtained by training experiment 1 (Table[2]). The systems were trained using the adamW optimizer [25], an initial learning rate of \( 3 \times 10^{-5} \), and a batch size of 256 for up to 20 epochs. The best model was chosen w.r.t. the lowest development loss with early stopping after 5 epochs without improvement. During training, the convolutional feature extractor at the beginning of the model was frozen. The main loss weight \( w_{\text{main}} \) and the FL parameters \( \alpha \) and \( \gamma \) were experimentally determined from \( w_{\text{main}} \in \{0.5, 0.6, \ldots, 0.9\} \), \( \gamma \in \{1, 2, 3\} \), and \( \alpha \in \{0.1, 0.2, \ldots, 0.9\} \), using grid-search on experiment 1 in Table[2]. The best performing parameter configuration was found to be \( w_{\text{main}} = 0.9 \), \( \alpha = 0.7 \), and \( \gamma = 3 \), and used in all subsequent experiments. Both, the ‘any’ label and gender classification are equally suited as a MTL target, leading to insignificant performance differences. The desired regularizing effect is achieved by both.

5. RESULTS AND DISCUSSION

In the interest of brevity, we only report F1-scores for all dysfluency types and modifications in Table[2]. Results were balanced w.r.t. precision and recall.

Bl can be difficult to detect using only one modality. Clinicians rely on signs of physical tension and grasping for air when assessing blocks. This is also reflected by low inter-rater reliability (IRR)(Fleiss κ, 0.25 SEP-28k, 0.37 KSoF) for Bl reported for the datasets [12, 17]. We hypothesize that the consistently better results for Bl on KSoF (exp. 3, 9, 12, 15, 18, 22, 26) might be due to KSoF consisting of therapy recordings that mostly include PWS who, on average, have more pronounced symptoms. The slightly higher κ supports this observation.

Wd are easy to detect for humans, who assess the meaning of a sentence while hearing it, which a system relying on acoustics features alone cannot deliver. Acoustically, there is little to no difference between words and their immediate repetition. There is an obvious language component to detecting Wd, as evidenced by the ALL-EN and multi-lingual experiments that perform best on SEP-28k-E but fail to recognize German Wd (exp. 16, 18, 24, 26). Data quantity also plays a role, as evidenced by the failure to detect word repetitions on models trained using only KSoF or FluencyBank or their combination Multi-S (exp. 4-9, 20-23). KSoF and FluencyBank contain only 212 and 430 clips labeled as word repetitions (comp. Table[1]), which is not enough to learn such an acoustically diverse pattern with this method.

Ints are generally well detected by all systems and across all datasets. The best results for KSoF were achieved with the model pre-trained on English stuttering data and fine-tuned on German data (exp. 15). The detection results for FluencyBank and SEP-28k-E profit from adding German training data (exp. 24, 25), as function and acoustic composition of those

https://tinyurl.com/3pvj547h
Table 2. Dysfluency detection results (F1-score) for E2E multi-label systems trained and evaluated on different combinations of the training data for each dysfluency class and modifications. (Mod = Modified Speech, Bl = Block, Int = Interjection, Pro = Prolongation, Snd = Sound repetition, Wd = Word repetition). Section headers indicate the training data, followed by the W2V2 weights used. N/A indicates cases where precision and recall are zero per definition, as there are no labeled clips in the respective split, i.e., F1, is undefined.

|       | Test   | Mod   | Bl    | Int   | Pro   | Snd   | Wd   |
|-------|--------|-------|-------|-------|-------|-------|------|
| SEP-28k-E (ASR BASE 960h EN) |
| 1     | -      | 0.29  | 0.74  | 0.52  | 0.48  | 0.54  |      |
| 2     | -      | 0.25  | 0.80  | 0.50  | 0.55  | 0.46  |      |
| 3     | -      | 0.33  | 0.61  | 0.32  | 0.43  | 0.20  |      |
| FluencyBank (ASR BASE 960h EN) |
| 4     | -      | 0.03  | 0.61  | 0.08  | 0.30  | 0.05  |      |
| 5     | -      | 0.05  | 0.73  | 0.33  | 0.35  | 0.10  |      |
| 6     | -      | 0.03  | 0.44  | 0.09  | 0.32  | 0.11  |      |
| KSoF (ASR BASE CV-9 DE) |
| 7     | -      | 0.27  | 0.48  | 0.26  | 0.33  | 0.00  |      |
| 8     | -      | 0.23  | 0.58  | 0.32  | 0.42  | 0.00  |      |
| 9     | -      | 0.80  | 0.61  | 0.76  | 0.48  | 0.42  | 0.00  |
| FluencyBank (SEP-28k-E) |
| 10    | -      | 0.26  | 0.76  | 0.49  | 0.46  | 0.54  |      |
| 11    | -      | 0.34  | 0.82  | 0.62  | 0.59  | 0.49  |      |
| 12    | -      | 0.38  | 0.58  | 0.37  | 0.40  | 0.16  |      |
| KSoF (SEP-28k-E) |
| 13    | -      | 0.28  | 0.68  | 0.46  | 0.39  | 0.00  |      |
| 14    | -      | 0.26  | 0.65  | 0.53  | 0.50  | 0.00  |      |
| 15    | KSoF  | 0.76  | 0.55  | 0.80  | 0.52  | 0.42  | 0.00  |
| ALL-EN (ASR BASE 960h EN) |
| 16    | -      | 0.32  | 0.77  | 0.54  | 0.50  | 0.56  |      |
| 17    | -      | 0.31  | 0.82  | 0.57  | 0.61  | 0.45  |      |
| 18    | -      | 0.41  | 0.57  | 0.34  | 0.42  | 0.14  |      |
| 19    | ALL-EN | -     | 0.31  | 0.79  | 0.55  | 0.52  | 0.55  |
| Multilingual-Small (ASR BASE 960h EN) |
| 20    | -      | 0.26  | 0.58  | 0.33  | 0.42  | 0.22  |      |
| 21    | -      | 0.27  | 0.69  | 0.49  | 0.55  | 0.30  |      |
| 22    | KSoF  | 0.74  | 0.49  | 0.67  | 0.46  | 0.44  | 0.06  |
| 23    | Multi-S| 0.75  | 0.46  | 0.68  | 0.49  | 0.42  | 0.21  |
| Multilingual (ASR BASE 960h EN) |
| 24    | -      | 0.31  | 0.79  | 0.54  | 0.50  | 0.56  |      |
| 25    | -      | 0.31  | 0.83  | 0.57  | 0.63  | 0.48  |      |
| 26    | KSoF  | 0.79  | 0.52  | 0.78  | 0.55  | 0.46  | 0.08  |
| 27    | Multi | 0.79  | 0.36  | 0.79  | 0.55  | 0.51  | 0.53  |

Functional dysfluencies are similar between English and German [26, p.17]. The jointly learned system creates features that transfer well between languages. Adding more training data introduces information that helps the model generalize.

**Mods** are characterized by prolonged uninterrupted phona-
tion and soft voice onset, making this universally taught pat-
tern relatively easy to detect acoustically [17]. The model 
based on German ASR and fine-tuned using KSoF achieved 
the highest F1 on KSoF (exp. 9). Evaluating the model on 
SEP-28k-E and FluencyBank leads to quite a few false pos-
itives, as the KSoF-only trained model does not generalize 
very well. This indicates that the model learned to recog-
nize Mod but has not seen enough other dysfluency data to 
differentiate outside its own training domain. Evaluating the 
recognition of Mod with the Multilingual model shows that 
language plays a role, as all samples of modified speech are 
in German. Adding more dysfluency training data helps the 
model to learn differentiate modified speech from other dys-
fluency patterns better, as indicated by the improved F1 score 
for Mod from Multi-S to Multi (exp. 22, 23, 26, 27). At the 
same time the amount of Mod clips stay fixed.

**Pro** and Snd change the natural flow and rhythm of 
speech independent of the language. Acoustically, repeating 
a plosive in English is similar to German, the same holds true 
for the prolongation of, e.g., a vowel. Differences mostly stem 
from the respective phoneme inventories. Therefore both 
patterns profit from more training data and transfer learning. 
The best results for these dysfluency types were achieved 
using the model trained on Multi (exp. 24-26). The model 
trained on Multi profits from jointly learning these patterns 
for both languages. Only **Pro** for FluencyBank (exp. 25) 
perform worse than the system pre-trained on SEP-28k-E and 
fine-tuned on FluencyBank (exp. 16).

Comparing results for SEP-28k-E and FluencyBank using 
the ALL-EN and Multilingual model shows that the overall 
performance does not suffer from adding the German stutter-
ing data. The model even slightly profits from the additional 
training data (exp. 16, 17, 24, 25). At the same time, re-
results achieved on KSoF improved substantially (exp. 18, 26). 
Adding the 3500 clips from the KSoF training set to the joint 
training data enabled the model to generalize to another 
language and learn to classify an additional pattern.

### 6. CONCLUSION

This paper has introduced a W2V2-based End-2-End stutter-
detection and classification system able to detect and 
classify five types of stuttering, and speech modifications, 
achieving state-of-the-art dysfluency detection results on 
SEP-28k-E. The best results achieved on KSoF and Fluency-
Bank are comparable to previous expert systems that only 
detect a single kind of dysfluency [3].

In future work, we will explore data augmentation and 
contrastive training, as data quantity and diversity play a role 
in creating more robust dysfluency detection systems. Espe-
cially with **Wd** and **Bl**, a system relying only on the in-
terpretation of acoustic features reaches its limits. While there 
might be no obvious solutions to improve actual recognition 
results for **Bl**, with the limited reliability of the labels, **Wd** 
recognition might profit from integrating phoneme posterior 
based features [27] or other ASR-based features [28].
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