Ensemble Models for Spoofing Detection in Automatic Speaker Verification

Bhusan Chettri\textsuperscript{1}, Daniel Stoller\textsuperscript{1}, Veronica Morfi\textsuperscript{1}, Marco A. Martínez Ramírez\textsuperscript{1}, Emmanouil Benetos\textsuperscript{1}, Bob L. Sturm\textsuperscript{2}

\textsuperscript{1}School of EECS, Queen Mary University of London, United Kingdom
\textsuperscript{2}School of EECS, KTH Royal Institute of Engineering, Stockholm, Sweden

Abstract

Detecting spoofing attempts of automatic speaker verification (ASV) systems is challenging, especially when using only one modeling approach. For robustness, we use both deep neural networks and traditional machine learning models and combine them as ensemble models through logistic regression. They are trained to detect logical access (LA) and physical access (PA) attacks on the dataset released as part of the ASV Spoofing and Countermeasures Challenge 2019. We propose dataset partitions that ensure different attack types are present during training and validation to improve system robustness. Our ensemble model outperforms all our single models and the baselines from the challenge for both attack types. We investigate why some models on the PA dataset strongly outperform others and find that spoofed recordings in the dataset tend to have longer silences at the end than genuine ones. By removing them, the PA task becomes much more challenging, with the minimum tandem detection cost function (m-\textit{DCF}) of our best single model rising from 0.1672 to 0.5018 and equal error rate (EER) increasing from 5.98\% to 19.8\% on the development set.

**Index Terms:** ASVspoof 2019, logical access attack, physical access attack, countermeasures, anti-spoofing, model ensemble.

1. Introduction

An automatic speaker verification (ASV) system aims at verifying the claimed identity of a speaker and is widely used for person authentication. Though the technology has matured immensely over the past few years, studies have confirmed its vulnerability in the face of spoofing, also known as a presentation attack. Mimicry, replay, text-to-speech (TTS) and voice-conversion (VC) technology are commonly used to perform logical access (LA) or physical access (PA) spoofing attacks in ASV system. While LA attacks (TTS and VC) are mounted by injecting synthetic/converted speech directly into the ASV pipeline bypassing its microphone, PA attacks (replay and mimicry), on the contrary, involves physical transmission of impersonated or playback speech through the systems’ microphone.

Spoofing countermeasures for reliable speaker verification are therefore of paramount interest. To this end, the ASV community has released standard spoofing datasets and countermeasures challenges (ASVspoof), promoting research in this direction. The ASVspoof 2019 challenge combines both LA and PA (excluding mimicry) attacks using the latest state-of-the-art TTS and VC methods and controlled-simulation setup for replay attacks, in contrast to the 2015 and 2017 spoofing datasets.

Designing a single model to robustly detect unseen spoofing attacks can be challenging, as demonstrated at the ASVspoof 2015 and 2017 challenges, where the best performing systems made use of an ensemble model combining features or scores. In this paper, we investigate LA and PA spoofing detection on the ASVspoof 2019 dataset using ensemble models. Below we summarise our contributions.

- We build our models by discarding data points (Section 5) ensuring non-overlap in spoofing condition between training and validation for better generalisation.
- We demonstrate that combining information from deep and traditional machine learning approaches along with our dataset partition can improve model generalisation.
- We find that spoofed audio recordings for the PA task tend to have more silence at the end than bonafide recordings. We perform three different interventions proving that models exploit this fault in the dataset and achieve lower performance without these cues.

Our results suggest that performance metrics reported on the current PA dataset may be overestimating the actual performance of the models, which might become somewhat of a “horse” that trivially sidesteps the actual problem, thus raising concerns about model validity as well as performance results. Prior work has addressed a similar issue of silence on the ASVspoof 2017 PA dataset, which calls for careful design and validation of the 2019 PA spoofing dataset.

2. Task description and dataset

Given a speech recording the task is to build a spoofing countermeasure, a model, to automatically determine whether it is a bonafide (genuine) or spoofed, either generated through TTS, VC or a replayed recording.

The ASVspoof 2019 LA and PA datasets were released as part of this year’s challenge. Both consist of 8 male and 12 female speakers in the training and development subsets. In LA, there are 2,580 bonafide and 22,900 spoofed utterances in the training set and 2,548 bonafide and 22,296 spoofed utterances in the development set. In PA, both the training and development sets have 5,400 bonafide utterances, and 48,600 and 24,300 spoofed utterances in the training and development sets, respectively. The evaluation set has around 80,000 and 70,000 test utterances in the LA and PA dataset.

The training and development subsets have similar spoofing data points (Section 4) ensuring non-overlap in spoofing condition between training and validation for better generalisation.

\textsuperscript{1}We have reported the “silence” issue to the challenge organisers.
and validation might lead to overfitting and poor generalisation on unseen attack conditions. Thus, we further partition the original training and development datasets for both LA and PA, ensuring non-overlapping in spoofing attack conditions. We partition the training (train) set into \textit{train}$_{tr}$ and \textit{train}$_{ds}$ and the development (dev) set into \textit{dev}$_{ws}$, \textit{dev}$_{tr}$ and \textit{dev}$_{ds}$. The spoofing attack conditions and speakers in \textit{train}$_{tr}$ and \textit{dev}$_{ws}$ are non-overlapping. In \textit{dev}$_{tr}$, we use all spoofing conditions of the dev set but discard speakers that have been used in \textit{dev}$_{ws}$. Though this approach requires removing many samples (we never use \textit{train}$_{ds}$ and \textit{dev}$_{ds}$), it allows us to test how well a model generalises previously unseen attack conditions. All details can be found online.

3. Models in the Proposed Ensembles

In this section, we describe the approach used to design countermeasures for the LA and PA tasks of the ASVspoof 2019 challenge. A model ensemble is used in order to combine information from different countermeasure models that use various features and training procedures. This diversity leads to a powerful ensemble with good generalisation.

3.1. Deep models

We train five deep models using raw audio or time-frequency representations as input to minimise a binary cross-entropy (CE) loss with an Adam optimiser and early stopping with a patience of $P$ epochs. As the dataset has more spoofed examples, we replicate the bonafide examples to ensure each batch contains an equal number of bonafide and spoofed examples, which helps stabilise the training. At inference time, we use the output layer sigmoid activation as a score. We provide model-specific training details below.

3.1.1. Convolutional Neural Network (CNN)

We use the CNN architecture from [21], featuring 50% dropout in the fully connected layers, a batch size of 32, and a learning rate of $10^{-4}$. We train the model for 100 epochs with an early stopping patience of $P = 5$ and $P = 2$ for the LA and PA tasks, respectively. We use a mean-variance normalized log spectrogram computed using a 1024-point FFT with a hop size of 160 samples, as the input. For each task, we train two such CNN models, model A and B, on the first and last 4 seconds of each audio sample. We truncate or loop the spectrogram time frames to obtain a unified time representation.

3.1.2. Convolutional Recurrent Neural Network (CRNN)

We use a modified version of the CRNN architecture from our prior work [20] (model C). We train the model for 500 epochs with early stopping patience of $P = 10$ for both the LA and PA tasks. As input, we use a mean-variance normalized log-Mel spectrogram of 40 Mel bands, computed on the first 5 seconds of truncated or looped audio samples, using a 1024-point FFT with a hop size of 256 samples. During training, we use a batch size of 8 and 32 for the LA and PA tasks, respectively, with an initial learning rate of $10^{-3}$ that is halved on validation loss plateau with a patience of $P = 5$ epochs, until $10^{-6}$.

3.1.3. 1D-Convolutional Neural Network

We use the network architecture from the sample-level 1D CNN [21] (model D). In total, the model consists of 9 ReSE-2 blocks. These blocks are a combination of ResNets [23] and SENets [24]. We use the multi-level feature aggregation, where the outputs of the last three blocks are concatenated and followed by a fully connected layer of 1024 units, batch normalisation and ReLU layers, a 50% dropout layer and a fully connected layer of 1 unit with sigmoid activation. Each convolutional layer has filters of size 3, $L_2$ weight regularizer of 0.0005 and all strides are of unit value. The raw audio input is 3.7 seconds in duration and randomly sampled segments of this size are selected from the recordings. We loop shorter samples to obtain a unified time representation. We train the model using a batch size of 16, learning rate of $10^{-4}$ and an early stopping patience of $P = 25$ epochs.

3.1.4. Wave-U-Net

We use a modified version of the Wave-U-Net [25], with five layers of stride four, and without upsampling blocks (model E). The outputs of the last convolution are max-pooled across time, reducing the parameter count and incorporating the intuition that the important features in the tasks are temporally local. Finally, we apply a fully connected layer with a single output to yield a classification probability. We train the model using a batch size of 64, a learning rate of $10^{-5}$ and early stopping patience of $P = 10$ for both the LA and PA tasks, where an epoch is defined as 500 update steps. To ensure the audio inputs have the same length, we pad all recordings with silence to 196608 audio samples ($= 12.23$ seconds). For the PA task, we also match real samples to their spoofed versions based on the speaker identity and utterance. We train on pairs of audio samples (discarding samples without any matches) and balanced batches, in order to stabilise the training process and improve generalisation by preventing the network from using speaker identity and utterance content for discrimination.

3.2. Shallow models

Additional to deep models, we use two different shallow models: Gaussian Mixture Models (GMMs) and Support Vector Machines (SVMs).

3.2.1. GMM

We train three GMM models using 60-dimensional static, delta and acceleration (SDA) mel frequency cepstral coefficients (MFCCs) [27] (model F), inverted mel frequency cepstral coefficients (IMFCCs) [30] (model G), and sub-band centroid magnitude coefficients (SCMCs) [29] (model H), due to their performance on the ASVspoof 2015 and 2017 spoofing datasets [20, 19]. We use 128 and 256 mixture components for the LA and PA tasks respectively and train one GMM each for bonafide and spoof class. At test time, the score of each test utterance is obtained as the average log-likelihood ratio between the bonafide and spoof GMMs. We use the feature configuration from [30].

3.2.2. SVM

We train two SVMs using i-vectors (model I) and the long-term-average-spectrum (LTAS) feature (model J) since they

---

2https://github.com/BhusanChettri/ASVspoof2019

3Power-spectrogram for the LA task and Mel-spectrogram with 80 mel bands for the PA task.

4Computed from a power spectrogram using a 1024-point FFT and a hop size of 160 samples.
have shown good performance on prior spoofing datasets [30, 31, 32]. Inspired from [32] we fuse multiple i-vectors in our approach, each based on complimentary hand-engineered features, and manage to improve performance over a single i-vector based SVM. We train four different i-vector extractors using 60-dimensional SDA MFCC, IMFCC, constant Q cepstral coefficients (CQCC) [33] and SCMC features. We train the T matrix with 100 total factors on both tasks and universal background model (UBM) with 128 and 256 mixtures on the LA and PA tasks, respectively and extract 4 different 100-dimensional i-vectors for every utterance. We use 400-dimensional fused i-vectors for LA and 300 for PA task. We perform mean-variance normalisation on the fused i-vectors and LTAS feature and train SVMs with a linear kernel and the default parameters of the Scikit-Learn [34] library. We train the UBM and T matrix using the MSR-Identity toolkit [35].

3.3. Ensemble models

We define three ensemble models E1, E2 and E3 using the logistic regression implementation of the Bosaris [36] toolkit. On the LA task, E1 combines models A, C through G and I, while E2 consists of A, B and G. On the PA task, E1 fuses all single models except D, and E2 combines models A through E. Finally, E3 combines models A and B on both LA and PA tasks.

4. Experiments

4.1. Experimental setup

We train our models (single and ensemble) described in Section 4 using the train.tr and dev.tr sets respectively. We use dev.ex for model validation, early stopping and hyper-parameter optimisation. We compare our models’ performance with the baseline LFCC (model B1) and CQCC (model B2) feature based GMM models provided by the ASVspoof 2019 challenge organisers.

We evaluate our models with the recently proposed minimum tandem detection cost function (m-tDCF) [37] metric, that takes both the ASV system and spoofing countermeasure errors into consideration. This metric is used as the primary evaluation metric in the ASVspoof 2019 challenge and the ASV system scores are provided by the organisers. We also evaluate our model performance independently with the equal error rate (EER) metric. Please refer to [7, 10] for details.

4.2. Results

4.2.1. Development set

Table 1 presents the results on the original development set for both LA and PA tasks. In general, the results suggest that PA task is harder than LA. For the PA task, our CNN performs noticeably better when operating on the last 4 seconds of audio (model B) instead of the first 4 seconds (model A), suggesting the presence of discriminative cues at the end of each audio signal which we confirm in Section 4. Furthermore, we observe a poor performance for models D and E. Apart from having to learn features directly from the raw audio, another reason could be that they involve zero-padding all signals or using a randomly selected audio segment for prediction, respectively, and thus might not be able to exploit such cues at the end of audio signals.

| Model | LA m-tDCF | EER% | PA m-tDCF | EER% |
|-------|-----------|------|-----------|------|
| B1    | 0.0063    | 2.71 | 0.2554    | 11.96|
| B2    | 0.0123    | 0.43 | 0.1953    | 9.87 |
| A     | 0.0074    | 0.32 | 0.2795    | 10.77|
| B     | 0.0040    | 0.27 | 0.1672    | 5.98 |
| C     | 0.1706    | 5.65 | 0.1223    | 5.0  |
| D     | 0.36      | 13.58| 0.9269    | 36.28|
| E     | 0.0745    | 2.43 | 0.4725    | 21.16|
| F     | 0.1805    | 7.46 | 0.2354    | 10.88|
| G     | 0.0438    | 1.73 | 0.2119    | 8.94 |
| H     | na        | na  | 0.2787    | 12.46|
| I     | 0.0045    | 0.16 | 0.2537    | 9.93 |
| J     | na        | na  | 0.3534    | 13.6 |

4.2.2. Evaluation set

Table 2 shows the results on the evaluation set. Bold: best performance, na: not applicable.

Table 2: Results on the LA and PA evaluation set. Bold, na: same as in Table 1

| Model | LA m-tDCF | EER% | PA m-tDCF | EER% |
|-------|-----------|------|-----------|------|
| B1    | 0.2116    | 8.09 | 0.3017    | 13.54|
| B2    | 0.2366    | 9.57 | 0.2454    | 11.04|
| A     | 0.1790    | 7.66 | na        | na  |
| B     | na        | na  | 0.1577    | 5.75 |
| E1    | 0.0755    | 2.64 | 0.1492    | 6.11 |
| E2    | 0.2136    | 9.57 | 0.2913    | 14.12|
| E3    | 0.2952    | 10.63| 0.1465    | 5.43 |

Our i-vector feature fusion approach (model I) shows impressive performance on the LA task but relatively poor performance on the PA task. One reason for this could be that the i-vectors extracted using hand-crafted features are not able to capture characteristics of unseen replay attack conditions. On both the LA and PA tasks, model G (IMFCC) outperforms model F (MFCC), suggesting that a focus on higher frequency information is beneficial as it might not be perfectly generated by the device properties may impact information in high frequencies. Finally, the poor performance of models H and J suggest that SCMC and LTAS features are not suitable for this task.

As expected, our ensemble model appears to benefit from combining different models for both tasks, as indicated by the strong reduction in m-tDCF and EER compared to all individual models. On both tasks, E1 performs better than E2 which in turn performs better than E3.

4.2.2. Evaluation set

Table 2 shows the results on the evaluation set. Bold: best performance, na: not applicable.

| Model | LA m-tDCF | EER% | PA m-tDCF | EER% |
|-------|-----------|------|-----------|------|
| B1    | 0.2116    | 8.09 | 0.3017    | 13.54|
| B2    | 0.2366    | 9.57 | 0.2454    | 11.04|
| A     | 0.1790    | 7.66 | na        | na  |
| B     | na        | na  | 0.1577    | 5.75 |
| E1    | 0.0755    | 2.64 | 0.1492    | 6.11 |
| E2    | 0.2136    | 9.57 | 0.2913    | 14.12|
| E3    | 0.2952    | 10.63| 0.1465    | 5.43 |

Our i-vector feature fusion approach (model I) shows impressive performance on the LA task but relatively poor performance on the PA task. One reason for this could be that the i-vectors extracted using hand-crafted features are not able to capture characteristics of unseen replay attack conditions. On both the LA and PA tasks, model G (IMFCC) outperforms model F (MFCC), suggesting that a focus on higher frequency information is beneficial as it might not be perfectly generated by the TTS and VC algorithms. Likewise, on the PA task, the playback device properties may impact information in high frequencies. Finally, the poor performance of models H and J suggest that SCMC and LTAS features are not suitable for this task.

As expected, our ensemble model appears to benefit from combining different models for both tasks, as indicated by the strong reduction in m-tDCF and EER compared to all individual models. On both tasks, E1 performs better than E2 which in turn performs better than E3.

6Computed by the ASVspoof 2019 challenge organisers.
models employing different features does provide complementary information useful for spoof detection.

However, on the PA tasks our single model B outperforms ensemble models E1 (on the EER) and E2 (on both metrics). Furthermore, our two model ensemble E2 (A+B) outperforms the five deep model ensemble E2 and nine model ensemble E1 reaching the lowest m-tDCF of 0.1465 and an EER of 5.43\%.

While these results suggest good model generalisation, it raises questions about the relevance of the cues used by model B as it is only trained on the last 4 seconds of each recording. Along with the poor performance of models D and E, an additional reason, to the inferior performance of ensemble models on the evaluation set compared to the development set (Table 1) might be the fact that model C makes random predictions on the evaluation data (due to a bug we found after the challenge submission), but not on the development set, and it’s the model that receive the second highest weight by logistic regression in both E1 and E2.

5. Interventions on the PA task

In Table 1 we find that for the PA task, the same CNN performs much better when trained on the last 4 seconds of audio (model B) than on the first 4 seconds (model A). We thus analyse a set of audio recordings for the PA task that were confidently classified by model B and find that spoofed audio tend to have more silence (zero-valued samples) at the end than bonafide examples. In comparison, silence at the beginning of the recordings is much less impact on performance and therefore do not report any intervention on it.

5.2. Intervention II

Here, we train the model with silence parts removed, but test on the original test recordings (with silence). The stable performance of the CNN (model B) over the GMMs in Table 3 might indicate that model B is more robust against silence. On the contrary, we find a dramatic increase in error rates for M1 and M2. One interpretation for this is that bonafide and spoof GMM may assign a low likelihood to silence frames as they have not seen them during training. Thus, silence frames do not offer significant contribution on the final score making the task much harder.

5.3. Intervention III

In this intervention, we remove silence during training and testing to ensure that the audio samples do not share an easily exploitable cue. This forces the models to learn about the actually relevant factors of interest and more realistic performance estimates are observed (Table 4). As in intervention II, model B shows stable performance indicating a good generalisation and discriminative capability of the model. M1 and M2, on the contrary show poor performance, possibly since their bonafide GMM model may assign a high likelihood to spoofed frames as they are very similar to bonafide ones when only considering the speech frames.

Table 3: Intervention (Int) results on the development set of PA tasks. Numbers to the left of arrow indicates performance without any intervention.

| Int | Model | m-tDCF | EER\% |
|-----|-------|--------|-------|
| I   | M1    | 0.2036 → 0.2741 | 9.18 → 13.27 |
|     | M2    | 0.1971 → 0.2950 | 10.06 → 15.59 |
|     | B     | 0.1672 → 0.5018 | 5.98 → 19.8 |
| II  | M1    | 0.2036 → 0.9528 | 9.18 → 54.76 |
|     | M2    | 0.1971 → 0.9463 | 10.06 → 57.98 |
|     | B     | 0.1672 → 0.2626 | 5.98 → 11.20 |
| III | M1    | 0.2036 → 0.8614 | 9.18 → 41.09 |
|     | M2    | 0.1971 → 0.9448 | 10.06 → 58.71 |
|     | B     | 0.1672 → 0.3129 | 5.98 → 12.85 |

5.1. Intervention I

In this intervention we train the models on the original recordings with the silence but remove them during testing[4]. In Table 4 a strong increase can be noticed in both EER and m-DCF for all models, suggesting that they indeed rely on the silence parts for prediction. We find that model B is more sensitive to this intervention, with m-tDCF and EER rising by 0.3346 and an absolute 13.82\%, respectively. This could be due to deep models focusing more strongly on the silence durations than the GMM models, which are trained on individual spectral frames and aggregate the score through averaging likelihoods.

6. Discussion and conclusion

In this paper, we investigate the logical access (TTS and VC) and physical access (replay) spoofing detection problem on the ASVspoof 2019 dataset using ensemble models, demonstrating that combining models trained on different feature representations can be effective in detecting unseen spoofing attacks. We achieve good performance on the PA and 3rd ranking on the LA tasks of the challenge. The PA task appears to be generally more difficult and should thus be the primary focus of future work. Our intervention experiments in Section 5 suggest that many models trained on the PA dataset can become somewhat of a “horse”, where solving the actual problem is unintentionally avoided by exploiting silence as trivial cues. As the evaluation set also contains such silences, the reported performance metrics in this task currently overestimate the actual performance.

In addition to removing silence from the end of recordings, we also removed them from the beginning, but found that it has much less impact on performance and therefore do not report the results in this paper. However, due to our simple approach at silence removal, near-silent segments and silences between words within the recording might remain and could also serve as an undesirable discriminative cue and so should be investigated in future work.

We aim to perform further analysis on our deep models once the test set labels are released to the public, including the impact of the faulty deep model that produced random predictions on the evaluation set.
7. References

[1] D. A. Reynolds, “Speaker identification and verification using gaussian mixture speaker models,” Speech Communication, vol. 17, no. 1, pp. 91–108, 1995.

[2] Z. Wu and H. Li, “Voice conversion and spoofing attack on speaker verification systems,” in APSIPA. IEEE, 2013, pp. 1–9.

[3] Z. Wu, N. Evans, T. Kinnunen, J. Yamagishi, F. Alegre, and H. Li, “Spoofing and countermeasures for speaker verification: A survey,” Speech Communication, vol. 66, pp. 130 – 153, 2015.

[4] ISO/IEC 30107-1:2016, “Information technology — Biometric presentation attack detection — part 1: Framework,” 2016. [Online]. Available: https://www.iso.org/obp/ui/#iso:std:iso-iec:30107:-1:ed-1:v1:en.

[5] Y. W. Lau, M. Wagner, and D. Tran, “Vulnerability of speaker verification to voice mimicking,” in Proceedings of 2004 International Symposium on Intelligent Multimedia, Video and Speech Processing, 2004., Oct 2004, pp. 145–148.

[6] Z. Wu, S. Gao, E. S. Cling, and H. Li, “A study on replay attack and anti-spoofing for text-dependent speaker verification,” in Signal and Information Processing Association Annual Summit and Conference (APSIPA), 2014 Asia-Pacific, Dec 2014, pp. 1–5.

[7] M. Todisco, X. Wang, V. Vestman, M. Sahidullah, H. Delgado, A. Nauth, J. Yamagishi, N. Evans, T. Kinnunen, and K. A. Lee, “ASVspoof 2019: Future Horizons in Spoofed and Fake Audio Detection,” in Interspeech, 2019 (submitted).

[8] Z. Wu, T. Kinnunen, N. Evans, J. Yamagishi, C. Hanilci, M. Sahidullah, and A. Sizov, “ASVspoof 2015: the First Automatic Speaker Verification Spoofing and Countermeasures Challenge,” in Interspeech, 2015.

[9] T. Kinnunen, M. Sahidullah, H. Delgado, M. Todisco, N. Evans, J. Yamagishi, and K. A. Lee, “The ASVspoof 2017 challenge: Assessing the limits of audio replay attack detection in the wild,” in Interspeech, 2017.

[10] ASVspoof 2019: the Automatic Speaker Verification Spoofing and Countermeasures Challenge Evaluation Plan. [Online]. Available: http://www.asvspoof.org/asvspoof2019/asvspoof2019_eval/evaluation_plan.pdf

[11] T. B. Patel and H. A. Patil, “Combining evidences from mel cepstral, cochlear filter cepstral and instantaneous frequency features for detection of natural vs. spoofed speech,” in Interspeech, 2015.

[12] S. Novoselov, A. Kozlov, G. Lavrenteva, K. Simonchik, and V. Shchemelinin, “STC Anti-spoofing Systems for the ASVspoof 2015 Challenge,” in 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), March 2016, pp. 5475–5479.

[13] G. Lavrenteva, S. Novoselov, E. Malychk, A. Kozlov, K. Oleg, and V. Shchemelinin, “Audio replay attack detection with deep learning frameworks,” August 2017, pp. 82–86.

[14] N. Nagarsheth, E. Khoury, K. Patil, and M. Garland, “Replay attack detection using DNN for channel discrimination,” Proc. Interspeech 2017, pp. 97–101, 2017.

[15] Z. Ji, Z.-Y. Li, P. Li, M. An, S. Gao, D. Wu, and F. Zhao, “Ensemble learning for countermeasure of audio replay spoofing attack in asvspoof2017,” in Proc. Interspeech 2017, 2017, pp. 87–91.

[16] Z. Chen, Z. Xie, W. Zhang, and X. Xu, “Resnet and model fusion for automatic spoofing detection,” Proc. Interspeech 2017, pp. 102–106, 2017.

[17] B. L. Sturm, “A simple method to determine if a music information retrieval system is a ‘horse’,” IEEE Transactions on Multimedia, vol. 16, no. 6, pp. 1636–1644, Oct 2014.

[18] B. Chetri and B. L. Sturm, “A Deeper Look at Gaussian Mixture Model Based Anti-Spoofing Systems,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), April 2018, pp. 5159–5163.

[19] B. Chetri, S. Mishra, B. Sturm, and E. Benetos, “Analysing the predictions of a CNN-Based replay spoofing detection system,” in Spoken Language Technology Workshop, December, 2018.

[20] V. Morfi and D. Stowell, “Deep learning for audio event detection and tagging on low-resource datasets,” Applied Sciences, vol. 8, no. 8, p. 1397, Aug 2018. [Online]. Available: http://dx.doi.org/10.3390/app8081397

[21] J. Lee et al., “Sample-level deep convolutional neural networks for music auto-tagging using raw waveforms,” in 14th International Conference on Sound and Music Computing (SMC), 2017.

[22] T. Kim, J. Lee, and J. Nam, “Sample-level cnn architectures for music auto-tagging using raw waveforms,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2018.

[23] K. He et al., “Deep residual learning for image recognition,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016.

[24] J. Hu, L. Shen, and G. Sun, “Squeeze-and-excitation networks,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2018.

[25] D. Stoller, S. Ewert, and S. Dixon, “Wave-U-Net: A multi-scale neural network for end-to-end source separation,” in Proceedings of the International Society for Music Information Retrieval Conference (ISMIR), vol. 19, 2018, pp. 334–340.

[26] J. Salamon, J. P. Bello, A. Farnsworth, and S. Kelling, “Fusing shallow and deep learning for bioacoustic bird species classification,” in 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), March 2017, pp. 141–145.

[27] S. Davis and P. Mermelstein, “Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences,” IEEE Transactions on Acoustics, Speech, and Signal Processing, vol. 28, no. 4, pp. 357–366, Aug 1980.

[28] S. Chakroborty et al., “Improved closed set text-independent speaker identification by combining mfc with evidence from flipped filter banks,” IJSP, vol. 4, no. 2, pp. 114–122, 2007.

[29] J. M. K. Kua, T. Thiruvaran, M. Nosratighods, E. Ambikairajah, and J. Epps, “Investigation of spectral centroid magnitude and frequency for speaker recognition,” in Proc. Odyssey Speaker and Language Recognition Workshop, 2010, pp. 34–39.

[30] M. Sahidullah, T. Kinnunen, and C. Hanilci, “A comparison of features for synthetic speech detection,” in Interspeech, 2015.

[31] H. Muckenhirn, P. Korshunov, M. Magimai-Doss, and S. Marcel, “Long-term spectral statistics for voice presentation attack detection,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 25, no. 11, pp. 2098–2111, Nov 2017.

[32] B. Chetri, B. L. Sturm, and E. Benetos, “Analysing replay spoofing countermeasure performance under varied conditions,” in 2018 IEEE International Workshop on Machine Learning for Signal Processing (MLSP), September 2018.

[33] M. Todisco, H. Delgado, and N. W. D. Evans, “A New Feature for Automatic Speaker Verification Anti-Spoofing: Constant Q Cepstral Coefficients,” in Odyssey, 2016.

[34] F. Pedregosa et al., “Scikit-learn: Machine learning in Python,” Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.

[35] S. O. Sadjadi et al., “MSR Identity Toolbox v1.0: A matlab toolbox for speaker recognition research,” Speech and Language Processing Technical Committee Newsletter, 2013.

[36] N. Brümmer and E. D. Villiers, “The bosaris toolkit: Theory, algorithms and code for surviving the new dcf,” arXiv preprint arXiv:1304.2865, 2013.

[37] T. Kinnunen, K. Lee, H. Delgado, N. Evans, M. Todisco, M. Sahidullah, J. Yamagishi, D.A, and Reynolds, “r-DCF: a Detection Cost Function for the Tandem Assessment of Spoofing Countermeasures and Automatic Speaker Verification,” in Speaker Odyssey, submitted on February 25, 2018.