DistriBlock: Identifying adversarial audio samples by leveraging characteristics of the output distribution

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Abstract

Adversarial attacks can mislead automatic speech recognition (ASR) systems into predicting an arbitrary target text, thus posing a clear security threat. To prevent such attacks, we propose DistriBlock, an efficient detection strategy applicable to any ASR system that predicts a probability distribution over output tokens in each time step. We measure a set of characteristics of this distribution: the median, maximum, and minimum over the output probabilities, the entropy of the distribution, as well as the Kullback-Leibler and the Jensen-Shannon divergence with respect to the distributions of the subsequent time step. Then, by leveraging the characteristics observed for both benign and adversarial data, we apply binary classifiers, including simple threshold-based classification, ensembles of such classifiers, and neural networks. Through extensive analysis across different state-of-the-art ASR systems and language data sets, we demonstrate the supreme performance of this approach, with a mean area under the receiver operating characteristic curve for distinguishing target adversarial examples against clean and noisy data of 99% and 97%, respectively. To assess the robustness of our method, we show that adaptive adversarial examples that can circumvent DistriBlock are much noisier, which makes them easier to detect through filtering and creates another avenue for preserving the system's robustness.

1 INTRODUCTION

Voice recognition technologies are widely used in the devices that we interact with daily—in smartphones or virtual assistants—and are also being adapted for more safety-critical tasks like self-driving cars [Wu et al., 2022] and healthcare applications. Safeguarding these systems from malicious attacks thus plays a more and more critical role, since manipulated erroneous transcriptions can potentially lead to severe security harms.

State-of-the-art automated speech recognition systems are based on deep learning [Kahn et al., 2020, Chung et al., 2021, Chen et al., 2022, Radford et al., 2023]. Unfortunately, deep neural networks (NNs) are highly vulnerable to adversarial attacks, since the inherent properties of the model make it easy to generate inputs—referred to as adversarial examples (AEs)—that are necessarily mislabeled, simply by incorporating a low-level additive perturbation [Szegedy et al., 2014, Goodfellow et al., 2015, Ilyas et al., 2019, Du et al., 2020]. A well-established method to generate AEs also applicable to ASR systems, is the Carlini & Wagner (C&W) attack [Carlini and Wagner, 2018]. It aims to minimize a perturbation δ that—when added to a benign audio signal x—induces the system to recognize a phrase chosen by the attacker. Moreover, attacks specifically developed for ASR systems shape the perturbations to fall below the estimated time-frequency masking threshold of human listeners, rendering δ hardly perceptible, and sometimes even *inaudible* to humans [Schönherr et al., 2019, Qin et al., 2019]. This underlines the urgent need for approaches to automatically detect AE attacks on ASR systems.

Motivated by the intuition that attacks may result in a higher prediction uncertainty displayed by the ASR system, we develop a novel detection technique that allows to efficiently distinguish adversarial from benign audio signals and can be used for any ASR system that estimates a probability distribution over tokens at each step of generating the output sequence—which is the case for the vast majority of state-of-the-art systems. More precisely, our contributions are as follows:

1. We propose DistriBlock: binary classifiers that build on characteristics of the probability distribution over tokens, which can be interpreted as a simple proxy of the prediction uncertainty of the ASR system.

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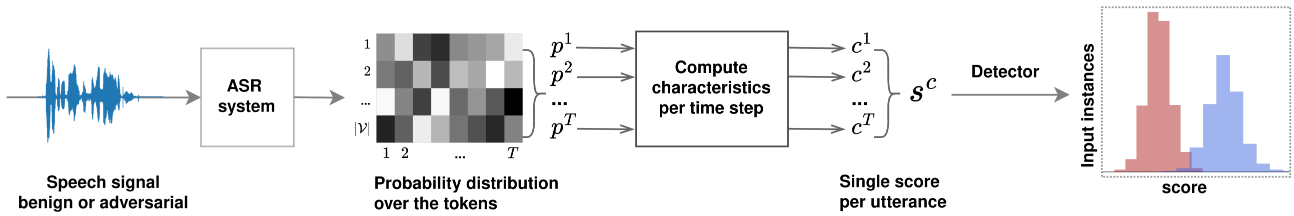


Figure 1: Proposed workflow to identify AEs: (1) compute output probability distribution characteristics per time step, (2) use a detector to tell benign data and AEs apart. c^1 to c^T represent input characteristics, while s^c denotes final scores.

2. We perform an extensive empirical analysis across diverse state-of-the-art ASR models, attack types, and datasets covering a range of languages, that demonstrate the superiority of DistriBlock over previous detection methods.
3. We propose adaptive attacks specifically designed to counteract DistriBlock, but show that the resulting adversarial examples contain a higher level of noise, which makes them easier to spot for human ears and identifiable using filtering techniques.

2 RELATED WORK

When it comes to mitigating the impact of adversarial attacks, there are two main research directions. On the one hand, there is a strand of research dedicated to enhancing the robustness of models. On the other hand, there is a separate research direction that focuses on designing detection mechanisms to recognize the presence of adversarial attacks.

Concerning the robustness of models, there are diverse strategies, one of which involves modifying the input data within the ASR system. This concept has been adapted from the visual to the auditory domain. Examples of input data modifications include quantization, temporal smoothing, down-sampling, low-pass filtering, slow feature analysis, and auto-encoder reformation [Meng and Chen, 2017, Guo et al., 2018, Pizarro et al., 2021]. However, these techniques become less effective once integrated into the attacker's deep learning framework [Yang et al., 2019]. Another strategy to mitigate adversarial attacks is to accept their existence and force them to be *perceivable* by humans [Eisenhofer et al., 2021], with the drawback that the AEs can continue misleading the system. Adversarial training [Madry et al., 2018], in contrast, involves employing AEs during training to enhance the NN's resiliency against adversarial attacks. Due to the impracticality of covering all potential attack classes through training, adversarial training has major limitations when applied to large and complex data sets, such as those commonly used in speech research [Zhang et al., 2019]. Additionally, this approach demands high computational costs and can result in reducing the accuracy of benign data. A recent method borrowed from the field of image recognition is adversarial purification, where generative models are employed to cleanse the input data prior to inference [Yoon et al., 2021, Nie et al., 2022]. However, only a few studies have investigated this strategy within the realm of audio. Presently, its ASR applications are confined to smaller vocabularies, and it necessitates substantial computational resources, while also resulting in decreased accuracy when applied to benign data [Wu et al., 2023].

In the context of improving the discriminative power against adversarial attacks, Rajaratnam and Kalita [2018] introduced a noise flooding (NF) detector method that quantifies the random noise needed to change the model's prediction, with smaller levels observed for AEs. Subsequently, they leverage this information to build binary classifiers. However, NF was only tested against a genetic untargeted attack [Alzantot et al., 2018] on a 10-word speech classification system. NF also needs to call the ASR system several times for making a prediction and is thus very time-consuming. A prominent non-differentiable approach uses the inherent temporal dependency (TD) in raw audio signals [Yang et al., 2019]. This strategy requires a minimal length of the audio stream for optimal performance. Unfortunately, Zhang et al. [2020] successfully evaded the detection mechanism of TD by preserving the necessary temporal correlations, leading to the generation of robust AEs once again. Däubener et al. [2020] proposed AEs detection based on uncertainty measures for hybrid ASR systems that utilize stochastic NNs. They applied their method to a limited vocabulary tailored for digit recognition. One of these uncertainty metrics—the mean-entropy—is also among those characteristics of the output distribution that we investigate, next to many others, for constructing defenses against AEs in this paper. It's worth noting that Meyer et al. [2016] utilized the averaged Kullback Leibler divergence between the output distributions of consecutive time steps (which they referred to as mean temporal distance), but in a different setting, namely to monitor the performance of ASR systems in noisy multichannel environments. In the field of computer vision, research has explored techniques for detecting and eliminating anomalies in the input pixels that are perceptible to humans and referred to as adversarial patches. In this context, the work of Tarchoun et al. [2023] basis its detection approach on an entropy analysis of the inputs (i.e. of pixels in a certain window).

3 BACKGROUND

Adversarial attacks Let $f(\cdot)$ be the ASR system's function, that maps an audio input to the sequence of words it most likely contains. Moreover, let x be an audio signal with label transcript y that is correctly predicted by the ASR, i.e., $y = f(x)$. A targeted AE can be created by finding a small perturbation δ that causes the ASR system to predict a desired transcript $\hat{y}$ given $x+\delta$, i.e., $f(x+\delta) = \hat{y} \neq y = f(x)$. This perturbation δ is usually estimated by gradient descent-based minimization of the following function

$$l(x, \delta, \hat{y}) = l_t(f(x + \delta), \hat{y}) + c \cdot l_a(x, \delta) \ , \quad (1)$$

which includes two loss functions: (1) a task-specific loss, $l_t(\cdot)$, to find a distortion that induces the model to output the desired transcription target $\hat{y}$, and (2) an acoustic loss, $l_a(\cdot)$, that is used to minimize the energy and/or the perceptibility of the noise signal δ. In the initial steps of the iterative optimization procedure, the weighting parameter *c* is usually set to small values to first find a viable AE. Later, *c* is often increased, in order to minimize the distortion, to render it as inconspicuous as possible.

The most prominent targeted attacks for audio are the C&W Attack and the *Imperceptible* also known as *Psychoacoustic Attack*, two well-established optimization-based adversarial algorithms. In the C&W attack [Carlini and Wagner, 2018], l_t is the negative log-likelihood of the target phrase and $l_a = |\delta|_2^2$. Moreover, $|\delta|$ is constrained to be smaller than a predefined value ϵ, which is decreased step-wise in an iterative process. The *Psychoacoustic Attack* [Schönherr et al., 2019, Qin et al., 2019] is divided into two stages. The first stage of the attack follows the approach outlined by C&W. The second stage of the algorithm aims to decrease the perceptibility of the noise by using frequency masking, following psychoacoustic principles. For untargeted adversarial attacks, the objective is to prevent models from predicting the correct output but no specific target transcription is given. Several untargeted attacks on ASR systems have been proposed. These include the projected gradient descent (PGD) [Madry et al., 2018], a well-known general attack method, as well as two black-box attacks—the Kenansville attack [Abdullah et al., 2020, 2021] utilizing signal processing methods to discard certain frequency components, and the genetic attack [Alzantot et al., 2018] that results from a gradient-free optimization algorithm.

End-to-end ASR systems An E2E ASR system [Prabhavalkar et al., 2024] can be described as a unified ASR model that directly transcribes a speech waveform into text, as opposed to orchestrating a pipeline of separate ASR components. In general terms, the input of the system is a series of acoustic features extracted from overlapping speech frames. The model processes this series of acoustic features and predicts a probability distribution over tokens (e.g., phonemes, characters, or sub-word units) in each time step. Subsequently, utilizing a decoding and alignment algorithm, it determines the output text. Ideally, E2E ASR models are fully differentiable and thus can be trained end-to-end by maximizing the conditional log-likelihood with respect to the desired output. Various E2E ASR models follow an encoder-only or an encoder-decoder architecture and typically are built using recurrent neural network (RNN) or transformer layers. Special care is taken of the unknown temporal alignments between the input waveform and output text, where the alignment can be modeled explicitly (e.g., CTC [Graves et al., 2006], RNN-T [Graves, 2012]), or implicitly using attention [Watanabe et al., 2017]. Furthermore, language models can be integrated to improve prediction accuracy by considering the most probable sequences [Toshniwal et al., 2018].

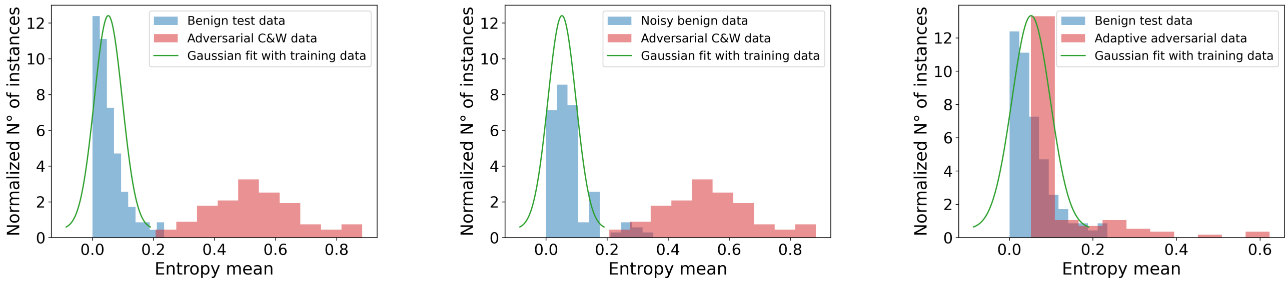
4 DETECTING ADVERSARIAL EXAMPLES WITH DISTRIBLOCK

We propose to leverage the probability distribution over the tokens from the output vocabulary to quantify uncertainty in order to identify adversarial attacks. This builds on the intuition that an adversarial input may lead to a higher uncertainty displayed by the ASR system. A schematic of our approach is displayed in Fig. 1. An audio clip—either benign or malicious—is fed to the ASR system. The system then generates probability distributions over the output tokens in each time step. The third step is to compute pertinent characteristics of these output distributions, as detailed below. Then, we use the mean, median, maximum, or minimum to aggregate the values of the characteristics into a single score per utterance. Lastly, we employ a binary classifier for differentiating adversarial instances from test data samples.

Characteristics of the output distribution We assume that for each time step t the ASR system produces a probability distribution $p^{(t)}$ over the tokens $i \in \mathcal{V}$ of a given output vocabulary $\mathcal{V}$. As a first characteristic, we use a common measure to quantify the total uncertainty in the predicted distribution of each time step, namely the **Shannon entropy**

$$H(p^{(t)}) = -\sum_{i=1}^{|\mathcal{V}|} p^{(t)}(i) \cdot \log p^{(t)}(i).$$

Moreover, since speech is processed sequentially from overlapping frames of the audio signal, acoustic features should transition gradually in the sequence (i.e., often the same token is predicted multiple times in a row). This should be displayed by a high similarity between probability distributions of subsequent time steps. However, the additional noise added to the speech signal of AEs potentially leads to larger changes. We, therefore, access the similarity between output distributions in two successive time steps in terms of



(a) Benign test-clean data vs. C&W AEs.

(b) Noisy benign data vs. C&W AEs.

(c) Benign test-clean data vs. adaptive C&W AEs.

Figure 2: Histograms of the mean-entropy of the LSTM model's predictive distribution for 100 benign test samples vs. 100 C&W AEs.

the **Kullback–Leibler divergence (KLD)**,

$$D_{\mathrm{KL}}(p^{(t)} \| p^{(t+1)}) = \sum_{i=1}^{|\mathcal{V}|} p^{(t)}(i) \cdot \log \frac{p^{(t)}(i)}{p^{(t+1)}(i)},$$

as well as the **Jensen-Shannon divergence (JSD)**,

$$D_{\mathrm{JS}}(p^{(t)}, p^{(t+1)}) = \frac{1}{2} D_{\mathrm{KL}}(p^{(t)} \| M) + \frac{1}{2} D_{\mathrm{KL}}(p^{(t+1)} \| M),$$

with $M = \frac{1}{2}(p^{(t)} + p^{(t+1)})$, which can be seen as a symmetrized version of the KLD. In addition, we compute simple characteristics of the distributions for every $t \in \{1, \ldots, T\}$:

- the **median** of $p^{(t)}(i), i = 1, 2, \ldots, |\mathcal{V}|$.
- the **minimum** $\min_{i \in \{1,\ldots,|\mathcal{V}|\}} p^{(t)}(i)$.
- the **maximum** $\max_{i \in \{1,\ldots,|\mathcal{V}|\}} p^{(t)}(i)$.

Finally, we aggregate the step-wise values of the different characteristics into a single score, respectively, by taking the mean, median, minimum, or maximum of the values for different time steps.

Binary classifier The extracted characteristics of the output distribution can then be used as features for different binary classifiers. An option to obtain simple classifiers is to fit a Gaussian distribution to each score computed for the utterances from a held-out set of benign data. If the probability of a new audio sample is below a chosen threshold under the Gaussian model, this example is classified as adversarial. The threshold can be chosen on the benign examples as a value that guarantees a small number of false positives. For illustration, Fig. 2 displays example histograms of the mean-entropy values of the predictive distribution given benign and adversarial inputs, respectively. A more sophisticated approach is to employ ensemble models (EMs), in which multiple Gaussian distributions, fitted to a single score each, produce a unified decision by a majority vote. Another option is to construct an NN that takes all the characteristics described above as input.

Adaptive attack An adversary with complete knowledge of the defense strategy can implement so-called adaptive attacks. We implement such attacks, to challenge the robustness of DistriBlock. For this, we construct a new loss l_k by adding a penalty l_s to the loss function in Equation (1), weighted with some factor α, that is

$$l_k(x, \delta, \hat{y}) = (1 - \alpha) \cdot l(x, \delta, \hat{y}) + \alpha \cdot l_s(x) \ . \quad (2)$$

When attacking a Gaussian classifier that is based on characteristic c, $l_s(x)$ corresponds to the L_1 norm of the difference between the mean $\overline{s}^c$ of the Gaussian fitted to the respective scores of benign data (resulting from aggregating c over each utterance) and the score of x. When attacking an EM, l_s is set to

$$l_s(x) = \sum_{i=1}^{I} |\overline{s}^{c_i} - s^{c_i}(x)| \ ,$$

where $c_1 \ldots c_I$ correspond to the characteristics used by the Gaussian classifiers of the ensemble is composed of. In the case of NNs, $l_s(x)$ is simply the L_1 norm, quantifying the difference between the NN's predicted outcome (a probability value) and one (indicating the highest probability for the benign category). We also investigated other options for choosing l_s, which are described in App. A.

5 EXPERIMENTS

This section provides information on experimental settings, assesses the quality of trained ASR systems, and evaluates both the strength of the adversarial attacks and the effectiveness of the proposed detection method.

5.1 EXPERIMENTAL SETTINGS

Datasets We used the LibriSpeech dataset [Panayotov et al., 2015] comprising approximately 1000 hours of English speech, sampled at a rate of 16 kHz, extracted from audiobooks. We further used Aishell [Bu et al., 2017], an open-source speech corpus for Mandarin Chinese. Since Chinese

Table 1: Performance of ASR systems on benign and noisy data, in terms of word and sentence error rate on 100 utterances. A cross in the LM column indicates that the ARS system integrates a language model.

			Benign data		Noisy data			
Model	Language	LM	WER	SER	WER	SER	SNR_{Seg}	dB_x
LSTM	Italian (It)	✗	15.65%	52%	31.74%	72%	-3.65	6.52
LSTM	English (En)	✗	5.37%	31%	8.46%	45%	2.75	6.67
LSTM	English (En-LM)	✓	4.23%	24%	5.68%	30%	2.75	6.67
wav2vec	Mandarin (Ma)	✓	4.37%	28%	8.49%	43%	5.25	4.50
wav2vec	German (Ge)	✗	8.65%	33%	16.08%	51%	-2.66	7.85
Trf	Mandarin (Ma)	✗	4.79%	29%	7.40%	40%	5.25	4.50
Trf	English (En)	✓	3.10%	20%	11.87%	44%	2.75	6.67

Table 2: Quality of different targeted attacks. Results are averaged over 100 adversarial examples. WER and SER are measured w.r.t. the target utterance. The adaptive attack is customized for mean-median GCs.

	C&W attack				Psychoacoustic attack				Adaptive attack			
Model	WER	SER	SNR_{Seg}	dB_x	WER	SER	SNR_{Seg}	dB_x	WER	SER	SNR_{Seg}	dB_x
LSTM (It)	0.84%	3.00%	17.79	44.51	0.84%	3.00%	18.17	38.52	0.84%	3.00%	-1.47	18.36
LSTM (En)	1.09%	2.00%	14.91	33.29	1.09%	2.00%	15.14	31.92	0.30%	1.00%	0.23	14.01
LSTM (En-LM)	1.19%	2.00%	17.50	36.46	1.19%	2.00%	17.82	33.93	1.19%	2.00%	3.81	17.45
wav2vec (Ma)	0.08%	1.00%	22.22	31.35	0.08%	1.00%	22.73	30.66	0.08%	0.00%	-4.28	4.55
wav2vec (Ge)	0.00%	0.00%	20.58	50.86	0.00%	0.00%	21.08	41.46	0.00%	0.00%	-12.12	11.23
Trf (Ma)	0.00%	0.00%	31.93	49.35	0.00%	0.00%	29.47	32.69	0.00%	0.00%	1.24	9.45
Trf (En)	0.00%	0.00%	27.85	53.54	0.00%	0.00%	25.70	37.68	0.00%	0.00%	1.99	15.52

is a tonal language, the speech of this corpus exhibits significant and meaningful variations in pitch. Additionally, we considerd the Common Voice (CV) corpus [Ardila et al., 2020], one of the largest multilingual open-source audio collections available in the public domain. Created through crowdsourcing, CV includes additional complexities within the recordings, such as background noise and reverberation.

ASR systems We analyzed a variety of fully integrated PyTorch-based state-of-the-art deep learning E2E speech engines. More specifically, we investigated three different models. The first employs a wav2vec2 encoder [Baevski et al., 2020] and a CTC decoder. The second integrates an encoder, a decoder, and an attention mechanism between them, as initially proposed with the Listen, Attend, and Spell (LAS) system [Chan et al., 2016], employing a CRDNN encoder and a LSTM for decoding [Chorowski et al., 2015]. The third model implements a transformer architecture relying on attention mechanisms for both encoding and decoding [Vaswani et al., 2017, Wolf et al., 2020]. The models are shortly referred to as wav2vec, LSTM, and Trf, respectively, in our tables. These models generate diverse output formats depending on their language and tokenizer selection, which can encode either characters or subwords. Specifically, they produce output structures with neuron counts of 32, 500, 1000, 5000, or 21128. In App. E, Tab. 18 we provide details regarding the specific tokenizer type employed by each ASR model. We trained these models on the data sets described above.

To improve generalization and make the classifiers more robust, we applied standard data augmentation techniques provided in SpeechBrain: corruption with random samples from a noise collection, removing portions of the audio, dropping frequency bands, and resampling the audio signal at a slightly different rate.

Adversarial attacks To generate the AEs, we utilized a repository that contains a PyTorch implementation of all considered attacks [Olivier and Raj, 2022]. For each data set, we randomly selected 200 samples that were not longer than five seconds from the test set [1]. Based on each sample, we generated adversarial examples for each adversarial attack type and ASR model. Then, all methods were tested on the task of distinguishing the first 100 test examples from the corresponding adversarial examples. So the same benign examples were used to test all different types of attacks. The additional 100 test examples and corresponding adversarial examples were used as a validation set for picking the best characteristic for the Gaussian classifiers for each model. For targeted attacks, each benign sample was assigned an adversarial target transcript sourced from the same dataset. Specifically, our selection process adhered to three guiding principles: (1) the audio file's original transcription cannot be used as the new target description, (2) there should be an equal number of tokens in both the original and target transcriptions, and (3) each audio file should receive a unique target transcription.

For the adaptive attack, 100 adaptive adversarial examples were generated starting from inputs that already mislead the system, i.e.by fine-tuning 100 adversarial examples used for testing. Fine-tuning was based on minimizing the loss function given in Equation (2) for 1000 steps of gradient descent. We kept α constant at a value of 0.3, while

[1] We reduced the audio clip length to save time and resources, as generating AEs for longer clips can take up to an hour [Carlini and Wagner, 2018], depending on the computer and model complexity. A 5-sec length was a favorable trade-off between time/resources, and the number of AEs created per model.

Table 3: Quality of different untargeted attacks. Results are averaged over 100 adversarial examples. WER and SER are measured w.r.t the predicted transcription from clean data given by the ASR system.

Model	PGD attack WER	SER	SNR_{Seg}	dB_x	Genetic attack WER	SER	SNR_{Seg}	dB_x	Kenansville attack WER	SER	SNR_{Seg}	dB_x
LSTM (It)	121%	100%	7.39	25.76	41.6%	83.0%	3.04	35.13	73.2%	95.0%	-6.1	6.32
LSTM (En)	95%	100%	15.13	25.91	24.5%	85.0%	6.49	33.59	49.8%	85.0%	1.32	7.4
LSTM (En-LM)	100%	100%	15.19	26.21	23.8%	83.0%	6.63	33.59	49.3%	78.0%	1.32	7.4
wav2vec (Ma)	90%	100%	20.09	23.68	36.2%	94.0%	6.24	23.74	62.4%	99.0%	6.18	6.33
wav2vec (Ge)	102%	100%	6.88	26.79	30.7%	78.0%	1.72	33.39	49.3%	86.0%	-5.73	6.89
Trf (Ma)	126%	100%	19.49	26.41	44.1%	96.0%	4.36	23.74	73.8%	98.0%	6.18	6.33
Trf (En)	102%	100%	14.88	26.58	17.8%	77.0%	8.79	33.59	40.7%	72.0%	1.32	7.4

Table 4: AUROC for DistriBlock models (mean-median-GC ad NN trained on C&W AEs) compared to baselines (NF and TD) w.r.t the task of distinguishing different types of targeted AEs from clean and noisy test data.

Model	Benign vs. C&W adversarial data NF	TD	GC	NN	Noisy vs. C&W adversarial data NF	TD	GC	NN	Benign vs. Psychoacoustic adversarial data NF	TD	GC	NN
LSTM (It)	0.8736	0.8564	**0.9980**	0.9955	0.9186	0.8237	**0.9686**	0.9103	0.8871	0.8557	**0.9972**	0.9943
LSTM (En)	0.8741	0.9695	**0.9993**	0.9982	0.9410	0.9694	**0.9966**	0.9940	0.8868	0.9697	**0.9993**	0.9982
LSTM (En-LM)	0.9345	0.9097	0.9508	**0.9825**	0.9680	0.8852	0.9454	**0.9775**	0.9447	0.9266	0.9557	**0.9840**
wav2vec (Ma)	0.8993	**0.9937**	0.9902	0.9852	0.9406	**0.9817**	0.9570	0.9427	0.9014	**0.9935**	0.9897	0.9853
wav2vec (Ge)	0.8725	0.9836	**0.9982**	0.9637	0.9372	0.9557	**0.9863**	0.9065	0.8749	0.9835	**0.9973**	0.9596
Trf (Ma)	0.9106	0.9828	0.9894	**0.9990**	0.9546	0.9790	0.9571	**0.9798**	0.9116	0.9910	0.9929	**0.9974**
Trf (En)	0.9100	0.9770	**1.0000**	0.9999	0.9728	0.9351	**0.9769**	0.9531	0.9098	0.9903	**1.0000**	0.9995
Avg. AUROC	0.8963	0.9532	**0.9894**	0.9892	0.9475	0.9328	**0.9697**	0.9520	0.9023	0.9586	**0.9903**	0.9883

δ remains unchanged during the initial 500 iterations, after which it is gradually reduced. This approach noticeably diminishes the discriminative capability of our defense across all models, but comes at the expense of generating noisy AEs. Other choices of hyperparameters resulted in less noisy AEs but also led to weaker attacks (most of the generated samples did not successfully deceive DistriBlock, see App. A.). A selection of benign, adversarial, and noisy data employed in our experiments, along with the code for our defense strategy, is available online at `https://github.com/matiuste/DistriBlock`.

Adversarial example detectors We construct three kinds of binary classifiers:

1. Based on the 24 scores (resulting from combing each of the 4 aggregation methods with the 6 characteristics) we obtain 24 simple Gaussian classifiers (GC) per model.
2. To construct an ensemble model, we implement a majority voting technique (i.e., the classification output that receives more than half of the votes), utilizing a total of 3, 5, 7, or 9 best-performing GCs. The choice of which GCs to incorporate is determined by evaluating the performance of each characteristic on the 100 C&W attacks (used for validation only) for each model and ranking them in descending order. The outcome of the ranking can be found in App. B.
3. The neural network architecture consists of three fully connected layers, each with 72 hidden nodes, followed by an output neuron with sigmoid activation function to generate a probability output in the range of 0 to 1. The network is trained on 80 C&W AEs and 80 test samples using ADAM optimization [Kingma and Ba, 2015] with an initial learning rate of 0.0001 for 250 epochs.

Running the assessment with our detectors took approximately an extra 20 msec per sample, utilizing an NVIDIA A40 with a memory capacity of 48 GB, see App. C for more details.

5.2 QUALITY OF ASR SYSTEMS AND ADVERSARIAL ATTACKS

To assess the quality of the trained models as well as the performance of the AEs, we measured the word error rate (WER), the character error rate (CER), the sentence error rate (SER), a noise distortion metric defined by Carlini and Wagner [2018] and referred to as dB_x, and the Segmental Signal-to-Noise Ratio (SNR_{Seg}). Definitions of all metrics are available in App. D.

Quality of ASR systems Tab. 1 presents the performance of the ASR systems on 100 test samples. In addition, we evaluated the models on noisy audio data to determine performance in a situation that better mimics reality. To do so, we obtained noisy versions of the 100 test samples by adding noise utilizing SpeechBrain's environmental corruption function. The noise instances were randomly sampled from the Freesound section of the MUSAN corpus [Snyder et al., 2015, Ko et al., 2017], which includes room impulse responses, as well as 929 background noise recordings. The impact of noisy data on system performance is evident, resulting in a significant rise of the WER.

As a sanity check, we checked that the performances of all

Table 5: Average classification accuracies with classification thresholds guaranteeing a maximum 1% FPR (if possible) and a minimum 50% TPR. FPRs are indicated after the slash and accuracies were averaged over the tasks of distinguishing 100 C&W and Psychoacoustic AEs from 100 noisy and clean test samples. Results related to each task are given in App. H

Model	**NF**	**TD**	**GC**	**EM=3**	**EM=5**	**EM=7**	**EM=9**	**NN**
LSTM (It)	79.5% / 0.05	76.3% / 0.09	**93.0% / 0.01**	87.8% / 0.00	84.5% / 0.00	82.0% / 0.01	82.0% / 0.00	90.5% / 0.01
LSTM (En)	79.3% / 0.02	82.4% / 0.01	**98.0% / 0.03**	97.5% / 0.00	97.8% / 0.00	97.8% / 0.00	97.3% / 0.00	96.7% / 0.01
LSTM (En-LM)	86.3% / 0.00	81.3% / 0.06	81.3% / 0.01	88.8% / 0.02	90.5% / 0.01	**95.0% / 0.01**	91.3% / 0.02	92.0% / 0.01
wav2vec (Ma)	68.0% / 0.01	**96.8% / 0.00**	87.8% / 0.00	90.8% / 0.01	89.5% / 0.00	85.3% / 0.00	85.0% / 0.00	89.5% / 0.01
wav2vec (Ge)	90.5% / 0.01	96.0% / 0.00	**97.3% / 0.00**	92.3% / 0.03	91.8% / 0.04	90.0% / 0.04	92.3% / 0.03	90.1% / 0.01
Trf (Ma)	**95.8% / 0.00**	81.8% / 0.01	86.0% / 0.00	86.8% / 0.00	87.0% / 0.00	87.3% / 0.00	85.0% / 0.00	94.5% / 0.01
Trf (En)	95.8% / 0.01	92.8% / 0.04	**98.0% / 0.01**	96.8% / 0.01	97.3% / 0.01	97.3% / 0.01	97.0% / 0.01	95.0% / 0.01
Avg. accuracy / FPR	85.0% / 0.01	86.7% / 0.03	91.6% / 0.01	91.5% / 0.01	91.2% / 0.01	90.6% / 0.01	90.0% / 0.01	**92.6% / 0.01**

Table 6: AUROC for DistriBlock models (mean-median-GC ad NN trained on C&W AEs) compared to baselines (NF and TD) w.r.t the task of distinguishing different types of untargeted AEs from clean test data.

	Benign vs. PGD adversarial data				**Benign vs. Genetic adversarial data**				**Benign vs. Kenansville adversarial data**			
Model	**NF**	**TD**	**GC**	**NN**	**NF**	**TD**	**GC**	**NN**	**NF**	**TD**	**GC**	**NN**
LSTM (It)	0.7109	0.6516	**0.9387**	0.9156	0.5653	0.5283	0.5788	**0.6791**	0.8076	0.7331	0.8246	**0.8992**
LSTM (En)	0.7790	0.6742	0.9595	**0.9643**	0.5756	0.5053	0.4969	**0.6814**	0.7677	0.7554	0.8878	**0.8972**
LSTM (En-LM)	0.8745	0.8093	**0.9984**	0.9098	0.6879	0.5277	0.6384	**0.7137**	0.8026	0.7365	0.7881	**0.8901**
wav2vec (Ma)	0.8130	0.7178	**0.8369**	0.8357	0.6203	0.6009	0.6656	**0.7067**	0.8938	0.8539	**0.9669**	0.9525
wav2vec (Ge)	0.67075	0.74645	**0.7785**	0.4983	0.4750	0.5832	**0.6482**	0.6310	0.7514	0.7883	**0.9273**	0.8685
Trf (Ma)	0.8637	0.8592	0.8020	**0.9311**	0.6130	0.5854	0.6938	**0.8402**	0.9042	0.8964	**0.9993**	**0.9993**
Trf (En)	**0.8590**	0.7388	0.7499	0.5192	**0.6185**	0.5190	0.4555	0.6081	0.7826	0.7159	0.8942	**0.9280**
Avg. AUROC	0.7958	0.7425	**0.8663**	0.7963	0.5936	0.5500	0.5967	**0.6943**	0.8157	0.7828	0.8983	**0.9193**

trained models on the full test set (see Tab. 18 in the appendix) are consistent with those documented by Ravanelli et al. [2021], where you can also find detailed hyperparameter information for all these models.

Quality of adversarial attacks To estimate the effectiveness of the targeted adversarial attacks, we measured the word and sentence error w.r.t. the target utterances, reported in Tab. 2. We achieved nearly 100% success in generating targeted adversarial data for all attack types across all models. For the C&W attack, the lowest average distortion dB_x achieved was 31.35 dB, while the least distorted AEs had a dB_x of 53.54 dB. In a related study by Carlini and Wagner [2018], they reported a mean distortion of 31 dB over a different model. The AEs generated with the proposed adaptive adversarial attack also achieve a success rate of almost 100%. However, the AEs turned out to be much noisier, as displayed by a maximum average distortion dB_x of 18.36 dB over all models. This makes the perturbations more easily perceptible to humans.

For untargeted attacks, we measured the word and sentence error relative to the true label, i.e., the higher the WER or SER the stronger the attack. Results are presented in Tab. 3. In the case of a genetic attack, we observed a minimal effect on the WER, with the rate remaining below 50% for all models. PGD and Kenansville both restrict the magnitude of the perturbation of an AE based on a predefined factor value that we set to 25 for PGD and to 10 for Kenansville. Results for different choices are shown in App. F.

5.3 PERFORMANCE OF ADVERSARIAL EXAMPLE DETECTORS

Detecting C&W and Psychoacoustic attacks We investigated the performance of our binary classifiers constructed as described in Sec. 4 by measuring the area under the receiver operating characteristic (AUROC) curve for the task of distinguishing different targeted attacks from clean and noisy test data (where we used 100 test samples and 100 AEs in each setting). Results for the neural network trained on C&W attacks and the GC using the mean-median characteristic are presented in Tab. 4. We compare the results obtained by our classifiers with those obtained by noise flooding (NF) and temporal dependency (TD) as baseline methods. It's worth noting that the performance of TD on noisy data hasn't been analyzed before, and former investigations were limited to the English language [Yang et al., 2019]. Similarly, NF was solely tested against the untargeted genetic attack in a 10-word classification system. Our findings show that DistriBlock consistently outperforms NF and TD across all models but one, achieving an average AUROC score of 99% for clean and 97% for noisy data.

Note that the GC does not need any adversarial data and only requires estimating the characteristics on benign data. While the mean-median performs well as characteristic of the GC for all models, the performance of single models can be further pushed by picking another characteristic based on the performance of a validation set, as discussed in App. G. A ranking of the GCs using different characteristics based on the AUROCs for detecting C&W AEs is shown in App. B. For us, it was a bit surprising, that the mean-median lead

Table 7: Average classification accuracies with classification thresholds guaranteeing a maximum 1% FPR (if possible) and a minimum 50% TPR. FPRs are indicated after the slash and accuracies were averaged over the tasks of distinguishing 100 PGD, genetic and Kenansville AEs from 100 clean test samples, respectively.

Model	NF	TD	GC	EM=3	EM=5	EM=7	EM=9	NN
LSTM (It)	67.3% / 0.32	60.3% / 0.43	73.5% / 0.49	**74.5% / 0.36**	73.8% / 0.31	71.0% / 0.31	70.5% / 0.32	71.3% / 0.11
LSTM (En)	67.5% / 0.27	61.1% / 0.44	69.7% / 0.61	73.5% / 0.50	74.5% / 0.49	**75.3% / 0.47**	75.2% / 0.47	70.7% / 0.14
LSTM (En-LM)	76.7% / 0.25	66.5% / 0.37	70.8% / 0.25	76.3% / 0.31	78.2% / 0.31	77.3% / 0.40	**79.7% / 0.31**	69.3% / 0.10
wav2vec (Ma)	69.3% / 0.08	63.8% / 0.67	75.0% / 0.31	77.8% / 0.33	**79.2% / 0.27**	75.5% / 0.23	74.2% / 0.25	68.3% / 0.12
wav2vec (Ge)	54.5% / 0.71	63.5% / 0.69	65.8% / 0.66	65.8% / 0.60	65.2% / 0.62	66.3% / 0.56	**66.7% / 0.58**	62.0% / 0.25
Trf (Ma)	62.8% / 0.64	69.2% / 0.26	73.8% / 0.27	**84.3% / 0.12**	84.0% / 0.12	84.2% / 0.13	81.2% / 0.13	81.5% / 0.03
Trf (En)	55.3% / 0.80	60.5% / 0.75	57.8% / 0.84	59.3% / 0.80	59.3% / 0.81	59.2% / 0.82	59.5% / 0.81	**60.8% / 0.27**
Avg. accuracy / FPR	64.8% / 0.44	63.6% / 0.52	69.5% / 0.49	73.1% / 0.43	**73.5% / 0.42**	72.7% / 0.42	72.4% / 0.41	69.1% / 0.15

Table 8: Classification accuracy based on WER & CER values after LPF and SG filtering. Evaluated on 100 clean test set samples and 100 adaptive C&W AEs, using a threshold aiming for a maximum 1% FPR when feasible.

	Pre-filtering					LPF+SG filtering. Results reported based on WER% and CER% values				
Model	GC	EM=3	EM=7	EM=9	NN	GC	EM=3	EM=7	EM=9	NN
LSTM (It)	50.0%	46.0%	43.5%	48.5%	49.5%	94.0% / 97.0%	91.5% / 95.0%	88.5% / 90.5%	87.0% / 88.5%	97.5% / 99.0%
LSTM (En)	51.5%	54.5%	65.5%	73.0%	65.5%	98.0% / 96.5%	98.0% / 96.5%	97.0% / 97.5%	97.0% / 97.0%	99.5% / 100.0%
LSTM (En-LM)	35.5%	50.0%	54.5%	54.5%	61.0%	98.0% / 99.5%	96.5% / 98.5%	91.0% / 99.0%	91.5% / 97.5%	98.5% / 99.5%
wav2vec (Ma)	43.5%	62.0%	57.5%	69.5%	59.0%	92.5% / 92.5%	93.5% / 93.5%	90.5% / 90.5%	93.0% / 93.0%	94.5% / 94.5%
wav2vec (Ge)	49.0%	46.0%	44.5%	90.0%	44.5%	95.5% / 93.0%	96.0% / 95.5%	92.0% / 93.5%	97.5% / 98.5%	98.5% / 98.5%
Trf (Ma)	38.0%	41.5%	40.5%	38.0%	49.5%	75.0% / 75.0%	78.0% / 78.0%	73.5% / 73.5%	71.0% / 71.0%	89.0% / 89.0%
Trf (En)	50.0%	49.5%	50.0%	50.0%	49.5%	93.5% / 98.5%	91.5% / 97.0%	82.5% / 88.0%	76.5% / 84.5%	98.5% / 100.0%
Avg. accuracy	45.4%	49.9%	50.9%	60.5%	54.1%	92.4% / 93.1%	92.1% / 93.4%	87.9% / 90.4%	87.6% / 90.0%	**96.6% / 97.2%**

to the best results. However, the mean-entropy, which has a clear notion as uncertainty measure and was used in the context of AE detection before, is about as good. The metrics measuring the distance between distributions in successive steps (KLD and JSD) are overall less effective. Finally, we note that the neural networks perform surprisingly well at identifying Psychoacoustic AEs, although they were trained only on a small set of C&W attacks, thus showing a good transferability between attack types.

To evaluate the classification accuracy of the AE detectors, we adopted a conservative threshold selection criterion based on a validation set: we picked the threshold with the highest false positive rate (FPR) below 1% (if available) while maintaining a minimum true positive rate (TPR) of 50%. Next to GCs and NNs we now as well consider EMs build on a total of 3, 5, 7, or 9 best-performing GCs. The resulting classification accuracies (averaged over the tasks of distinguishing C&W and Psychoacoustic attacks from noisy and clean test samples, respectively) are shown in Tab. 5. DistriBlock again outperforms NF and TD on 5 of the 7 models. Detailed results can be found in App. H.

Detecting untargeted attacks To assess the transferability of our detectors to untargeted attacks, we investigated the defense performance of GCs based on the mean-median characteristic and NNs trained on C&W AEs when exposed to PGD, genetic, or Kenansville attacks. Results are reported in Tab. 6. Although the detection performance decreases in comparison to targeted attacks, our methods are still way more efficient than NF and TD, with AUROCs even exceeding 90% for the Kenansville attack. While NF and TD received (with thresholds picked as before) an average accuracy of 64,8% and 63,6% over all models and all three untargeted attacks, DistriBlock achieved with GC 69,5% and with an ensemble of 5 GCs 73,5% accuracy, as reported in Tab. 7. Detailed results can be found in App. I.

In general, AEs resulting from the genetic attack prove challenging to detect, which may be attributed to its limited impact on the output text as displayed by a relatively low WER (compare Tab. 3). Luckily, untargeted attacks are in general less threatening and all AEs we investigated are characterized by noise, making them easily noticeable by human hearing.

Detecting adaptive adversarial attacks We evaluate the detection performance of our classifiers when challenged with the adaptive attack. Again, we calculated the classification accuracy based on a threshold aiming for a maximum FPR smaller than 1% (where feasible). The results shown on the left side of Tab. 8 demonstrate that the defense provided by DistriBlock can be easily mitigated if the adversary knows about the defense mechanism. However, one can leverage the fact that the adaptive attacks result in much noisier examples. To do so, we compare the predicted transcription of an input signal with the transcription of its filtered version using metrics like WER and CER. More specifically, we employed two filtering methods: a low-pass filter (LPF) eliminating high-frequency components with a 7 kHz cutoff frequency [Monson et al., 2014] and a PyTorch-based Spectral Gating (SG) [Sainburg, 2019, Sainburg et al., 2020], an audio-denoising algorithm that calculates noise thresholds for each frequency band and generates masks

Table 9: Classification accuracy based on WER & CER values after LPF and SG filtering. Evaluated on 100 noisy samples and 100 adaptive C&W AEs, using a threshold aiming for a maximum 1% FPR when feasible.

Model	GC	EM=3	EM=7	EM=9	NN
LSTM (It)	89.5% / 90.5%	87.0% / 88.5%	84.0% / 84.0%	82.5% / 82.0%	93.0% / 92.5%
LSTM (En)	96.5% / 95.0%	96.5% / 95.0%	95.5% / 96.0%	95.5% / 95.5%	98.0% / 98.5%
LSTM (En-LM)	97.0% / 98.5%	95.5% / 97.5%	90.0% / 98.0%	90.5% / 96.5%	97.5% / 98.5%
wav2vec (Ma)	91.5% / 91.5%	92.5% / 92.5%	89.5% / 89.5%	92.0% / 92.0%	93.5% / 93.5%
wav2vec (Ge)	93.5% / 92.5%	94.0% / 95.0%	90.0% / 93.0%	95.5% / 98.0%	96.5% / 98.0%
Trf (Ma)	73.0% / 73.0%	76.0% / 76.0%	71.5% / 71.5%	69.0% / 69.0%	87.0% / 87.0%
Trf (En)	92.0% / 96.0%	90.0% / 94.5%	81.0% / 85.5%	75.0% / 82.0%	97.0% / 97.5%
Avg. accuracy	90.4% / 91.0%	90.2% / 91.3%	85.9% / 88.2%	85.7% / 87.9%	**94.6% / 95.1%**

to suppress noise below these thresholds. We then tried to distinguish attacks from benign data based on the WER and CER resulting from comparing the transcription after filtering to that before filtering. For that we again constructed a simple Gaussian classifier, i.e., we performed threshold-based classification. The resulting accuracies are shown on the right side of Tab. 8, and demonstrate that the adaptive AEs can be efficiently detected due to their noisiness. We studied alternative ways to generate adaptive AEs, using different hyperparameters and loss functions, as outlined in App. A. In settings that lead to less noisy adaptive AEs, DistriBlock demonstrated high robustness in the detection of AEs. In summary, either DistriBlock could defend even adaptive attacks, or the attacks got that noisy, that the suggested filtering-based technique could be used for defense.

Finally, we test the robustness of our filtering methods when dealing with noisy data. We employed the same noisy data set used for testing ASR robustness, as detailed in subsection. 5.2. We then applied the WER and CER based classifiers described above to task of distinguishing noisy benign data from adaptive AEs. The resulting classification accuracies are shown in Tab. 9. Notably, the performance slightly decreases with noisy data compared to distinguishing benign data from adaptive AEs. However, the adaptive adversarial examples can still be detected with an average accuracy up to 95.1% in the case of NNs.

6 DISCUSSION & CONCLUSION

In this work we propose DistriBlock, a novel detection strategy for adversarial attacks on neural network-based state-of-the-art ASR systems. DistriBlock constructs simple classifiers based on features extracted from the distribution over tokens produced by the ASR models in each prediction step. We performed an extensive empirical analysis including 3 state-of-the-art neural ASR systems trained on 4 different languages, 5 prominent attack types (two targeted and one untargeted white-box attack, as well as two untargeted black-box attacks), and settings with clean and noisy benign data. Our results demonstrate that simple Gaussian classifiers based on the mean-median probability and mean-entropy of the distributions over all time steps are highly effective adversarial example detectors. Notably, their construction is simple and only requires benign data, and the computational overhead during prediction is negligible. While the entropy is a measure of total prediction uncertainty and the results are in accordance with our intuition that attacks result in higher uncertainty, the effectiveness of the median as a decision criterion remains to be understood.

We also investigated neural network-based classifiers using a larger variety of distributional characteristics as input features. Although the neural networks were small and only trained on a tiny data set with only one kind of AEs, they generalized well to other kind of attacks. We suspect that the performance and robustness could be further increased by training larger models on bigger datasets containing different kind of AEs (maybe even resulting from adaptive attacks) and noisy data. DistriBlock clearly outperformed two existing detection methods that we used as baselines in the detection of all investigated attacks (and that to the best of our knowledge presented state of the art so far), showing an average accuracy increase of 5.89% for detection of targeted attacks and an increase of 8.67% for untargeted attacks compared to the better performing baseline.

To challenge our defense strategy, we proposed specific adaptive attacks that aim at generating AEs that are indistinguishable from benign data based on the induced distributional characteristics. These adaptive attacks can either be still detected by DistriBlock with high accuracy or are that noisy that they can be identified efficiently by comparing the difference in output transcripts before and after applying a noise-filter. In future work, it will be interesting to evaluate if the investigated characteristics of output distributions can also serve as indicators of other pertinent aspects, such as speech quality and intelligibility, which is a target for future work.

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DistriBlock: Identifying adversarial audio samples by leveraging characteristics of the output distribution (Supplementary Material)

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This Supplementary Material contains additional experiments that support the findings presented in the main paper, these experiments are related to:

A Adaptive attack—Additional settings
B Characteristic ranking
C Computational overhead
D Performance indicators of ASR systems
E Performance of ASR systems
F Untargeted attacks
G Performance of Gaussian classifiers
H Evaluation of binary classifiers for identifying targeted attacks
I Evaluation of binary classifiers for identifying untargeted attacks
J Word sequence length impact
K Transfer attack

A ADAPTIVE ATTACK—ADDITIONAL SETTINGS

For an adaptive attack, we construct a new loss, l_k explained in detail in Section 4.

$$l_k(x, \delta, \hat{y}) = (1 - \alpha) \cdot l(x, \delta, \hat{y}) + \alpha \cdot l_s(x) \ .$$

We perform 1,000 iterations on 100 randomly selected examples from the adversarial dataset, beginning with inputs that already mislead the system. We evaluated the adaptive attacks resulting from different settings:

1. We kept α constant at 0.3, while δ remained only unchanged during the initial 500 iterations. Afterward, δ is gradually reduced each time the perturbed signal successfully deceives the system.
2. We experimented with three fixed α values: 0.3, 0.6, and 0.9, while δ is gradually reduced each time the perturbed signal successfully deceives the system.
3. We increased the α value by 20% after each successful attack, while the δ factor remains unchanged during the initial 30 iterations.
4. We kept α constant at 0.3 and set the l_s for attacking an EM, as defined in Section 4. We employed an EM-based on two characteristics: the median-mean and the mean-KLD.

5. We kept α constant at 0.3, and we redefined the l_s term from the loss l_k as follows:

$$l_s(x,\hat{x}) = \sum_{t=1}^{T-1} |D_{\mathrm{KL}}(p_x^{(t)} \| p_x^{(t+1)}) - D_{\mathrm{KL}}(p_{\hat{x}}^{(t)} \| p_{\hat{x}}^{(t+1)})| \ . \tag{3}$$

   We assume that for each time step $t \in \{1, \ldots, T\}$ the ASR system produces a probability distribution $p^{(t)}$ over the tokens $i \in \mathcal{V}$ of a given output vocabulary $\mathcal{V}$. Where x represents the benign example, and $\hat{x}$ is its adversarial counterpart.

6. To minimize the statistical distance from the benign data distribution, we calculated for the same time step $t \in \{1, \ldots, T\}$ the KLD between the output probability distribution $p^{(t)}$ related to the benign data x and its adversarial counterpart $\hat{x}$. We kept α constant at 0.3, then we set the l_s term to:

$$l_s(x,\hat{x}) = \sum_{t=1}^{T} |D_{\mathrm{KL}}(p_x^{(t)} \| p_{\hat{x}}^{(t)})| \ . \tag{4}$$

Results for the second setting are reported in Tab. 10. Regardless of the chosen α value, the second setting is unable to produce robust adversarial samples and has only a minimal effect on our proposed defense. This is due to the faster reduction of δ, making it harder to generate an adaptive AE that circumvents DistriBlock. Similar outcomes are evident in the fifth and sixth settings, where the modified loss l_s does not yield improvement, as illustrated in Tab. 13, and Tab. 14. In the third configuration, some models exhibit enhanced outcomes by diminishing the discriminative capability of our defense. Nevertheless, the adaptive AEs generated in this scenario are characterized by noise, as indicated in Tab. 11, with SNR_{Seg} values below 16 dB. The fourth setting presents a noise improvement with higher SNR_{Seg} values compared to prior settings, as shown in Tab. 12. However, detectors are still able to discriminate many AEs from benign data. We opt for the first setting in the main paper, as it substantially diminishes our defense's discriminative power across all models. But, this comes at the expense of generating noisy data, results are presented in Tab. 15. To mitigate this issue, we propose the use of filtering as an additional method to maintain the system's robustness. We demonstrate that adaptive AEs can be efficiently detected due to their noisiness, as described in subsection. 5.3. In general, we observe that using an α value above 0.3 increases the difficulty of generating adaptive adversarial examples.

Table 10: Average SNR of 100 adaptive C&W AEs generated with different α values and AUROC with respect to these AEs and 100 test samples. $^{(*)}$ denotes best-performing score-characteristic.

		$\alpha = 0.3$		$\alpha = 0.6$		$\alpha = 0.9$	
Model	**Score-Characteristic$^{(*)}$**	**SNR_{Seg}**	**GC AUROC**	**SNR_{Seg}**	**GC AUROC**	**SNR_{Seg}**	**GC AUROC**
LSTM (It)	Mean-Median	17.5	0.9635	17.13	0.8882	17.4	0.964
LSTM (En)	Mean-Median	14.78	0.9875	14.78	0.9741	14.75	0.9735
LSTM (En-LM)	Max-Max	17.42	0.9869	17.39	0.9762	17.37	0.9567
wav2vec (Ma)	Mean-Entropy	22.18	0.9912	22.16	0.9849	22.13	0.9779
wav2vec (Ge)	Max-Min	20.27	0.9774	19.82	0.8516	20.55	0.9803
Trf (Ma)	Median-Max	31.69	0.9893	31.74	0.9891	31.8	0.977
Trf (En)	Max-Median	27.54	1.000	27.61	1.000	27.65	1.000

Table 11: Average SNR of 100 adaptive C&W AEs generated with adapted α value and AUROC with respect to these AEs and 100 test samples. $^{(*)}$ denotes best-performing score-characteristic.

Model	**Score-Characteristic$^{(*)}$**	**WER/CER**	**SER**	**SNR_{Seg}**	**dB_{x}**	**GC AUROC**
LSTM (It)	Mean-Median	0.84%	3.00%	6.64	27.29	0.4656
LSTM (En)	Mean-Median	0.20%	1.00%	9.51	24.2	0.5333
LSTM (En-LM)	Max-Max	0.40%	1.00%	12.91	29.77	0.7437
wav2vec (Ma)	Mean-Entropy	0.08%	1.00%	13.76	21.34	0.9146
wav2vec (Ge)	Max-Min	0.00%	0.00%	12.21	33.7	0.6666
Trf (Ma)	Median-Max	0.00%	0.00%	14.48	24.71	0.7857
Trf (En)	Max-Median	0.00%	0.00%	15.91	35.49	0.9835

Table 12: Average SNR of 100 adaptive C&W AEs generated with constant $\alpha = 0.3$ and l_s aiming to attack an ensemble of GCs with mean-median and mean-KLD characteristics, and AUROC with respect to these AEs and 100 test samples.

Model	WER/CER	SER	SNR_{Seg}	dB_x	GC AUROC
LSTM (It)	0.84%	3.00%	16	38.77	0.8014
LSTM (En)	1.09%	2.00%	14.08	30.29	0.8509
LSTM (En-LM)	1.19%	2.00%	17.25	35.37	0.8701
wav2vec (Ma)	0.08%	1.00%	21.91	29.83	0.523
wav2vec (Ge)	0.00%	0.00%	17.61	41.65	0.4437
Trf (Ma)	0.00%	0.00%	27.58	35.52	0.5286
Trf (En)	0.00%	0.00%	22.84	39.82	0.7631

Table 13: Average SNR of 100 adaptive C&W AEs generated with constant $\alpha = 0.3$ and l_s as defined in Equation (3), and AUROC with respect to these AEs and 100 test samples.

Model	WER/CER	SER	SNR_{Seg}	dB_x	GC AUROC
LSTM (It)	0.84%	3.00%	17.73	44.37	0.9976
LSTM (En)	1.09%	2.00%	14.91	33.29	0.9993
LSTM (En-LM)	1.19%	2.00%	17.5	36.45	0.957
wav2vec (Ma)	0.08%	1.00%	22.22	31.35	0.9904
wav2vec (Ge)	0.00%	0.00%	20.58	50.86	0.9982
Trf (Ma)	0.00%	0.00%	30.41	42.81	0.9921

Table 14: Average SNR of 100 adaptive C&W AEs generated with constant $\alpha = 0.3$ and l_s as defined in Equation (4), and AUROC with respect to these AEs and 100 test samples.

Model	WER/CER	SER	SNR_{Seg}	dB_x	GC AUROC
LSTM (It)	0.84%	3.00%	17.76	44.5	0.9978
LSTM (En)	1.09%	2.00%	14.91	33.29	0.9993
LSTM (En-LM)	1.19%	2.00%	17.5	36.46	0.9551
wav2vec (Ma)	0.08%	1.00%	22.22	31.35	0.9902
wav2vec (Ge)	0.00%	0.00%	20.58	50.86	0.9982
Trf (Ma)	0.00%	0.00%	28.29	35.09	0.7562
Trf (En)	0.00%	0.00%	24.78	43.55	0.995

Table 15: Average SNR of 100 adaptive C&W AEs generated with constant $\alpha = 0.3$ and keeping δ unchanged during the initial 500 iterations, and AUROC with respect to these AEs and 100 test samples. $^{(*)}$ denotes best-performing score-characteristic.

Model	Score-Characteristic$^{(*)}$	WER/CER	SER	SNR_{Seg}	dB_x	GC AUROC
LSTM (It)	Mean-Median	0.84%	3.00%	-1.47	18.36	0.335
LSTM (En)	Mean-Median	0.30%	1.00%	0.23	14.01	0.295
LSTM (En-LM)	Max-Max	0.40%	1.00%	3.18	16.82	0.425
wav2vec (Ma)	Mean-Entropy	0.08%	1.00%	-4.30	4.09	0.375
wav2vec (Ge)	Max-Min	0.00%	0.00%	-12.96	10.88	0.255
Trf (Ma)	Median-Max	0.00%	0.00%	-1.09	8.01	0.285
Trf (En)	Max-Median	0.00%	0.00%	-0.19	14.69	0.250

B CHARACTERISTIC RANKING

For the GCs, we determine the best-performing characteristics by ranking them according to the average AUROC on a validation set across all models. This ranking, which is shown in Tab. 16, determines the choice of characteristics to utilize for the EMs, where we implement a majority voting technique, using a total of 3, 5, 7, or 9 GCs.

Table 16: Ranking of best-performing characteristic. AUROC with respect to 100 benign data and 100 C&W AEs. $^{()}$ indicates the characteristic chosen for a specific EM.

Score-Characteristic	Benign data vs. C&W AEs	Score-Characteristic	Benign data vs. C&W AEs
Mean-Median$^{(3,5,7,9)}$	**0.9872**	Mean-KLD	0.9162
Mean-Entropy$^{(3,5,7,9)}$	**0.9871**	Max-JSD	0.8480
Max-Entropy$^{(3,5,7,9)}$	**0.9808**	Max-KLD	0.8319
Median-Entropy$^{(5,7,9)}$	**0.9796**	Min-Median	0.8242
Max-Median$^{(5,7,9)}$	**0.9759**	Max-Max	0.7764
Median-Max$^{(7,9)}$	**0.9733**	Min-Min	0.7751
Mean-Max$^{(7,9)}$	**0.9617**	Min-Entropy	0.7703
Mean-Min$^{(9)}$	**0.9541**	Min-KLD	0.7066
Min-Max$^{(9)}$	**0.9523**	Mean-JSD	0.6717
Median-Median	0.9488	Median-KLD	0.6706
Max-Min	0.9365	Min-JSD	0.6669
Median-Min	0.9339	Median-JSD	0.6368

C COMPUTATIONAL OVERHEAD

The computational overhead assessment involves measuring the overall duration the system requires to predict 100 audio clips, utilizing an NVIDIA A40 with a memory capacity of 48 GB. As a result, running the assessment with our NN detectors took approximately an extra 20 msec per sample, therefore the proposed method is suitable for real-time usage. Results are reported in Tab. 17.

Table 17: Computational overhead to predict 100 audio clips measured in seconds.

Model	Elapsed time	With NN detector	Overhead	Avg. time/sample
LSTM (It)	53.005	53.452	0.447	0.004
LSTM (En)	55.742	58.038	2.295	0.023
LSTM (En-LM)	46.358	48.252	1.894	0.019
wav2vec (Ma)	13.339	14.772	1.432	0.014
wav2vec (Ge)	13.736	14.992	1.255	0.013
Trf (Ma)	32.070	34.656	2.586	0.026
Trf (En)	63.460	66.671	3.211	0.032
Avg. across all models	39.67	41.55	1.87	0.02

D PERFORMANCE INDICATORS OF ASR SYSTEMS

We used the following, standard performance indicators:

WER The word error rate, is given by

$$\text{WER} = 100 \cdot \frac{S + D + I}{N} \quad ,$$

where S, D, and I are the number of words that were substituted, deleted, and inserted, respectively, and N is the reference text's total word count. When evaluating ARS systems, the reference text corresponds to the label utterance of the test sample, and when evaluating adversarial attacks it corresponds to the malicious target transcription of the AE. We aim for ASR models with low WER on the original data, i.e., modes that recognize the ground-truth transcript with high accuracy. From the attacker's standpoint, the aim of targeted attacks is to minimize the WER as well, but relative to the target transcription. In untargeted attacks, the objective is to have a model with a high WER w.r.t. the ground-truth text.

CER The character error rate, is calculated like the WER, with the difference that instead of counting word errors, it counts character errors, with N representing the total character count of the reference text.

SER The sentence error rate is defined as

$$\text{SER} = 100 \cdot \frac{N_E}{N_T} \quad ,$$

where N_E is the number of audio clips that have at least one transcription error, and N_T is the total number of examples. Again N_T may correspond to either the number of samples in the test set or the number of adversarial examples.

$\mathbf{dB_x}$ Carlini and Wagner [2018] quantified the relative loudness of an audio signal x as

$$dB(x) = \max_{t\in\{0,\dots,|x|-1\}} 20 \cdot \log_{10} x(t).$$

Then, the level of distortion given by a perturbation δ to an audio signal x is defined as

$$dB_x(\delta) = dB(x) - dB(\delta),$$

where a higher $\mathrm{dB_x}$ indicates a lower level of added noise and where we assume equal lengths of x and δ.

$\mathbf{SNR}_{Seg}$ The Segmental Signal-to-Noise Ratio measures the noise energy in Decibels and considers the entire audio signal. To obtain it, the energy ratios are computed segment by segment, which better reflects human perception than the non-segmental version [Mermelstein, 1979]. The results are then averaged:

$$\mathrm{SNR_{Seg}} = \frac{10}{M} \cdot \sum_{m=0}^{M-1} \log_{10} \frac{\sum_{t=mF}^{mF+F-1} x(t)^2}{\sum_{t=mF}^{mF+F-1} \delta(t)^2} \ ,$$

where M is the number of frames in a signal and F is the frame length, x represents the clean audio signal and δ the perturbation. Thus, a higher SNR_{Seg} indicates less additional noise. We assume equal lengths of x and δ.

E PERFORMANCE OF ASR SYSTEMS

Tab. 18 presents the performance of the different models on the indicated datasets. The results align with those reported by Ravanelli et al. [2021], where detailed hyperparameter information for (the training of) all models can be found. Moreover, we provide the links to the detailed descriptions of each ASR system in the SpeechBrain repository.

Table 18: Performance of the ASR systems on benign data, in terms of word and sentence error rate, on the full test sets.

Model-Language	Data	Pre-trained model	# Utterances	Subword-base Tokenizer	# of tokens	WER	SER
LSTM-Italian [1]	CV-Corpus	✗	12,444	Unigram: Converts words into subwords	500	17.78%	69.68%
LSTM-English	Librispeech	✗	2,620	Unigram: Converts words into subwords	1,000	4.24%	42.44%
LSTM-English [2]	Librispeech	RNN Language Model [3]	2,620	Unigram: Converts words into subwords	5,000	2.91%	32.06%
wav2vec-Mandarin [4]	Aishell	Large Fairseq Chinese wav2vec2 [5]	7,176	WordPiece: Converts words into chars	21,128	5.05%	39.30%
wav2vec-German [6]	CV-Corpus	Large Fairseq German wav2vec2 [7]	15,415	Char: Converts words into chars	32	10.31%	46.56%
Trf-Mandarin [8]	Aishell	✗	7,176	Unigram: Converts words into subwords	5,000	6.23%	42.35%
Trf-English [9]	Librispeech	Transformer Language Model [10]	2,620	Unigram: Converts words into subwords	5,000	2.21%	26.03%

[1] CRDNN with CTC/Attention trained on CommonVoice Italian, see code:
`https://huggingface.co/speechbrain/asr-crdnn-commonvoice-it`

[2] CRDNN with CTC/Attention trained on LibriSpeech , see code:
`https://huggingface.co/speechbrain/asr-crdnn-rnnlm-librispeech`

[3] RNN language model, see code:
`https://speechbrain.readthedocs.io/en/latest/API/speechbrain.lobes.models.RNNLM.html`

[4] wav2vec 2.0 with CTC trained on Aishell, see code:
`https://huggingface.co/speechbrain/asr-wav2vec2-ctc-aishell`

[5] Chinese-wav2vec2-large-fairseq model, see code:
`https://huggingface.co/TencentGameMate/chinese-wav2vec2-large`

[6] wav2vec 2.0 with CTC trained on CommonVoice German, see code:
`https://huggingface.co/speechbrain/asr-wav2vec2-commonvoice-de`

[7] German-wav2vec2-large-fairseq model, see code:
`https://huggingface.co/jonatasgrosman/wav2vec2-large-xlsr-53-german`

[8] Transformer trained on Aishell, see code:
`https://huggingface.co/speechbrain/asr-transformer-aishell`

[9] Transformer trained on LibriSpeech, see code:
`https://huggingface.co/speechbrain/asr-transformer-transformerlm-librispeech`

[10] Transformer language model, see code:
`https://speechbrain.readthedocs.io/en/latest/API/speechbrain.lobes.models.transformer.TransformerLM.html`

F UNTARGETED ATTACKS

To expand the range of adversarial attacks, we explore three untargeted attacks: PGD, genetic, and Kenansville. The primary objective is to achieve a high WER w.r.t the ground-truth transcription. Each adversarial attack type is evaluated under distinct settings. Regarding PGD, the perturbation δ is limited to a predefined value ϵ, calculated as $\epsilon = ||x||_2/10^{\frac{SNR}{20}}$. We experimented with SNR values of 10 and 25. For Kenansville, the perturbation δ is controlled by removing frequencies that have a magnitude below a certain threshold θ, determined by scaling the power of a signal with an SNR factor given by $10^{\frac{-SNR}{10}}$. Subsequently, all frequencies that have a cumulative power spectral density smaller than θ are set to zero, and the reconstructed signal is formed using the remaining frequencies. Our Kenansville experiments involve a factor of 10, 15, and 25. Similar to PGD and Kenansville, the smaller perturbation is associated with higher SNR values. In genetic attack, the settings vary based on the number of iterations, we experimented with 1,000 and 2,000 iterations. The outcomes are detailed in Tab. 19 and Tab. 20 respectively.

In the main paper, in the case of PGD, we choose a factor of 25, as it induces a WER exceeding 50% across all models and maintains a higher segmental SNR. As for Kenansville, we opt for a factor of 10, as it is the only setting that demonstrates a genuine threat to the system by yielding a higher WER. In the context of a genetic attack, we choose 1,000 iterations, however adjusting the number of iterations doesn't result in a significant difference.

Table 19: Performance of PGD and genetic attacks. Results are averaged over 100 adversarial examples. WER and SER are measured w.r.t the ground truth transcription.

	PGD: Factor values of 10 – 25				Genetic: Number of iterations 1,000 - 2,000			
Model	**WER**	**SER**	**SNR_{Seg}**	**dB_x**	**WER**	**SER**	**SNR_{Seg}**	**dB_x**
LSTM (It)	119% - 121%	100% - 100%	-7.64 - 7.39	11.38 - 25.76	39.9% - 41.6%	81% - 83%	3.67 - 3.04	35.13 - 35.13
LSTM (En)	107% - 95%	100% - 100%	-0.12 - 15.13	12.62 - 25.91	22.9% - 24.5%	86% - 85%	6.58 - 6.49	33.59 - 33.59
LSTM (En-LM)	108% - 100%	100% - 100%	0.01 - 15.19	12.59 - 26.21	20.7% - 23.8%	79% - 83%	7.00 - 6.63	33.59 - 33.59
wav2vec (Ma)	120% - 90%	100% - 100%	4.56 - 20.09	10.38 - 23.68	36.6% - 36.2%	94% - 94%	6.21 - 6.24	23.74 - 23.74
wav2vec (Ge)	118% - 102%	100% - 100%	-8.28 - 6.88	12.45 - 26.79	28.4% - 30.7%	76% - 78%	2.44 - 1.72	33.39 - 33.39
Trf (Ma)	128% - 126%	100% - 100%	4.35 - 19.49	12.15 - 26.41	44.1% - 44.1%	96% - 96%	4.36 - 4.36	23.74 - 23.74
Trf (En)	109% - 102%	100% - 100%	-0.49 - 14.88	13.10 - 26.58	15.9% - 17.8%	74% - 77%	9.16 - 8.79	33.59 - 33.59

Table 20: Performance of Kenansville attack. Results are averaged over 100 adversarial examples. WER and SER are measured w.r.t the ground truth transcription

	Kenansville: Factor values of 10 – 15 – 25			
Model	**WER**	**SER**	**SNR_{Seg}**	**dB_x**
LSTM (It)	73.19% - 46.38% - 21.01%	95.00% - 83.00% - 63.00%	-6.10 / -1.37 / 7.94	6.32 / 10.58 / 20.48
LSTM (En)	49.85% - 20.95% - 7.33%	85.00% - 65.00% - 42.00%	1.32 / 6.06 / 15.38	7.40 / 12.42 / 23.28
LSTM (En-LM)	49.33% - 19.92% - 5.26%	78.00% - 56.00% - 29.00%	1.32 / 6.06 / 15.38	7.40 / 12.42 / 23.28
wav2vec (Ma)	62.41% - 22.04% - 5.13%	99.00% - 69.00% - 35.00%	6.18 / 11.12 / 20.43	6.33 / 10.80 / 21.28
wav2vec (Ge)	49.32% - 26.71% - 10.62%	86.00% - 67.00% - 35.00%	-5.73 / -1.22 / 7.83	6.89 / 11.93 / 22.83
Trf (Ma)	73.84% - 43.99% - 8.49%	98.00% - 88.00% - 38.00%	6.18 / 11.12 / 20.43	6.33 / 10.80 / 21.28
Trf (En)	40.66% - 13.73% - 4.02%	72.00% - 46.00% - 24.00%	1.32 / 6.06 / 15.38	7.40 / 12.42 / 23.28

G PERFORMANCE OF GAUSSIAN CLASSIFIERS

We fit 24 Gaussian classifiers for each model based on 24 characteristics. We then evaluate the performance of these GCs by measuring the AUROC and the area under the precision-recall curve (AUPRC) for the tasks of distinguishing AEs from clean and noisy data. For the calculation we used 100 samples from the clean test dataset, 100 C&W AEs, and 100 Psychoacoustic AEs. The results are presented in the following tables: Tab. 21 corresponds to the LSTM (It) model, Tab. 22 corresponds to the LSTM (En) model, Tab. 23 corresponds to the LSTM (En-LM) model, Tab. 24 corresponds to the wav2vec (Ma) model, Tab. 25 corresponds to the wav2vec (Ge) model, Tab. 26 corresponds to the Trf (Ma) model, and Tab. 27 corresponds to the Trf (En) model. The best AUROC values are shown in bold, as well as the top-performing score characteristic for detecting the C&W attack.

Table 21: Comparing GCs on clean and noisy data for the LSTM (It) model, assessing AUROC/AUPRC with 100 samples each from clean test data, C&W AEs, and Psychoacoustic AEs.

	C&W attack		Psychoacoustic attack	
Score-Characteristic	**Noisy data vs. AEs**	**Benign data vs. AEs**	**Noisy data vs. AEs**	**Benign data vs. AEs**
Mean-Entropy	0.9360 / 0.9542	0.9812 / 0.9850	0.9301 / 0.9461	0.9769 / 0.9800
Max-Entropy	0.8122 / 0.8577	0.9571 / 0.9580	0.8072 / 0.8507	0.9513 / 0.9490
Min-Entropy	0.6496 / 0.5446	0.6602 / 0.5476	0.7240 / 0.6108	0.7372 / 0.6216
Median-Entropy	0.9092 / 0.8770	0.9276 / 0.8847	0.9011 / 0.8769	0.9196 / 0.8762
Mean-Max	0.9288 / 0.9414	0.9628 / 0.9709	0.9214 / 0.9244	0.9556 / 0.9535
Max-Max	0.7395 / 0.6594	0.7426 / 0.6606	0.7436 / 0.6637	0.7482 / 0.6659
Min-Max	0.8064 / 0.8377	0.9081 / 0.9077	0.7998 / 0.8285	0.8984 / 0.8924
Median-Max	0.8930 / 0.8459	0.9027 / 0.8259	0.8803 / 0.8254	0.8911 / 0.8168
Mean-Min	0.9457 / 0.9602	0.9879 / 0.9895	0.9460 / 0.9611	**0.9887 / 0.9903**
Max-Min	0.8090 / 0.8615	0.9706 / 0.9722	0.8084 / 0.8629	0.9720 / 0.9736
Min-Min	0.7582 / 0.7201	0.7492 / 0.6992	0.7675 / 0.7228	0.7565 / 0.7016
Median-Min	0.9285 / 0.9522	0.9855 / 0.9883	0.9292 / 0.9533	0.9860 / 0.9888
Mean-Median	**0.9591 / 0.9681**	**0.9887 / 0.9900**	**0.9592 / 0.9687**	0.9887 / 0.9902
Max-Median	0.8401 / 0.8829	0.9621 / 0.9698	0.8332 / 0.8782	0.9602 / 0.9687
Min-Median	0.8240 / 0.7814	0.8003 / 0.7435	0.8050 / 0.7384	0.7883 / 0.7163
Median-Median	0.9387 / 0.9573	0.9805 / 0.9851	0.9395 / 0.9585	0.9815 / 0.9860
Mean-JSD	0.4435 / 0.4813	0.4917 / 0.5387	0.4334 / 0.4666	0.4806 / 0.5375
Max-JSD	0.8556 / 0.8674	0.9479 / 0.9238	0.8433 / 0.8218	0.9337 / 0.8759
Min-JSD	0.5727 / 0.4897	0.5589 / 0.4916	0.5554 / 0.4803	0.5405 / 0.4818
Median-JSD	0.4651 / 0.4471	0.4316 / 0.4221	0.4630 / 0.4399	0.4305 / 0.4229
Mean-KLD	0.6444 / 0.6914	0.7538 / 0.7860	0.6472 / 0.6994	0.7550 / 0.7886
Max-KLD	0.6996 / 0.6959	0.7928 / 0.7890	0.7062 / 0.7210	0.7967 / 0.7953
Min-KLD	0.6573 / 0.5420	0.6487 / 0.5439	0.6419 / 0.5316	0.6302 / 0.5306
Median-KLD	0.4087 / 0.4123	0.4029 / 0.4131	0.4152 / 0.4145	0.4065 / 0.4147

Table 22: Comparing GCs on clean and noisy data for the LSTM (En) model, assessing AUROC/AUPRC with 100 samples each from clean test data, C&W AEs, and Psychoacoustic AEs.

	C&W attack		Psychoacoustic attack	
Score-Characteristic	**Noisy data vs. AEs**	**Benign data vs. AEs**	**Noisy data vs. AEs**	**Benign data vs. AEs**
Mean-Entropy	0.9946 / 0.9943	0.9979 / 0.9979	0.9951 / 0.9949	0.9981 / 0.9981
Max-Entropy	0.9832 / 0.9833	0.9945 / 0.9939	0.9847 / 0.9855	0.9960 / 0.9959
Min-Entropy	0.6962 / 0.6150	0.6792 / 0.6143	0.6884 / 0.6119	0.6686 / 0.6079
Median-Entropy	0.9928 / 0.9938	0.9909 / 0.9946	0.9945 / 0.9954	0.9913 / 0.9950
Mean-Max	0.9819 / 0.9559	0.9854 / 0.9625	0.9824 / 0.9706	0.9863 / 0.9744
Max-Max	0.6823 / 0.6131	0.6855 / 0.6175	0.6847 / 0.6143	0.6881 / 0.6184
Min-Max	0.9618 / 0.9551	0.9805 / 0.9656	0.9623 / 0.9497	0.9808 / 0.9577
Median-Max	0.9920 / 0.9930	0.9900 / 0.9937	0.9933 / 0.9943	0.9907 / 0.9943
Mean-Min	0.9743 / 0.9783	0.9897 / 0.9902	0.9758 / 0.9790	0.9897 / 0.9899
Max-Min	0.9252 / 0.9311	0.9471 / 0.9508	0.9255 / 0.9304	0.9488 / 0.9521
Min-Min	0.5512 / 0.5324	0.5895 / 0.5646	0.5652 / 0.5470	0.5994 / 0.5726
Median-Min	0.9737 / 0.9790	0.9910 / 0.9919	0.9778 / 0.9825	0.9935 / 0.9940
Mean-Median	**0.9981 / 0.9982**	**0.9998 / 0.9998**	**0.9982 / 0.9983**	**0.9996 / 0.9996**
Max-Median	0.9883 / 0.9903	0.9994 / 0.9994	0.9879 / 0.9899	0.9992 / 0.9992
Min-Median	0.6964 / 0.7068	0.7100 / 0.7143	0.6719 / 0.6884	0.6854 / 0.6941
Median-Median	0.9928 / 0.9937	0.9981 / 0.9980	0.9920 / 0.9929	0.9974 / 0.9971
Mean-JSD	0.9306 / 0.9407	0.9312 / 0.9435	0.9305 / 0.9408	0.9314 / 0.9440
Max-JSD	0.9792 / 0.9784	0.9872 / 0.9808	0.9793 / 0.9784	0.9871 / 0.9807
Min-JSD	0.8813 / 0.7833	0.8855 / 0.8071	0.8715 / 0.7847	0.8775 / 0.8133
Median-JSD	0.2499 / 0.4439	0.2407 / 0.4258	0.2511 / 0.4472	0.2414 / 0.4302
Mean-KLD	0.9925 / 0.9943	0.9803 / 0.9887	0.9926 / 0.9943	0.9803 / 0.9887
Max-KLD	0.8043 / 0.7857	0.7832 / 0.7830	0.7790 / 0.7212	0.7580 / 0.7218
Min-KLD	0.8651 / 0.7926	0.8598 / 0.7856	0.8619 / 0.7783	0.8537 / 0.7693
Median-KLD	0.2970 / 0.4802	0.2591 / 0.4639	0.2960 / 0.4806	0.2571 / 0.4643

Table 23: Comparing GCs on clean and noisy data for the LSTM (En-LM) model, assessing AUROC/AUPRC with 100 samples each from clean test data, C&W AEs, and Psychoacoustic AEs.

	C&W attack		**Psychoacoustic attack**	
Score-Characteristic	**Noisy data vs. AEs**	**Benign data vs. AEs**	**Noisy data vs. AEs**	**Benign data vs. AEs**
Mean-Entropy	0.9889 / 0.9923	0.9895 / 0.9931	0.9899 / 0.9927	0.9906 / 0.9936
Max-Entropy	0.9604 / 0.9574	0.9775 / 0.9727	0.9587 / 0.9545	0.9745 / 0.9682
Min-Entropy	0.9922 / 0.9935	0.9913 / 0.9925	0.9908 / 0.9923	0.9895 / 0.9908
Median-Entropy	0.9846 / 0.9903	0.9935 / 0.9950	0.9858 / 0.9908	**0.9943 / 0.9955**
Mean-Max	0.9760 / 0.9838	0.9850 / 0.9914	0.9775 / 0.9846	0.9858 / 0.9917
Max-Max	**0.9949 / 0.9954**	**0.9946 / 0.9950**	**0.9939 / 0.9946**	0.9936 / 0.9941
Min-Max	0.9361 / 0.9053	0.9606 / 0.9245	0.9316 / 0.8820	0.9543 / 0.8989
Median-Max	0.9829 / 0.9891	0.9867 / 0.9921	0.9843 / 0.9899	0.9877 / 0.9925
Mean-Min	0.7303 / 0.7413	0.7314 / 0.7406	0.7405 / 0.7486	0.7405 / 0.7480
Max-Min	0.6505 / 0.6348	0.6734 / 0.6645	0.6444 / 0.6030	0.6639 / 0.6477
Min-Min	0.7277 / 0.7242	0.7140 / 0.6860	0.7293 / 0.7233	0.7140 / 0.6817
Median-Min	0.6071 / 0.5909	0.6065 / 0.5799	0.6152 / 0.5908	0.6137 / 0.5798
Mean-Median	0.9603 / 0.9648	0.9557 / 0.9598	0.9631 / 0.9669	0.9601 / 0.9629
Max-Median	0.9294 / 0.9210	0.9519 / 0.9481	0.9311 / 0.9265	0.9537 / 0.9524
Min-Median	0.8821 / 0.8876	0.8650 / 0.8693	0.8726 / 0.8657	0.8538 / 0.8477
Median-Median	0.7448 / 0.7329	0.7455 / 0.7365	0.7636 / 0.7668	0.7651 / 0.7686
Mean-JSD	0.9808 / 0.9866	0.9845 / 0.9903	0.9818 / 0.9874	0.9853 / 0.9909
Max-JSD	0.9706 / 0.9727	0.9756 / 0.9742	0.9668 / 0.9643	0.9717 / 0.9668
Min-JSD	0.6186 / 0.5869	0.6481 / 0.5707	0.6304 / 0.5882	0.6587 / 0.5735
Median-JSD	0.9848 / 0.9901	0.9875 / 0.9920	0.9855 / 0.9904	0.9873 / 0.9920
Mean-KLD	0.9836 / 0.9909	0.9866 / 0.9922	0.9840 / 0.9910	0.9870 / 0.9924
Max-KLD	0.8095 / 0.7712	0.8165 / 0.7515	0.8102 / 0.7734	0.8183 / 0.7604
Min-KLD	0.8343 / 0.8542	0.8807 / 0.8805	0.8316 / 0.8520	0.8787 / 0.8753
Median-KLD	0.9808 / 0.9875	0.9873 / 0.9919	0.9826 / 0.9892	0.9887 / 0.9932

Table 24: Comparing GCs on clean and noisy data for the wav2vec (Ma) model, assessing AUROC/AUPRC with 100 samples each from clean test data, C&W AEs, and Psychoacoustic AEs.

	C&W attack		**Psychoacoustic attack**	
Score-Characteristic	**Noisy data vs. AEs**	**Benign data vs. AEs**	**Noisy data vs. AEs**	**Benign data vs. AEs**
Mean-Entropy	0.9304 / 0.9516	**0.9847 / 0.9861**	**0.9359 / 0.9563**	**0.9877 / 0.9890**
Max-Entropy	0.9191 / 0.9464	0.9656 / 0.9757	0.9168 / 0.9449	0.9651 / 0.9751
Min-Entropy	0.4755 / 0.4991	0.4801 / 0.4981	0.4738 / 0.4991	0.4786 / 0.4984
Median-Entropy	0.8618 / 0.8151	0.8742 / 0.8076	0.8602 / 0.8284	0.8725 / 0.8293
Mean-Max	0.8018 / 0.7473	0.8562 / 0.7748	0.8205 / 0.7615	0.8777 / 0.7978
Max-Max	0.4655 / 0.4928	0.4710 / 0.5065	0.4881 / 0.4987	0.4935 / 0.5146
Min-Max	**0.9413 / 0.9488**	0.9752 / 0.9700	0.9341 / 0.9404	0.9686 / 0.9623
Median-Max	0.6932 / 0.6398	0.7052 / 0.6190	0.6779 / 0.6409	0.6910 / 0.6198
Mean-Min	0.8056 / 0.7694	0.8624 / 0.8121	0.8098 / 0.7834	0.8665 / 0.8325
Max-Min	0.8944 / 0.9026	0.9587 / 0.9433	0.9044 / 0.9236	0.9688 / 0.9671
Min-Min	0.4487 / 0.4762	0.4448 / 0.4822	0.4693 / 0.4943	0.4634 / 0.4911
Median-Min	0.8804 / 0.8710	0.9144 / 0.8960	0.8889 / 0.8911	0.9215 / 0.9185
Mean-Median	0.9383 / 0.9526	0.9814 / 0.9820	0.9431 / 0.9575	0.9859 / 0.9866
Max-Median	0.8783 / 0.8795	0.9119 / 0.8954	0.8933 / 0.9180	0.9272 / 0.9385
Min-Median	0.7322 / 0.6711	0.7558 / 0.7082	0.7264 / 0.6731	0.7504 / 0.7058
Median-Median	0.8705 / 0.8471	0.8981 / 0.8685	0.8870 / 0.8770	0.9142 / 0.8931
Mean-JSD	0.8066 / 0.7671	0.8121 / 0.7649	0.7888 / 0.7128	0.7904 / 0.7022
Max-JSD	0.9295 / 0.8795	0.9422 / 0.8917	0.9357 / 0.9023	0.9497 / 0.9110
Min-JSD	0.5726 / 0.5591	0.6205 / 0.5930	0.5966 / 0.5652	0.6435 / 0.6042
Median-JSD	0.8090 / 0.7942	0.7787 / 0.7749	0.8008 / 0.7889	0.7691 / 0.7689
Mean-KLD	0.9226 / 0.8971	0.9505 / 0.9198	0.9240 / 0.9090	0.9533 / 0.9327
Max-KLD	0.6909 / 0.6416	0.7639 / 0.7198	0.7057 / 0.6566	0.7748 / 0.7335
Min-KLD	0.5710 / 0.5529	0.6131 / 0.5778	0.5926 / 0.5774	0.6330 / 0.5976
Median-KLD	0.8711 / 0.8661	0.8685 / 0.8733	0.8759 / 0.8824	0.8735 / 0.8885

Table 25: Comparing GCs on clean and noisy data for the wav2vec (Ge) model, assessing AUROC/AUPRC with 100 samples each from clean test data, C&W AEs, and Psychoacoustic AEs.

	C&W attack		**Psychoacoustic attack**	
Score-Characteristic	**Noisy data vs. AEs**	**Benign data vs. AEs**	**Noisy data vs. AEs**	**Benign data vs. AEs**
Mean-Entropy	0.9659 / 0.9609	0.9782 / 0.9755	0.9394 / 0.9313	0.9577 / 0.9506
Max-Entropy	0.9587 / 0.9682	0.9832 / 0.9867	0.9314 / 0.9181	0.9612 / 0.9333
Min-Entropy	0.6523 / 0.5829	0.6677 / 0.6020	0.6885 / 0.6313	0.7070 / 0.6421
Median-Entropy	0.9707 / 0.9674	0.9782 / 0.9720	0.9592 / 0.9482	0.9713 / 0.9534
Mean-Max	0.9000 / 0.8961	0.9176 / 0.9178	0.8729 / 0.8650	0.8958 / 0.8915
Max-Max	0.6418 / 0.5844	0.6521 / 0.5904	0.6518 / 0.5915	0.6621 / 0.5975
Min-Max	0.9277 / 0.9422	0.9313 / 0.9528	0.8933 / 0.8756	0.9003 / 0.8866
Median-Max	0.9652 / 0.9483	0.9722 / 0.9522	0.9571 / 0.9413	0.9697 / 0.9493
Mean-Min	0.9842 / 0.9878	0.9916 / 0.9951	0.9661 / 0.9673	0.9849 / 0.9874
Max-Min	0.9653 / 0.9725	**0.9955 / 0.9968**	0.9430 / 0.9515	0.9871 / 0.9886
Min-Min	0.6702 / 0.6191	0.7755 / 0.7527	0.6530 / 0.6029	0.7652 / 0.7377
Median-Min	0.9820 / 0.9867	0.9907 / 0.9949	0.9632 / 0.9668	0.9863 / 0.9902
Mean-Median	**0.9882 / 0.9916**	0.9925 / 0.9957	0.9762 / 0.9796	**0.9904 / 0.9936**
Max-Median	0.9722 / 0.9786	0.9945 / 0.9963	0.9512 / 0.9587	0.9886 / 0.9909
Min-Median	0.7049 / 0.6920	0.7855 / 0.7429	0.6907 / 0.6369	0.7594 / 0.6767
Median-Median	0.9871 / 0.9906	0.9920 / 0.9954	0.9739 / 0.9777	0.9901 / 0.9937
Mean-JSD	0.5886 / 0.5690	0.5926 / 0.5952	0.5925 / 0.5803	0.5955 / 0.5980
Max-JSD	0.6457 / 0.5488	0.6500 / 0.5470	0.5896 / 0.5152	0.5940 / 0.5139
Min-JSD	0.4062 / 0.4272	0.4276 / 0.4314	0.3717 / 0.4086	0.3920 / 0.4135
Median-JSD	0.4632 / 0.4811	0.4463 / 0.4690	0.4833 / 0.4844	0.4714 / 0.4742
Mean-KLD	0.9848 / 0.9881	0.9842 / 0.9882	**0.9769 / 0.9805**	0.9758 / 0.9802
Max-KLD	0.8647 / 0.8146	0.8945 / 0.8332	0.8966 / 0.8950	0.9299 / 0.9218
Min-KLD	0.4115 / 0.4252	0.4535 / 0.4692	0.3802 / 0.4101	0.4160 / 0.4386
Median-KLD	0.7156 / 0.7853	0.5832 / 0.7004	0.7028 / 0.7222	0.5787 / 0.6448

Table 26: Comparing GCs on clean and noisy data for the Trf (Ma) model, assessing AUROC/AUPRC with 100 samples each from clean test data, C&W AEs, and Psychoacoustic AEs.

	C&W attack		**Psychoacoustic attack**	
Score-Characteristic	**Noisy data vs. AEs**	**Benign data vs. AEs**	**Noisy data vs. AEs**	**Benign data vs. AEs**
Mean-Entropy	0.9640 / 0.9643	0.9845 / 0.9806	0.9652 / 0.9723	**0.9902 / 0.9913**
Max-Entropy	0.9449 / 0.9462	0.9714 / 0.9686	0.9405 / 0.9470	0.9710 / 0.9704
Min-Entropy	0.7269 / 0.6768	0.7623 / 0.6765	0.7659 / 0.7399	0.8011 / 0.7427
Median-Entropy	**0.9758 / 0.9516**	0.9888 / 0.9651	**0.9768 / 0.9672**	0.9900 / 0.9756
Mean-Max	0.9370 / 0.9383	0.9640 / 0.9596	0.9350 / 0.9459	0.9658 / 0.9697
Max-Max	0.6942 / 0.6329	0.7444 / 0.6672	0.6895 / 0.6258	0.7362 / 0.6587
Min-Max	0.9392 / 0.9287	0.9616 / 0.9456	0.9279 / 0.9254	0.9532 / 0.9420
Median-Max	0.9754 / 0.9686	**0.9902 / 0.9800**	0.9749 / 0.9630	0.9898 / 0.9720
Mean-Min	0.9574 / 0.9604	0.9877 / 0.9846	0.9617 / 0.9670	0.9898 / 0.9895
Max-Min	0.9312 / 0.9381	0.9734 / 0.9694	0.9272 / 0.9415	0.9772 / 0.9782
Min-Min	0.8524 / 0.8271	0.8882 / 0.8563	0.8686 / 0.8486	0.9013 / 0.8673
Median-Min	0.9304 / 0.9414	0.9744 / 0.9755	0.9309 / 0.9420	0.9743 / 0.9766
Mean-Median	0.9501 / 0.9526	0.9813 / 0.9778	0.9552 / 0.9594	0.9838 / 0.9826
Max-Median	0.9135 / 0.9084	0.9288 / 0.9194	0.9056 / 0.9123	0.9221 / 0.9243
Min-Median	0.8269 / 0.8071	0.8673 / 0.8325	0.8516 / 0.8230	0.8908 / 0.8554
Median-Median	0.9126 / 0.9240	0.9582 / 0.9587	0.9155 / 0.9259	0.9600 / 0.9610
Mean-JSD	0.5298 / 0.5220	0.5471 / 0.5346	0.5321 / 0.5281	0.5448 / 0.5420
Max-JSD	0.7353 / 0.6682	0.7415 / 0.6570	0.8301 / 0.7646	0.8450 / 0.7649
Min-JSD	0.9071 / 0.8349	0.9096 / 0.8314	0.8217 / 0.7458	0.8222 / 0.7262
Median-JSD	0.9445 / 0.9453	0.9653 / 0.9551	0.9407 / 0.9305	0.9601 / 0.9355
Mean-KLD	0.8082 / 0.7941	0.8447 / 0.8413	0.8027 / 0.7663	0.8415 / 0.8126
Max-KLD	0.7386 / 0.6619	0.7507 / 0.6879	0.7329 / 0.6543	0.7450 / 0.6851
Min-KLD	0.8820 / 0.8628	0.8943 / 0.8720	0.7920 / 0.7664	0.8091 / 0.7729
Median-KLD	0.9443 / 0.9482	0.9689 / 0.9578	0.9364 / 0.9161	0.9637 / 0.9315

Table 27: Comparing GCs on clean and noisy data for the Trf (En) model, assessing AUROC/AUPRC with 100 samples each from clean test data, C&W AEs, and Psychoacoustic AEs.

Score-Characteristic	C&W attack		Psychoacoustic attack	
	Noisy data vs. AEs	**Benign data vs. AEs**	**Noisy data vs. AEs**	**Benign data vs. AEs**
Mean-Entropy	**0.9897 / 0.9911**	0.9999 / 0.9999	0.9794 / 0.9796	0.9959 / 0.9951
Max-Entropy	0.9509 / 0.9663	0.9989 / 0.9989	0.9397 / 0.9380	0.9895 / 0.9700
Min-Entropy	0.9352 / 0.9142	0.9635 / 0.9272	0.9271 / 0.9184	0.9629 / 0.9421
Median-Entropy	0.9846 / 0.9885	0.9997 / 0.9997	0.9789 / 0.9836	0.9984 / 0.9985
Mean-Max	0.9861 / 0.9880	0.9994 / 0.9994	0.9672 / 0.9635	0.9884 / 0.9844
Max-Max	0.9248 / 0.9088	0.9633 / 0.9428	0.9138 / 0.8991	0.9619 / 0.9395
Min-Max	0.9252 / 0.9097	0.9682 / 0.9417	0.9032 / 0.8830	0.9486 / 0.9134
Median-Max	0.9835 / 0.9878	0.9992 / 0.9992	0.9787 / 0.9834	0.9983 / 0.9984
Mean-Min	0.9733 / 0.9808	0.9985 / 0.9987	0.9666 / 0.9761	0.9979 / 0.9983
Max-Min	0.9005 / 0.9425	0.9999 / 0.9999	0.9009 / 0.9422	0.9999 / 0.9999
Min-Min	0.9054 / 0.8908	0.9338 / 0.9183	0.8948 / 0.8617	0.9248 / 0.8941
Median-Min	0.9717 / 0.9787	0.9984 / 0.9986	0.9618 / 0.9709	0.9975 / 0.9980
Mean-Median	0.9864 / 0.9900	0.9998 / 0.9998	0.9821 / 0.9867	0.9993 / 0.9993
Max-Median	0.9299 / 0.9566	**1.0000 / 1.0000**	0.9269 / 0.9541	**1.0000 / 1.0000**
Min-Median	0.9307 / 0.9256	0.9560 / 0.9516	0.9230 / 0.9137	0.9498 / 0.9435
Median-Median	**0.9897 / 0.9919**	0.9999 / 0.9999	**0.9860 / 0.9892**	0.9996 / 0.9996
Mean-JSD	0.5715 / 0.5876	0.5621 / 0.5674	0.5934 / 0.5940	0.5864 / 0.5836
Max-JSD	0.9664 / 0.9657	0.9840 / 0.9756	0.9660 / 0.9655	0.9851 / 0.9761
Min-JSD	0.8169 / 0.7506	0.8112 / 0.7362	0.7960 / 0.7053	0.7899 / 0.6875
Median-JSD	0.9180 / 0.8757	0.9400 / 0.8769	0.8828 / 0.8001	0.9039 / 0.8093
Mean-KLD	0.8612 / 0.9011	0.8797 / 0.9104	0.8683 / 0.9056	0.8868 / 0.9165
Max-KLD	0.8734 / 0.8825	0.8912 / 0.8982	0.8833 / 0.8808	0.8986 / 0.8947
Min-KLD	0.7115 / 0.6631	0.7557 / 0.6719	0.6937 / 0.6744	0.7463 / 0.6902
Median-KLD	0.8882 / 0.8065	0.9094 / 0.8030	0.8670 / 0.7941	0.8863 / 0.7789

H EVALUATION OF BINARY CLASSIFIERS FOR IDENTIFYING TARGETED ATTACKS

To evaluate the performance of our classifiers, we compute various metrics, including accuracy, false positive rate (FPR), true positive rate (TPR), precision, recall, and F1 score. These metrics are derived from the analysis of two types of errors: false positives (FP) and true negatives (TN) across all models. To calculate these metrics, we employ a conservative threshold chosen based on a validation set to achieve a maximum 1% FPR (if applicable) while maintaining a minimum 50% TPR. To determine the threshold, the validation set considers only benign data and C&W AEs, which is then applied to noisy data and Psychoacoustic AEs.

LSTM (It) model performance Tab. 28: C&W AEs vs. benign data, Tab. 29: C&W AEs vs. noisy data, Tab. 30: Psychoacoustic AEs vs. benign data, Tab. 31: Psychoacoustic AEs vs. noisy data.

Table 28: LSTM (It) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 C&W AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	80.50%	67	6	94	33	0.06	0.67	0.9178	0.6700	0.7746
TD	77.50%	64	9	91	36	0.09	0.64	0.8767	0.6400	0.7399
GC	98.00%	96	0	100	4	0.00	0.96	1.0000	0.9600	0.9796
EM=3	92.50%	85	0	100	15	0.00	0.85	1.0000	0.8500	0.9189
EM=5	89.50%	79	0	100	21	0.00	0.79	1.0000	0.7900	0.8827
EM=7	86.50%	73	0	100	27	0.00	0.73	1.0000	0.7300	0.8439
EM=9	86.50%	73	0	100	27	0.00	0.73	1.0000	0.7300	0.8439
NN	96.00%	92	0	100	8	0.00	0.92	1.0000	0.9200	0.9583

Table 29: LSTM (It) binary classifiers' metrics, using a threshold of maximum 1% FPR (if applicable) and a minimum 50% TPR, with 100 noisy data and 100 C&W AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	77.00%	60	6	94	40	0.06	0.60	0.9091	0.6000	0.7229
TD	75.00%	59	9	91	41	0.09	0.59	0.8676	0.5900	0.7024
GC	88.50%	77	0	100	23	0.00	0.77	1.0000	0.7700	0.8701
EM=3	83.00%	66	0	100	34	0.00	0.66	1.0000	0.6600	0.7952
EM=5	79.50%	59	0	100	41	0.00	0.59	1.0000	0.5900	0.7421
EM=7	78.00%	56	0	100	44	0.00	0.56	1.0000	0.5600	0.7179
EM=9	77.50%	55	0	100	45	0.00	0.55	1.0000	0.5500	0.7097
NN	85.00%	71	1	99	29	0.01	0.71	0.9861	0.7100	0.8256

Table 30: LSTM (It) binary classifiers' metrics, with a threshold of maximum 1% FPR (if exist) and a minimum 50% TPR, with 100 benign and 100 Psychoacoustic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	82.00%	67	3	97	33	0.03	0.67	0.9571	0.6700	0.7882
TD	77.50%	64	9	91	36	0.09	0.64	0.8767	0.6400	0.7399
GC	97.50%	96	1	99	4	0.01	0.96	0.9897	0.9600	0.9746
EM=3	92.50%	85	0	100	15	0.00	0.85	1.0000	0.8500	0.9189
EM=5	89.50%	79	0	100	21	0.00	0.79	1.0000	0.7900	0.8827
EM=7	86.00%	73	1	99	27	0.01	0.73	0.9865	0.7300	0.8391
EM=9	86.50%	73	0	100	27	0.00	0.73	1.0000	0.7300	0.8439
NN	96.00%	92	0	100	8	0.00	0.92	1.0000	0.9200	0.9583

Table 31: LSTM (It) binary classifiers' metrics, with a threshold of maximum 1% FPR (if exist) and a minimum 50% TPR, with 100 noisy data and 100 Psychoacoustic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	78.50%	60	3	97	40	0.03	0.60	0.9524	0.6000	0.7362
TD	75.00%	59	9	91	41	0.09	0.59	0.8676	0.5900	0.7024
GC	88.00%	77	1	99	23	0.01	0.77	0.9872	0.7700	0.8652
EM=3	83.00%	66	0	100	34	0.00	0.66	1.0000	0.6600	0.7952
EM=5	79.50%	59	0	100	41	0.00	0.59	1.0000	0.5900	0.7421
EM=7	77.50%	56	1	99	44	0.01	0.56	0.9825	0.5600	0.7134
EM=9	77.50%	55	0	100	45	0.00	0.55	1.0000	0.5500	0.7097
NN	85.00%	71	1	99	29	0.01	0.71	0.9861	0.7100	0.8256

LSTM (En) model performance Tab. 32: C&W AEs vs. benign data, Tab. 33: C&W AEs vs. noisy data, Tab. 34: Psychoacoustic AEs vs. benign data, Tab. 35: Psychoacoustic AEs vs. noisy data.

Table 32: LSTM (En) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 C&W AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	80.50%	62	1	99	38	0.01	0.62	0.9841	0.6200	0.7607
TD	82.41%	65	1	99	34	0.01	0.66	0.9848	0.6566	0.7879
GC	98.50%	100	3	97	0	0.03	1.00	0.9709	1.0000	0.9852
EM=3	98.50%	97	0	100	3	0.00	0.97	1.0000	0.9700	0.9848
EM=5	99.00%	98	0	100	2	0.00	0.98	1.0000	0.9800	0.9899
EM=7	99.00%	98	0	100	2	0.00	0.98	1.0000	0.9800	0.9899
EM=9	98.50%	97	0	100	3	0.00	0.97	1.0000	0.9700	0.9848
NN	98.00%	97	1	99	3	0.01	0.97	0.9898	0.9700	0.9798

Table 33: LSTM (En) binary classifiers' metrics, using a threshold of maximum 1% FPR (if applicable) and a minimum 50% TPR, with 100 noisy data and 100 C&W AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	78.50%	58	1	99	42	0.01	0.58	0.9831	0.5800	0.7296
TD	82.41%	65	1	99	34	0.01	0.66	0.9848	0.6566	0.7879
GC	97.50%	98	3	97	2	0.03	0.98	0.9703	0.9800	0.9751
EM=3	96.50%	93	0	100	7	0.00	0.93	1.0000	0.9300	0.9637
EM=5	96.50%	93	0	100	7	0.00	0.93	1.0000	0.9300	0.9637
EM=7	96.50%	93	0	100	7	0.00	0.93	1.0000	0.9300	0.9637
EM=9	96.00%	92	0	100	8	0.00	0.92	1.0000	0.9200	0.9583
NN	95.50%	92	1	99	8	0.01	0.92	0.9892	0.9200	0.9534

Table 34: LSTM (En) binary classifiers' metrics, with a threshold of maximum 1% FPR (if exist) and a minimum 50% TPR, with 100 benign and 100 Psychoacoustic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	80.00%	62	2	98	38	0.02	0.62	0.9688	0.6200	0.7561
TD	82.41%	65	1	99	34	0.01	0.66	0.9848	0.6566	0.7879
GC	98.50%	100	3	97	0	0.03	1.00	0.9709	1.0000	0.9852
EM=3	98.50%	97	0	100	3	0.00	0.97	1.0000	0.9700	0.9848
EM=5	99.00%	98	0	100	2	0.00	0.98	1.0000	0.9800	0.9899
EM=7	99.00%	98	0	100	2	0.00	0.98	1.0000	0.9800	0.9899
EM=9	98.50%	97	0	100	3	0.00	0.97	1.0000	0.9700	0.9848
NN	98.00%	97	1	99	3	0.01	0.97	0.9898	0.9700	0.9798

Table 35: LSTM (En) binary classifiers' metrics, with a threshold of maximum 1% FPR (if exist) and a minimum 50% TPR, with 100 noisy data and 100 Psychoacoustic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	78.00%	58	2	98	42	0.02	0.58	0.9667	0.5800	0.7250
TD	82.41%	65	1	99	34	0.01	0.66	0.9848	0.6566	0.7879
GC	97.50%	98	3	97	2	0.03	0.98	0.9703	0.9800	0.9751
EM=3	96.50%	93	0	100	7	0.00	0.93	1.0000	0.9300	0.9637
EM=5	96.50%	93	0	100	7	0.00	0.93	1.0000	0.9300	0.9637
EM=7	96.50%	93	0	100	7	0.00	0.93	1.0000	0.9300	0.9637
EM=9	96.00%	92	0	100	8	0.00	0.92	1.0000	0.9200	0.9583
NN	95.50%	92	1	99	8	0.01	0.92	0.9892	0.9200	0.9534

LSTM (En-LM) model performance Tab. 36: C&W AEs vs. benign data, Tab. 37: C&W AEs vs. noisy data, Tab. 38: Psychoacoustic AEs vs. benign data, Tab. 39: Psychoacoustic AEs vs. noisy data.

Table 36: LSTM (En-LM) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 C&W AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	89.00%	78	0	100	22	0.00	0.78	1.0000	0.7800	0.8764
TD	81.50%	70	7	93	30	0.07	0.70	0.9091	0.7000	0.7910
GC	83.00%	67	1	99	33	0.01	0.67	0.9853	0.6700	0.7976
EM=3	91.00%	84	2	98	16	0.02	0.84	0.9767	0.8400	0.9032
EM=5	93.00%	87	1	99	13	0.01	0.87	0.9886	0.8700	0.9255
EM=7	97.00%	95	1	99	5	0.01	0.95	0.9896	0.9500	0.9694
EM=9	94.00%	90	2	98	10	0.02	0.90	0.9783	0.9000	0.9375
NN	92.50%	86	1	99	14	0.01	0.86	0.9885	0.8600	0.9198

Table 37: LSTM (En-LM) binary classifiers' metrics, using a threshold of maximum 1% FPR (if applicable) and a minimum 50% TPR, with 100 noisy data and 100 C&W AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	83.50%	67	0	100	33	0.00	0.67	1.0000	0.6700	0.8024
TD	80.00%	67	7	93	33	0.07	0.67	0.9054	0.6700	0.7701
GC	79.00%	59	1	99	41	0.01	0.59	0.9833	0.5900	0.7375
EM=3	86.50%	75	2	98	25	0.02	0.75	0.9740	0.7500	0.8475
EM=5	88.00%	77	1	99	23	0.01	0.77	0.9872	0.7700	0.8652
EM=7	93.00%	87	1	99	13	0.01	0.87	0.9886	0.8700	0.9255
EM=9	88.00%	78	2	98	22	0.02	0.78	0.9750	0.7800	0.8667
NN	91.50%	84	1	99	16	0.01	0.84	0.9882	0.8400	0.9081

Table 38: LSTM (En-LM) binary classifiers' metrics, with a threshold of maximum 1% FPR (if exist) and a minimum 50% TPR, with 100 benign and 100 Psychoacoustic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	89.00%	78	0	100	22	0.00	0.78	1.0000	0.7800	0.8764
TD	82.50%	70	5	95	30	0.05	0.70	0.9333	0.7000	0.8000
GC	83.50%	67	0	100	33	0.00	0.67	1.0000	0.6700	0.8024
EM=3	91.00%	84	2	98	16	0.02	0.84	0.9767	0.8400	0.9032
EM=5	93.00%	87	1	99	13	0.01	0.87	0.9886	0.8700	0.9255
EM=7	97.00%	95	1	99	5	0.01	0.95	0.9896	0.9500	0.9694
EM=9	94.50%	90	1	99	10	0.01	0.90	0.9890	0.9000	0.9424
NN	92.50%	86	1	99	14	0.01	0.86	0.9885	0.8600	0.9198

Table 39: LSTM (En-LM) binary classifiers' metrics, with a threshold of maximum 1% FPR (if exist) and a minimum 50% TPR, with 100 noisy data and 100 Psychoacoustic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	83.50%	67	0	100	33	0.00	0.67	1.0000	0.6700	0.8024
TD	81.00%	67	5	95	33	0.05	0.67	0.9306	0.6700	0.7791
GC	79.50%	59	0	100	41	0.00	0.59	1.0000	0.5900	0.7421
EM=3	86.50%	75	2	98	25	0.02	0.75	0.9740	0.7500	0.8475
EM=5	88.00%	77	1	99	23	0.01	0.77	0.9872	0.7700	0.8652
EM=7	93.00%	87	1	99	13	0.01	0.87	0.9886	0.8700	0.9255
EM=9	88.50%	78	1	99	22	0.01	0.78	0.9873	0.7800	0.8715
NN	91.50%	84	1	99	16	0.01	0.84	0.9882	0.8400	0.9081

wav2vec (Ma) model performance Tab. 40: C&W AEs vs. benign data, Tab. 41: C&W AEs vs. noisy data, Tab. 42: Psychoacoustic AEs vs. benign data, Tab. 43: Psychoacoustic AEs vs. noisy data.

Table 40: wav2vec (Ma) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 C&W AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	73.00%	47	1	99	53	0.01	0.47	0.9792	0.4700	0.6351
TD	97.50%	95	0	100	5	0.00	0.95	1.0000	0.9500	0.9744
GC	90.50%	81	0	100	19	0.00	0.81	1.0000	0.8100	0.8950
EM=3	94.00%	89	1	99	11	0.01	0.89	0.9889	0.8900	0.9368
EM=5	92.50%	85	0	100	15	0.00	0.85	1.0000	0.8500	0.9189
EM=7	87.00%	74	0	100	26	0.00	0.74	1.0000	0.7400	0.8506
EM=9	86.50%	73	0	100	27	0.00	0.73	1.0000	0.7300	0.8439
NN	93.50%	88	1	99	12	0.01	0.88	0.9888	0.8800	0.9312

Table 41: wav2vec (Ma) binary classifiers' metrics, using a threshold of maximum 1% FPR (if applicable) and a minimum 50% TPR, with 100 noisy data and 100 C&W AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	63.00%	27	1	99	73	0.01	0.27	0.9643	0.2700	0.4219
TD	96.00%	92	0	100	8	0.00	0.92	1.0000	0.9200	0.9583
GC	85.00%	70	0	100	30	0.00	0.70	1.0000	0.7000	0.8235
EM=3	87.50%	76	1	99	24	0.01	0.76	0.9870	0.7600	0.8588
EM=5	86.50%	73	0	100	27	0.00	0.73	1.0000	0.7300	0.8439
EM=7	83.50%	67	0	100	33	0.00	0.67	1.0000	0.6700	0.8024
EM=9	83.50%	67	0	100	33	0.00	0.67	1.0000	0.6700	0.8024
NN	85.50%	72	1	99	28	0.01	0.72	0.9863	0.7200	0.8324

Table 42: wav2vec (Ma) binary classifiers' metrics, with a threshold of maximum 1% FPR (if exist) and a minimum 50% TPR, with 100 benign and 100 Psychoacoustic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	73.00%	47	1	99	53	0.01	0.47	0.9792	0.4700	0.6351
TD	97.50%	95	0	100	5	0.00	0.95	1.0000	0.9500	0.9744
GC	90.50%	81	0	100	19	0.00	0.81	1.0000	0.8100	0.8950
EM=3	94.00%	89	1	99	11	0.01	0.89	0.9889	0.8900	0.9368
EM=5	92.50%	85	0	100	15	0.00	0.85	1.0000	0.8500	0.9189
EM=7	87.00%	74	0	100	26	0.00	0.74	1.0000	0.7400	0.8506
EM=9	86.50%	73	0	100	27	0.00	0.73	1.0000	0.7300	0.8439
NN	93.50%	88	1	99	12	0.01	0.88	0.9888	0.8800	0.9312

Table 43: wav2vec (Ma) binary classifiers' metrics, with a threshold of maximum 1% FPR (if exist) and a minimum 50% TPR, with 100 noisy data and 100 Psychoacoustic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	63.00%	27	1	99	73	0.01	0.27	0.9643	0.2700	0.4219
TD	96.00%	92	0	100	8	0.00	0.92	1.0000	0.9200	0.9583
GC	85.00%	70	0	100	30	0.00	0.70	1.0000	0.7000	0.8235
EM=3	87.50%	76	1	99	24	0.01	0.76	0.9870	0.7600	0.8588
EM=5	86.50%	73	0	100	27	0.00	0.73	1.0000	0.7300	0.8439
EM=7	83.50%	67	0	100	33	0.00	0.67	1.0000	0.6700	0.8024
EM=9	83.50%	67	0	100	33	0.00	0.67	1.0000	0.6700	0.8024
NN	85.50%	72	1	99	28	0.01	0.72	0.9863	0.7200	0.8324

wav2vec (Ge) model performance Tab. 44: C&W AEs vs. benign data, Tab. 45: C&W AEs vs. noisy data, Tab. 46: Psychoacoustic AEs vs. benign data, Tab. 47: Psychoacoustic AEs vs. noisy data.

Table 44: wav2vec (Ge) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 C&W AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	89.50%	80	1	99	20	0.01	0.80	0.9877	0.8000	0.8840
TD	98.00%	96	0	100	4	0.00	0.96	1.0000	0.9600	0.9796
GC	99.00%	98	0	100	2	0.00	0.98	1.0000	0.9800	0.9899
EM=3	96.00%	92	0	100	8	0.00	0.92	1.0000	0.9200	0.9583
EM=5	96.00%	92	0	100	8	0.00	0.92	1.0000	0.9200	0.9583
EM=7	94.50%	89	0	100	11	0.00	0.89	1.0000	0.8900	0.9418
EM=9	95.50%	91	0	100	9	0.00	0.91	1.0000	0.9100	0.9529
NN	94.00%	89	1	99	11	0.01	0.89	0.9889	0.8900	0.9368

Table 45: wav2vec (Ge) binary classifiers' metrics, using a threshold of maximum 1% FPR (if applicable) and a minimum 50% TPR, with 100 noisy data and 100 C&W AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	91.50%	84	1	99	16	0.01	0.84	0.9882	0.8400	0.9081
TD	94.00%	88	0	100	12	0.00	0.88	1.0000	0.8800	0.9362
GC	95.50%	91	0	100	9	0.00	0.91	1.0000	0.9100	0.9529
EM=3	91.50%	83	0	100	17	0.00	0.83	1.0000	0.8300	0.9071
EM=5	91.50%	83	0	100	17	0.00	0.83	1.0000	0.8300	0.9071
EM=7	89.50%	79	0	100	21	0.00	0.79	1.0000	0.7900	0.8827
EM=9	91.50%	83	0	100	17	0.00	0.83	1.0000	0.8300	0.9071
NN	88.00%	77	1	99	23	0.01	0.77	0.9872	0.7700	0.8652

Table 46: wav2vec (Ge) binary classifiers' metrics, with a threshold of maximum 1% FPR (if exist) and a minimum 50% TPR, with 100 benign and 100 Psychoacoustic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	89.50%	80	1	99	20	0.01	0.80	0.9877	0.8000	0.8840
TD	98.00%	96	0	100	4	0.00	0.96	1.0000	0.9600	0.9796
GC	99.00%	98	0	100	2	0.00	0.98	1.0000	0.9800	0.9899
EM=3	93.00%	92	6	94	8	0.06	0.92	0.9388	0.9200	0.9293
EM=5	92.00%	92	8	92	8	0.08	0.92	0.9200	0.9200	0.9200
EM=7	90.50%	89	8	92	11	0.08	0.89	0.9175	0.8900	0.9036
EM=9	93.00%	91	5	95	9	0.05	0.91	0.9479	0.9100	0.9286
NN	92.50%	86	1	99	14	0.01	0.86	0.9885	0.8600	0.9198

Table 47: wav2vec (Ge) binary classifiers' metrics, with a threshold of maximum 1% FPR (if exist) and a minimum 50% TPR, with 100 noisy data and 100 Psychoacoustic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	91.50%	84	1	99	16	0.01	0.84	0.9882	0.8400	0.9081
TD	94.00%	88	0	100	12	0.00	0.88	1.0000	0.8800	0.9362
GC	95.50%	91	0	100	9	0.00	0.91	1.0000	0.9100	0.9529
EM=3	88.50%	83	6	94	17	0.06	0.83	0.9326	0.8300	0.8783
EM=5	87.50%	83	8	92	17	0.08	0.83	0.9121	0.8300	0.8691
EM=7	85.50%	79	8	92	21	0.08	0.79	0.9080	0.7900	0.8449
EM=9	89.00%	83	5	95	17	0.05	0.83	0.9432	0.8300	0.8830
NN	86.00%	73	1	99	27	0.01	0.73	0.9865	0.7300	0.8391

Trf (Ma) model performance Tab. 48: C&W AEs vs. benign data, Tab. 49: C&W AEs vs. noisy data, Tab. 50: Psychoacoustic AEs vs. benign data, Tab. 51: Psychoacoustic AEs vs. noisy data.

Table 48: Trf (Ma) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 C&W AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	95.00%	90	0	100	10	0.00	0.90	1.0000	0.9000	0.9474
TD	81.00%	64	2	98	36	0.02	0.64	0.9697	0.6400	0.7711
GC	87.50%	75	0	100	25	0.00	0.75	1.0000	0.7500	0.8571
EM=3	90.50%	81	0	100	19	0.00	0.81	1.0000	0.8100	0.8950
EM=5	90.00%	80	0	100	20	0.00	0.80	1.0000	0.8000	0.8889
EM=7	90.50%	81	0	100	19	0.00	0.81	1.0000	0.8100	0.8950
EM=9	87.50%	75	0	100	25	0.00	0.75	1.0000	0.7500	0.8571
NN	98.50%	98	1	99	2	0.01	0.98	0.9899	0.9800	0.9849

Table 49: Trf (Ma) binary classifiers' metrics, using a threshold of maximum 1% FPR (if applicable) and a minimum 50% TPR, with 100 noisy data and 100 C&W AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	96.50%	93	0	100	7	0.00	0.93	1.0000	0.9300	0.9637
TD	81.50%	65	2	98	35	0.02	0.65	0.9701	0.6500	0.7784
GC	84.50%	69	0	100	31	0.00	0.69	1.0000	0.6900	0.8166
EM=3	83.00%	66	0	100	34	0.00	0.66	1.0000	0.6600	0.7952
EM=5	84.00%	68	0	100	32	0.00	0.68	1.0000	0.6800	0.8095
EM=7	84.00%	68	0	100	32	0.00	0.68	1.0000	0.6800	0.8095
EM=9	82.50%	65	0	100	35	0.00	0.65	1.0000	0.6500	0.7879
NN	91.50%	84	1	99	16	0.01	0.84	0.9882	0.8400	0.9081

Table 50: Trf (Ma) binary classifiers' metrics, with a threshold of maximum 1% FPR (if exist) and a minimum 50% TPR, with 100 benign and 100 Psychoacoustic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	95.00%	90	0	100	10	0.00	0.90	1.0000	0.9000	0.9474
TD	82.00%	64	0	100	36	0.00	0.64	1.0000	0.6400	0.7805
GC	87.50%	75	0	100	25	0.00	0.75	1.0000	0.7500	0.8571
EM=3	90.50%	81	0	100	19	0.00	0.81	1.0000	0.8100	0.8950
EM=5	90.00%	80	0	100	20	0.00	0.80	1.0000	0.8000	0.8889
EM=7	90.50%	81	0	100	19	0.00	0.81	1.0000	0.8100	0.8950
EM=9	87.50%	75	0	100	25	0.00	0.75	1.0000	0.7500	0.8571
NN	97.50%	96	1	99	4	0.01	0.96	0.9897	0.9600	0.9746

Table 51: Trf (Ma) binary classifiers' metrics, with a threshold of maximum 1% FPR (if exist) and a minimum 50% TPR, with 100 noisy data and 100 Psychoacoustic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	96.50%	93	0	100	7	0.00	0.93	1.0000	0.9300	0.9637
TD	82.50%	65	0	100	35	0.00	0.65	1.0000	0.6500	0.7879
GC	84.50%	69	0	100	31	0.00	0.69	1.0000	0.6900	0.8166
EM=3	83.00%	66	0	100	34	0.00	0.66	1.0000	0.6600	0.7952
EM=5	84.00%	68	0	100	32	0.00	0.68	1.0000	0.6800	0.8095
EM=7	84.00%	68	0	100	32	0.00	0.68	1.0000	0.6800	0.8095
EM=9	82.50%	65	0	100	35	0.00	0.65	1.0000	0.6500	0.7879
NN	90.50%	82	1	99	18	0.01	0.82	0.9880	0.8200	0.8962

Trf (En) model performance Tab. 52: C&W AEs vs. benign data, Tab. 53: C&W AEs vs. noisy data, Tab. 54: Psychoacoustic AEs vs. benign data, Tab. 55: Psychoacoustic AEs vs. noisy data.

Table 52: Trf (En) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 C&W AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	95.00%	91	1	99	9	0.01	0.91	0.9891	0.9100	0.9479
TD	95.00%	96	6	94	4	0.06	0.96	0.9412	0.9600	0.9505
GC	100.00%	100	0	100	0	0.00	1.00	1.0000	1.0000	1.0000
EM=3	99.50%	99	0	100	1	0.00	0.99	1.0000	0.9900	0.9950
EM=5	100.00%	100	0	100	0	0.00	1.00	1.0000	1.0000	1.0000
EM=7	100.00%	100	0	100	0	0.00	1.00	1.0000	1.0000	1.0000
EM=9	100.00%	100	0	100	0	0.00	1.00	1.0000	1.0000	1.0000
NN	99.00%	99	1	99	1	0.01	0.99	0.9900	0.9900	0.9900

Table 53: Trf (En) binary classifiers' metrics, using a threshold of maximum 1% FPR (if applicable) and a minimum 50% TPR, with 100 noisy data and 100 C&W AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	96.50%	94	1	99	6	0.01	0.94	0.9895	0.9400	0.9641
TD	88.00%	82	6	94	18	0.06	0.82	0.9318	0.8200	0.8723
GC	96.50%	93	0	100	7	0.00	0.93	1.0000	0.9300	0.9637
EM=3	94.50%	89	0	100	11	0.00	0.89	1.0000	0.8900	0.9418
EM=5	95.00%	90	0	100	10	0.00	0.90	1.0000	0.9000	0.9474
EM=7	95.00%	90	0	100	10	0.00	0.90	1.0000	0.9000	0.9474
EM=9	94.50%	89	0	100	11	0.00	0.89	1.0000	0.8900	0.9418
NN	92.50%	86	1	99	14	0.01	0.86	0.9885	0.8600	0.9198

Table 54: Trf (En) binary classifiers' metrics, with a threshold of maximum 1% FPR (if exist) and a minimum 50% TPR, with 100 benign and 100 Psychoacoustic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	95.00%	91	1	99	9	0.01	0.91	0.9891	0.9100	0.9479
TD	97.50%	96	1	99	4	0.01	0.96	0.9897	0.9600	0.9746
GC	99.50%	100	1	99	0	0.01	1.00	0.9901	1.0000	0.9950
EM=3	99.00%	99	1	99	1	0.01	0.99	0.9900	0.9900	0.9900
EM=5	99.50%	100	1	99	0	0.01	1.00	0.9901	1.0000	0.9950
EM=7	99.50%	100	1	99	0	0.01	1.00	0.9901	1.0000	0.9950
EM=9	99.50%	100	1	99	0	0.01	1.00	0.9901	1.0000	0.9950
NN	98.50%	98	1	99	2	0.01	0.98	0.9899	0.9800	0.9849

Table 55: Trf (En) binary classifiers' metrics, with a threshold of maximum 1% FPR (if exist) and a minimum 50% TPR, with 100 noisy data and 100 Psychoacoustic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	96.50%	94	1	99	6	0.01	0.94	0.9895	0.9400	0.9641
TD	90.50%	82	1	99	18	0.01	0.82	0.9880	0.8200	0.8962
GC	96.00%	93	1	99	7	0.01	0.93	0.9894	0.9300	0.9588
EM=3	94.00%	89	1	99	11	0.01	0.89	0.9889	0.8900	0.9368
EM=5	94.50%	90	1	99	10	0.01	0.90	0.9890	0.9000	0.9424
EM=7	94.50%	90	1	99	10	0.01	0.90	0.9890	0.9000	0.9424
EM=9	94.00%	89	1	99	11	0.01	0.89	0.9889	0.8900	0.9368
NN	90.00%	81	1	99	19	0.01	0.81	0.9878	0.8100	0.8901

I EVALUATION OF BINARY CLASSIFIERS FOR IDENTIFYING UNTARGETED ATTACKS

To evaluate the performance of our classifiers, we compute the same metrics as defined in Section H. To determine the threshold, the validation set considers only benign data and C&W AEs, which is then applied to PGD, genetic and Kenansville AEs.

LSTM (It) model performance Tab. 56: PGD AEs vs. benign data, Tab. 57: genetic AEs vs. benign data, Tab. 58: Kenansville AEs vs. benign data.

Table 56: LSTM (It) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 PGD AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	69.50%	67	28	72	33	0.28	0.67	0.7053	0.6700	0.6872
TD	64.00%	64	36	64	36	0.36	0.64	0.6400	0.6400	0.6400
GC	86.50%	96	23	77	4	0.23	0.96	0.8067	0.9600	0.8767
EM=3	85.00%	85	15	85	15	0.15	0.85	0.8500	0.8500	0.8500
EM=5	83.50%	79	12	88	21	0.12	0.79	0.8681	0.7900	0.8272
EM=7	81.00%	73	11	89	27	0.11	0.73	0.8690	0.7300	0.7935
EM=9	80.50%	73	12	88	27	0.12	0.73	0.8588	0.7300	0.7892
NN	81.00%	63	1	99	37	0.01	0.63	0.9844	0.6300	0.7683

Table 57: LSTM (It) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 genetic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	53.50%	67	60	40	33	0.60	0.67	0.5276	0.6700	0.5903
TD	51.00%	64	62	38	36	0.62	0.64	0.5079	0.6400	0.5664
GC	56.00%	96	84	16	4	0.84	0.96	0.5333	0.9600	0.6857
EM=3	55.50%	85	74	26	15	0.74	0.85	0.5346	0.8500	0.6564
EM=5	55.50%	79	68	32	21	0.68	0.79	0.5374	0.7900	0.6397
EM=7	52.00%	73	69	31	27	0.69	0.73	0.5141	0.7300	0.6033
EM=9	51.50%	73	70	30	27	0.70	0.73	0.5105	0.7300	0.6008
NN	62.50%	49	24	76	51	0.24	0.49	0.6712	0.4900	0.5665

Table 58: LSTM (It) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 Kenansville AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	79.00%	67	9	91	33	0.09	0.67	0.8816	0.6700	0.7614
TD	65.99%	64	31	66	36	0.32	0.64	0.6737	0.6400	0.6564
GC	78.00%	96	40	60	4	0.40	0.96	0.7059	0.9600	0.8136
EM=3	83.00%	85	19	81	15	0.19	0.85	0.8173	0.8500	0.8333
EM=5	82.50%	79	14	86	21	0.14	0.79	0.8495	0.7900	0.8187
EM=7	80.00%	73	13	87	27	0.13	0.73	0.8488	0.7300	0.7849
EM=9	79.50%	73	14	86	27	0.14	0.73	0.8391	0.7300	0.7807
NN	70.50%	49	8	92	51	0.08	0.49	0.8596	0.4900	0.6242

LSTM (En) model performance Tab. 59: PGD AEs vs. benign data, Tab. 60: genetic AEs vs. benign data, Tab. 61: Kenansville AEs vs. benign data.

Table 59: LSTM (En) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 PGD AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	79.00%	62	4	96	38	0.04	0.62	0.9394	0.6200	0.7470
TD	64.82%	65	36	64	34	0.36	0.66	0.6436	0.6566	0.6500
GC	76.00%	100	48	52	0	0.48	1.00	0.6757	1.0000	0.8065
EM=3	84.00%	97	29	71	3	0.29	0.97	0.7698	0.9700	0.8584
EM=5	87.00%	98	24	76	2	0.24	0.98	0.8033	0.9800	0.8829
EM=7	88.50%	98	21	79	2	0.21	0.98	0.8235	0.9800	0.8950
EM=9	88.00%	97	21	79	3	0.21	0.97	0.8220	0.9700	0.8899
NN	83.50%	68	1	99	32	0.01	0.68	0.9855	0.6800	0.8047

Table 60: LSTM (En) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 genetic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	51.00%	62	60	40	38	0.60	0.62	0.5082	0.6200	0.5586
TD	50.51%	65	64	35	34	0.65	0.66	0.5039	0.6566	0.5702
GC	50.50%	100	99	1	0	0.99	1.00	0.5025	1.0000	0.6689
EM=3	53.00%	97	91	9	3	0.91	0.97	0.5160	0.9700	0.6736
EM=5	52.50%	98	93	7	2	0.93	0.98	0.5131	0.9800	0.6735
EM=7	53.50%	98	91	9	2	0.91	0.98	0.5185	0.9800	0.6782
EM=9	53.00%	97	91	9	3	0.91	0.97	0.5160	0.9700	0.6736
NN	58.50%	49	32	68	51	0.32	0.49	0.6049	0.4900	0.5414

Table 61: LSTM (En) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 Kenansville AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	72.50%	62	17	83	38	0.17	0.62	0.7848	0.6200	0.6927
TD	67.84%	65	30	70	34	0.30	0.66	0.6842	0.6566	0.6701
GC	82.50%	100	35	65	0	0.35	1.00	0.7407	1.0000	0.8511
EM=3	83.50%	97	30	70	3	0.30	0.97	0.7638	0.9700	0.8546
EM=5	84.00%	98	30	70	2	0.30	0.98	0.7656	0.9800	0.8596
EM=7	84.00%	98	30	70	2	0.30	0.98	0.7656	0.9800	0.8596
EM=9	84.50%	97	28	72	3	0.28	0.97	0.7760	0.9700	0.8622
NN	70.00%	49	9	91	51	0.09	0.49	0.8448	0.4900	0.6203

LSTM (En-LM) model performance Tab. 62: PGD AEs vs. benign data, Tab. 63: genetic AEs vs. benign data, Tab. 64: Kenansville AEs vs. benign data.

Table 62: LSTM (En-LM) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 PGD AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	89.00%	78	0	100	22	0.00	0.78	1.0000	0.7800	0.8764
TD	77.00%	70	16	84	30	0.16	0.70	0.8140	0.7000	0.7527
GC	83.50%	67	0	100	33	0.00	0.67	1.0000	0.6700	0.8024
EM=3	87.50%	84	9	91	16	0.09	0.84	0.9032	0.8400	0.8705
EM=5	92.50%	87	2	98	13	0.02	0.87	0.9775	0.8700	0.9206
EM=7	90.00%	95	15	85	5	0.15	0.95	0.8636	0.9500	0.9048
EM=9	93.50%	90	3	97	10	0.03	0.90	0.9677	0.9000	0.9326
NN	72.50%	49	4	96	51	0.04	0.49	0.9245	0.4900	0.6405

Table 63: LSTM (En-LM) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 genetic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	63.50%	78	51	49	22	0.51	0.78	0.6047	0.7800	0.6812
TD	53.00%	70	64	36	30	0.64	0.70	0.5224	0.7000	0.5983
GC	58.50%	67	50	50	33	0.50	0.67	0.5726	0.6700	0.6175
EM=3	63.00%	84	58	42	16	0.58	0.84	0.5915	0.8400	0.6942
EM=5	63.50%	87	60	40	13	0.60	0.87	0.5918	0.8700	0.7045
EM=7	60.00%	95	75	25	5	0.75	0.95	0.5588	0.9500	0.7037
EM=9	65.00%	90	60	40	10	0.60	0.90	0.6000	0.9000	0.7200
NN	63.50%	49	22	78	51	0.22	0.49	0.6901	0.4900	0.5731

Table 64: LSTM (En-LM) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 Kenansville AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	77.50%	78	23	77	22	0.23	0.78	0.7723	0.7800	0.7761
TD	69.50%	70	31	69	30	0.31	0.70	0.6931	0.7000	0.6965
GC	70.50%	67	26	74	33	0.26	0.67	0.7204	0.6700	0.6943
EM=3	78.50%	84	27	73	16	0.27	0.84	0.7568	0.8400	0.7962
EM=5	78.50%	87	30	70	13	0.30	0.87	0.7436	0.8700	0.8018
EM=7	82.00%	95	31	69	5	0.31	0.95	0.7540	0.9500	0.8407
EM=9	80.50%	90	29	71	10	0.29	0.90	0.7563	0.9000	0.8219
NN	72.00%	49	5	95	51	0.05	0.49	0.9074	0.4900	0.6364

wav2vec (Ma) model performance Tab. 65: PGD AEs vs. benign data, Tab. 66: genetic AEs vs. benign data, Tab. 67: Kenansville AEs vs. benign data.

Table 65: wav2vec (Ma) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 PGD AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	73.50%	47	0	100	53	0.00	0.47	1.0000	0.4700	0.6395
TD	59.00%	95	77	23	5	0.77	0.95	0.5523	0.9500	0.6985
GC	77.50%	81	26	74	19	0.26	0.81	0.7570	0.8100	0.7826
EM=3	80.50%	89	28	72	11	0.28	0.89	0.7607	0.8900	0.8203
EM=5	84.00%	85	17	83	15	0.17	0.85	0.8333	0.8500	0.8416
EM=7	82.50%	74	9	91	26	0.09	0.74	0.8916	0.7400	0.8087
EM=9	80.00%	73	13	87	27	0.13	0.73	0.8488	0.7300	0.7849
NN	68.00%	49	13	87	51	0.13	0.49	0.7903	0.4900	0.6049

Table 66: wav2vec (Ma) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 genetic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	61.50%	47	24	76	53	0.24	0.47	0.6620	0.4700	0.5497
TD	57.00%	95	81	19	5	0.81	0.95	0.5398	0.9500	0.6884
GC	59.50%	81	62	38	19	0.62	0.81	0.5664	0.8100	0.6667
EM=3	60.50%	89	68	32	11	0.68	0.89	0.5669	0.8900	0.6926
EM=5	63.50%	85	58	42	15	0.58	0.85	0.5944	0.8500	0.6996
EM=7	60.00%	74	54	46	26	0.54	0.74	0.5781	0.7400	0.6491
EM=9	58.50%	73	56	44	27	0.56	0.73	0.5659	0.7300	0.6376
NN	64.50%	49	20	80	51	0.20	0.49	0.7101	0.4900	0.5799

Table 67: wav2vec (Ma) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 Kenansville AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	73.00%	47	1	99	53	0.01	0.47	0.9792	0.4700	0.6351
TD	75.50%	95	44	56	5	0.44	0.95	0.6835	0.9500	0.7950
GC	88.00%	81	5	95	19	0.05	0.81	0.9419	0.8100	0.8710
EM=3	92.50%	89	4	96	11	0.04	0.89	0.9570	0.8900	0.9223
EM=5	90.00%	85	5	95	15	0.05	0.85	0.9444	0.8500	0.8947
EM=7	84.00%	74	6	94	26	0.06	0.74	0.9250	0.7400	0.8222
EM=9	84.00%	73	5	95	27	0.05	0.73	0.9359	0.7300	0.8202
NN	72.50%	49	4	96	51	0.04	0.49	0.9245	0.4900	0.6405

wav2vec (Ge) model performance Tab. 68: PGD AEs vs. benign data, Tab. 69: genetic AEs vs. benign data, Tab. 70: Kenansville AEs vs. benign data.

Table 68: wav2vec (Ge) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 PGD AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	46.00%	80	88	12	20	0.88	0.80	0.4762	0.8000	0.5970
TD	64.50%	96	67	33	4	0.67	0.96	0.5890	0.9600	0.7300
GC	63.50%	98	71	29	2	0.71	0.98	0.5799	0.9800	0.7286
EM=3	69.00%	92	54	46	8	0.54	0.92	0.6301	0.9200	0.7480
EM=5	67.00%	92	58	42	8	0.58	0.92	0.6133	0.9200	0.7360
EM=7	68.50%	89	52	48	11	0.52	0.89	0.6312	0.8900	0.7386
EM=9	69.00%	91	53	47	9	0.53	0.91	0.6319	0.9100	0.7459
NN	53.00%	49	43	57	51	0.43	0.49	0.5326	0.4900	0.5104

Table 69: wav2vec (Ge) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 genetic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	48.00%	80	84	16	20	0.84	0.80	0.4878	0.8000	0.6061
TD	54.50%	96	87	13	4	0.87	0.96	0.5246	0.9600	0.6784
GC	52.00%	98	94	6	2	0.94	0.98	0.5104	0.9800	0.6712
EM=3	51.50%	92	89	11	8	0.89	0.92	0.5083	0.9200	0.6548
EM=5	51.00%	92	90	10	8	0.90	0.92	0.5055	0.9200	0.6525
EM=7	54.00%	89	81	19	11	0.81	0.89	0.5235	0.8900	0.6593
EM=9	52.50%	91	86	14	9	0.86	0.91	0.5141	0.9100	0.6570
NN	62.00%	49	25	75	51	0.25	0.49	0.6622	0.4900	0.5632

Table 70: wav2vec (Ge) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 Kenansville AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	69.50%	80	41	59	20	0.41	0.80	0.6612	0.8000	0.7240
TD	71.50%	96	53	47	4	0.53	0.96	0.6443	0.9600	0.7711
GC	82.00%	98	34	66	2	0.34	0.98	0.7424	0.9800	0.8448
EM=3	77.00%	92	38	62	8	0.38	0.92	0.7077	0.9200	0.8000
EM=5	77.50%	92	37	63	8	0.37	0.92	0.7132	0.9200	0.8035
EM=7	76.50%	89	36	64	11	0.36	0.89	0.7120	0.8900	0.7911
EM=9	78.50%	91	34	66	9	0.34	0.91	0.7280	0.9100	0.8089
NN	71.00%	49	7	93	51	0.07	0.49	0.8750	0.4900	0.6282

Trf (Ma) model performance Tab. 71: PGD AEs vs. benign data, Tab. 72: genetic AEs vs. benign data, Tab. 73: Kenansville AEs vs. benign data.

Table 71: Trf (Ma) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 PGD AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	55.00%	90	80	20	10	0.80	0.90	0.5294	0.9000	0.6667
TD	74.50%	64	15	85	36	0.15	0.64	0.8101	0.6400	0.7151
GC	70.50%	75	34	66	25	0.34	0.75	0.6881	0.7500	0.7177
EM=3	90.50%	81	0	100	19	0.00	0.81	1.0000	0.8100	0.8950
EM=5	90.00%	80	0	100	20	0.00	0.80	1.0000	0.8000	0.8889
EM=7	90.50%	81	0	100	19	0.00	0.81	1.0000	0.8100	0.8950
EM=9	87.50%	75	0	100	25	0.00	0.75	1.0000	0.7500	0.8571
NN	75.00%	51	1	99	49	0.01	0.51	0.9808	0.5100	0.6711

Table 72: Trf (Ma) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 genetic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	46.00%	90	98	2	10	0.98	0.90	0.4787	0.9000	0.6250
TD	56.50%	64	51	49	36	0.51	0.64	0.5565	0.6400	0.5953
GC	63.50%	75	48	52	25	0.48	0.75	0.6098	0.7500	0.6726
EM=3	72.00%	81	37	63	19	0.37	0.81	0.6864	0.8100	0.7431
EM=5	72.00%	80	36	64	20	0.36	0.80	0.6897	0.8000	0.7407
EM=7	71.50%	81	38	62	19	0.38	0.81	0.6807	0.8100	0.7397
EM=9	68.50%	75	38	62	25	0.38	0.75	0.6637	0.7500	0.7042
NN	71.00%	49	7	93	51	0.07	0.49	0.8750	0.4900	0.6282

Table 73: Trf (Ma) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 Kenansville AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	87.50%	90	15	85	10	0.15	0.90	0.8571	0.9000	0.8780
TD	76.50%	64	11	89	36	0.11	0.64	0.8533	0.6400	0.7314
GC	87.50%	75	0	100	25	0.00	0.75	1.0000	0.7500	0.8571
EM=3	90.50%	81	0	100	19	0.00	0.81	1.0000	0.8100	0.8950
EM=5	90.00%	80	0	100	20	0.00	0.80	1.0000	0.8000	0.8889
EM=7	90.50%	81	0	100	19	0.00	0.81	1.0000	0.8100	0.8950
EM=9	87.50%	75	0	100	25	0.00	0.75	1.0000	0.7500	0.8571
NN	98.50%	98	1	99	2	0.01	0.98	0.9899	0.9800	0.9849

Trf (En) model performance Tab. 74: PGD AEs vs. benign data, Tab. 75: genetic AEs vs. benign data, Tab. 76: Kenansville AEs vs. benign data.

Table 74: Trf (En) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 PGD AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	47.50%	91	96	4	9	0.96	0.91	0.4866	0.9100	0.6341
TD	61.50%	96	73	27	4	0.73	0.96	0.5680	0.9600	0.7138
GC	50.00%	100	100	0	0	1.00	1.00	0.5000	1.0000	0.6667
EM=3	50.00%	99	99	1	1	0.99	0.99	0.5000	0.9900	0.6644
EM=5	50.50%	100	99	1	0	0.99	1.00	0.5025	1.0000	0.6689
EM=7	50.50%	100	99	1	0	0.99	1.00	0.5025	1.0000	0.6689
EM=9	50.50%	100	99	1	0	0.99	1.00	0.5025	1.0000	0.6689
NN	53.00%	49	43	57	51	0.43	0.49	0.5326	0.4900	0.5104

Table 75: Trf (En) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 genetic AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	50.00%	91	91	9	9	0.91	0.91	0.5000	0.9100	0.6454
TD	51.50%	96	93	7	4	0.93	0.96	0.5079	0.9600	0.6644
GC	50.00%	100	100	0	0	1.00	1.00	0.5000	1.0000	0.6667
EM=3	51.00%	99	97	3	1	0.97	0.99	0.5051	0.9900	0.6689
EM=5	51.00%	100	98	2	0	0.98	1.00	0.5051	1.0000	0.6711
EM=7	51.00%	100	98	2	0	0.98	1.00	0.5051	1.0000	0.6711
EM=9	51.00%	100	98	2	0	0.98	1.00	0.5051	1.0000	0.6711
NN	56.50%	49	36	64	51	0.36	0.49	0.5765	0.4900	0.5297

Table 76: Trf (En) binary classifiers' metrics, using a threshold of maximum 1% FPR (if available) and a minimum 50% TPR, with 100 benign data and 100 Kenansville AEs.

Classifier	Accuracy	TP	FP	TN	FN	FPR	TPR	Precision	Recall	F1
NF	68.50%	91	54	46	9	0.54	0.91	0.6276	0.9100	0.7429
TD	68.50%	96	59	41	4	0.59	0.96	0.6194	0.9600	0.7529
GC	73.50%	100	53	47	0	0.53	1.00	0.6536	1.0000	0.7905
EM=3	77.00%	99	45	55	1	0.45	0.99	0.6875	0.9900	0.8115
EM=5	76.50%	100	47	53	0	0.47	1.00	0.6803	1.0000	0.8097
EM=7	76.00%	100	48	52	0	0.48	1.00	0.6757	1.0000	0.8065
EM=9	77.00%	100	46	54	0	0.46	1.00	0.6849	1.0000	0.8130
NN	73.00%	49	3	97	51	0.03	0.49	0.9423	0.4900	0.6447

J WORD SEQUENCE LENGTH IMPACT

In nearly all instances, we noticed no substantial decrease in performance, consistently maintaining an AUROC score exceeding 98% across all models, regardless of the word sequence length, supported by the results given in Table 77.

Table 77: Comparing AUROC scores across various word sequence lengths using a combined dataset of 100 benign samples and 100 C&W AEs.

Model \ # of words	2	3	4	5	6	7	8	9	10+
LSTM (It)	-	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.994
LSTM (En)	1.000	-	1.000	1.000	1.000	1.000	1.000	1.000	0.998
LSTM (En-LM)	1.000		0.917	1.000	1.000	1.000	1.000	1.000	0.995
wav2vec (Ma)		-	1.000	1.000	0.986	1.000	0.991	1.000	1.000
wav2vec (Ge)	-		1.000	1.000	1.000	0,992	1.000	1.000	1.000
Trf (Ma)	-	-	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Trf (En)	1.000	-	1.000	1.000	1.000	1.000	1.000	1.000	1.000

K TRANSFER ATTACK

To assess the transferability of targeted adversarial attacks between models, we tested whether the effectiveness of these attacks, specifically tailored to one model, remains consistent when tested on another ASR system. The results indicate a lack of transferability, as the WER in all cases is much closer to 100% than the expected 0%, as depicted in Tab. 78.

Table 78: WER performance of transfer attacks on chosen pairs of source and target models with 100 samples each from C&W AEs, and Psychoacoustic AEs.

Source Model	Target model	C&W attack	Psychoacoustic attack
wav2vec (Ma)	Trf (Ma)	99.33%	99.24%
Trf (Ma)	wav2vec (Ma)	99.41%	99.41%
LSTM (En)	LSTM (En-LM)	103.58%	103.28%
LSTM (En)	Trf (En)	104.48%	104.58%
LSTM (En-LM)	LSTM (En)	104.98%	104.68%
LSTM (En-LM)	Trf (En)	104.68%	104.68%
Trf (En)	LSTM (En)	106.17%	105.37%
Trf (En)	LSTM (En-LM)	104.68%	104.78%