DEFENDING AGAINST ADVERSARIAL AUDIO VIA DIFFUSION MODEL

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ABSTRACT

Deep learning models have been widely used in commercial acoustic systems in recent years. However, adversarial audio examples can cause abnormal behaviors for those acoustic systems, while being hard for humans to perceive. Various methods, such as transformation-based defenses and adversarial training, have been proposed to protect acoustic systems from adversarial attacks, but they are less effective against adaptive attacks. Furthermore, directly applying the methods from the image domain can lead to suboptimal results because of the unique properties of audio data. In this paper, we propose an adversarial purification-based defense pipeline, AudioPure, for acoustic systems via off-the-shelf diffusion models. Taking advantage of the strong generation ability of diffusion models, AudioPure first adds a small amount of noise to the adversarial audio and then runs the reverse sampling step to purify the noisy audio and recover clean audio. AudioPure is a plug-and-play method that can be directly applied to any pretrained classifier without any fine-tuning or re-training. We conduct extensive experiments on speech command recognition task to evaluate the robustness of AudioPure. Our method is effective against diverse adversarial attacks (e.g. $\mathcal{L}_2$ or $\mathcal{L}_\infty$-norm). It outperforms the existing methods under both strong adaptive white-box and black-box attacks bounded by $\mathcal{L}_2$ or $\mathcal{L}_\infty$-norm (up to +54% in robust accuracy). Besides, we also evaluate the certified robustness for perturbations bounded by $\mathcal{L}_2$-norm via randomized smoothing. Our pipeline achieves a higher certified accuracy than baselines.

1 INTRODUCTION

Deep neural networks (DNNs) have demonstrated great successes for different tasks in the audio domain, such as speech command recognition, keyword spotting, speaker identification, and automatic speech recognition. Acoustic systems built by DNNs (Amodei et al., 2016; Shen et al., 2019) are applied in safety-critical applications ranging from making phone calls to controlling household security systems. Although DNN-based models have exhibited significant performance improvement, extensive studies have shown that they are vulnerable to adversarial examples (Szegedy et al., 2014; Carlini & Wagner, 2018; Qin et al., 2019; Du et al., 2020; Abdullah et al., 2021; Chen et al., 2021a), where attackers add imperceptible and carefully crafted perturbations to the original audio to mislead the system with incorrect predictions. Thus, it becomes crucial to design robust DNN-based acoustic systems against adversarial examples.

To address it, existing works (e.g., Rajaratnam & Alshemali, 2018; Yang et al., 2019) have tried to leverage the temporal dependency property of audio to defend against adversarial examples. They apply the time-domain and frequency-domain transformations to the adversarial examples to improve the robustness. Although they can alleviate this problem to some extent, they are still vulnerable against strong adaptive attacks where the attacker obtains full knowledge of the whole acoustic system (Tramer et al., 2020). Another way to enhance the robustness against adversarial examples is adversarial training (Goodfellow et al., 2015; Madry et al., 2018) that adversarial perturbations have been added to the training stage. Although it has been acknowledged as the most effective defense, the training process will require expensive computational resources and the model is still vulnerable to other types of adversarial examples that are not similar to those used in the training process (Tramer & Boneh, 2019).

Adversarial purification (Yoon et al., 2021; Shi et al., 2021; Nie et al., 2022) is another family of defense methods that utilizes generative models to purify the adversarial perturbations of the input examples before they are fed into neural networks. The key of such methods is to design an effective generative model for purification. Recently, diffusion models have been shown to be the state-of-the-art models for images (Song & Ermon, 2019; Ho et al., 2020; Nichol & Dhariwal, 2021; Dhariwal & Nichol, 2021) and audio synthesis (Kong et al., 2021; Chen et al., 2021b). It motivates the community to use it for purification. In particular, in the image domain, DiffPure (Nie et al., 2022) applies diffusion models as purifiers and obtains good performance in terms of both clean and robust accuracy on various image classification tasks. Since such methods do not require training the model with pre-defined adversarial examples, they can generalize to diverse threats. Given the significant progress of diffusion model made in the image domain, it motivates us to ask: *is it possible to obtain the similar success in the audio domain?*

Unlike the image domain, audio signals have some unique properties. There are different choices of audio representations, including raw waveforms and various types of time-frequency representations (e.g., Mel spectrogram, MFCC). When designing an acoustic system, some particular audio representations may be selected as the target features, and defenses that work well on some features may perform poorly on other features. In addition, one may think of treating the 2-D time-frequency representations (i.e., spectrogram) as images, where the frequency-axis is set as height and the time-axis is set as width, then directly apply the successful DiffPure (Nie et al., 2022) from the image domain for spectrogram. Despite the simplicity, there are two major issues: *i)* the acoustic system can take audio with variable time duration as the input, while the underlying diffusion model within DiffPure can only handle inputs with fixed width and height. *ii)* Even if we apply it in a fixed-length segment-wise manner for the time being, it still achieves the suboptimal results as we will demonstrate in this work. These unique issues pose a new challenge of designing and evaluating defense systems in the audio domain.

In this work, we aim to defend against diverse unseen adversarial examples without adversarial training. We propose a play-and-plug purification pipeline named AudioPure based on a pre-trained diffusion model by leveraging the unique properties of audio. In specific, our model consists of two main components: (1) a waveform-based diffusion model and (2) a classifier. It takes the audio waveform as input and leverages the diffusion model to purify the adversarial audio perturbations. Given an adversarial input formatted with waveform, AudioPure first adds a small amount of noise via the diffusion process to override the adversarial perturbations, and then uses the truncated reverse process to recover the clean sample. The recovered sample is fed into the classifier.

We conduct extensive experiments to evaluate the robustness of our method on the task of speech command recognition. We carefully design the adaptive attacks so that the attacker can accurately compute the full gradients to evaluate the effectiveness of our method. In addition, we also comprehensively evaluate the robustness of our method against different black-box attacks and the Expectation Over Transformation (EOT) attack. Our method shows a much better performance under both white-box and black-box attacks. Moreover, we also evaluate the certified robustness of AudioPure via randomized smoothing, which offers a provable guarantee of model robustness against $\mathcal{L}_2$-based perturbation. We show that our method achieves better certified robustness than baselines. Specifically, our method obtains a significant improvement (up to +54% at most in robust accuracy) compared to adversarial training, and over 5% higher certified robust accuracy than baselines. To the best of our knowledge, we are the first to use diffusion models to enhance the security of acoustic systems and investigate how different working domains of defenses affect the adversarial robustness.

2 Related work

2.1 Adversarial attacks and defenses

Szegedy et al. (2014) introduce adversarial examples, which look similar to normal examples but will fool the neural networks to give incorrect predictions. Usually, adversarial examples are constrained by $\mathcal{L}_p$ norm to ensure the imperceptibility. Recently, stronger attack methods are emerging (Madry et al., 2018; Carlini & Wagner, 2017; Andriushchenko et al., 2020; Croce & Hein, 2020). In the audio domain, Carlini & Wagner (2018) introduce audio adversarial examples, and Qin et al.

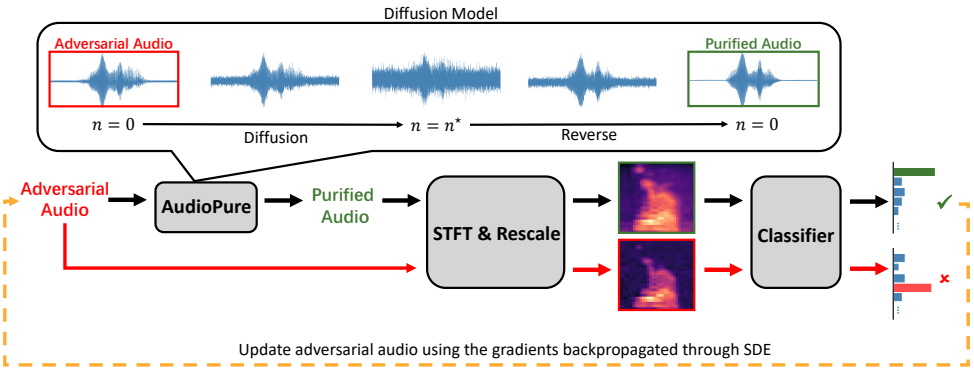


Figure 1: The architecture of the whole acoustic system protected by AudioPure (black line in the figure) and the adaptive attack (orange line in the figure). AudioPure first adds noise to the adversarial audio and then runs the reverse process to recover purified audio. Next, the purified audio is transformed into the spectrogram, and the spectrogram is fed into the classifier to get predictions. The attacker updates the adversarial audio based on the gradients backpropagated through SDE. Without AudioPure , the adversarial audio transfers to the spectrogram and feeds into the classifier directly.

(2019) manage to make them more imperceptible. Black-box attacks (Du et al., 2020; Chen et al., 2021a) are also developed, aiming to mislead the end-to-end acoustic systems.

In order to protect neural networks from adversarial attacks, different defense methods are proposed. The most widely used one is adversarial training (Madry et al., 2018), which deliberately uses adversarial examples as the training data of neural networks. The main problems of adversarial training are the accuracy drop of benign examples and the expensive computational cost. Many improved versions of adversarial training aim to alleviate these problems (Wong et al., 2020; Shafahi et al., 2019; Zhang et al., 2019b;a). Another line of work is adversarial purification (Yoon et al., 2021; Shi et al., 2021; Nie et al., 2022), which uses generative models to remove the adversarial perturbations before classification. Both of these two types of defenses are mainly developed for computer vision tasks and cannot be directly applied to the audio domain. In this paper, we explicitly design a defense pipeline according to the characteristics of audio data.

2.2 Speech Processing

Many speech processing applications are vulnerable to adversarial attacks, including speech command recognition (Warden, 2018), keyword spotting (Chen et al., 2014; Li et al., 2019), speaker identification (Reynolds et al., 2000; Ravanelli & Bengio, 2018; Snyder et al., 2018), and speech recognition (Amodei et al., 2016; Shen et al., 2019; Ravanelli et al., 2019). In particular, speech command recognition is closely related to keyword spotting, and can be viewed as speech recognition with limited vocabulary. In this work, we choose speech command recognition as the testbed for the proposed AudioPure pipeline. The proposed pipeline is applicable for keyword spotting and speech recognition.

A speech command recognition system consists of a feature extractor and a classifier. The feature extractor processes the raw audio waveforms and outputs acoustic features, *e.g.* Mel spectrograms or Mel-frequency cepstral coefficients (MFCC). Then these features are fed into the classifier, and the classifier gives predictions. Given the 2-D spectrogram features, convolutional neural networks for images are readily applicable (Simonyan & Zisserman, 2015; He et al., 2016; Zagoruyko & Komodakis, 2016; Xie et al., 2017; Huang et al., 2017).

3 Method

3.1 Background of Diffusion Models

Diffusion model normally consists of a forward diffusion process and a reverse sampling process. The forward diffusion process gradually adds gaussian noise to the input data until the distribution

of the noisy data converges to a standard Gaussian distribution. The reverse sampling process takes the standard gaussian noise as input and gradually denoises the noisy data to recover clean data. At present, diffusion models can be divided into two different types: discrete-time diffusion models based on sequential sampling, such as SMLD Song & Ermon (2019), DDPM (Ho et al., 2020), and DDIM (Song et al., 2021a), and continuous-time diffusion models based on SDEs (Song et al., 2021b). Song et al. (2021b) also build the connection between these two types of diffusion models.

Denoising Diffusion Probabilistic Models (DDPM) (Ho et al., 2020) is one of the most widely used diffusion models. Many of the subsequently proposed diffusion models, including DiffWave for audio (Kong et al., 2021), are based on the DDPM formulation. In DDPM, both the diffusion and reverse processes are defined by Markov chains. For input data $\mathbf{x}_0 \in \mathbb{R}^d$, we denote $\mathbf{x}_0 \sim q(\mathbf{x}_0)$ as the original data distribution, and $\mathbf{x}_1, \ldots, \mathbf{x}_N$ are intermediate latent variables from the distributions $q(\mathbf{x}_1|\mathbf{x}_0), \ldots, q(\mathbf{x}_N|\mathbf{x}_{N-1})$, where N is the total number of steps. Generally, with a pre-defined or learned variance schedule $\beta_1, \ldots, \beta_N$ (usually linearly increasing small constants), the forward transition probablity $q(\mathbf{x}_n|\mathbf{x}_{n-1})$ can be formulated as:

$$q(\mathbf{x}_n|\mathbf{x}_{n-1}) = \mathcal{N}(\mathbf{x}_n; \sqrt{1-\beta_n}\mathbf{x}_{n-1}, \beta_n \mathbf{I}), \tag{1}$$

Based on the variance schedule $\{\beta_n\}$, a set of constants is defined as:

$$\alpha_n = 1 - \beta_n, \quad \bar{\alpha}_n = \prod_{n=1}^{N} \alpha_n, \quad \tilde{\beta}_n = \begin{cases} \frac{1-\bar{\alpha}_{n-1}}{1-\bar{\alpha}_n}\beta_n, & n > 1 \\ \beta_1, & n = 1 \end{cases}, \tag{2}$$

and using the reparameterization trick, we have:

$$q(\mathbf{x}_n|\mathbf{x}_0) = \mathcal{N}(\mathbf{x}_n; \sqrt{\bar{\alpha}_n}\mathbf{x}_0, (1-\bar{\alpha}_n)\mathbf{I}) \tag{3}$$

When n gradually gets larger to infinity, $q(\mathbf{x}_n|\mathbf{x}_0)$ will converge to a standard Gaussian distribution. Meanwhile, for the reverse process we have:

$$\mathbf{x}_{n-1} \sim p_\theta(\mathbf{x}_{n-1}|\mathbf{x}_n) = \mathcal{N}(\mathbf{x}_{n-1}; \mu_\theta(\mathbf{x}_n, n), \sigma_\theta^2(\mathbf{x}_n, n)\mathbf{I}), \tag{4}$$

where the mean term $\mu_\theta(\mathbf{x}_n, n)$ and the variance term $\sigma_\theta^2(\mathbf{x}_n, n)$ is instantiated by parameter θ. Ho et al. (2020); Kong et al. (2021) use a neural network $\boldsymbol{\epsilon}_\theta$ to define μ_θ, and σ_θ is fixed to a constant:

$$\mu_\theta(\mathbf{x}_n, n) = \frac{1}{\sqrt{\alpha_n}}\left(\mathbf{x}_n - \frac{\beta_n}{\sqrt{1-\bar{\alpha}_n}}\boldsymbol{\epsilon}_\theta(\mathbf{x}_n, n)\right), \quad \sigma_\theta(\mathbf{x}_n, n) = \sqrt{\tilde{\beta}_n}. \tag{5}$$

We denote $\mathbf{x}_n(\mathbf{x}_0, \boldsymbol{\epsilon}) = \sqrt{\bar{\alpha}_n}\mathbf{x}_0 + \sqrt{(1-\bar{\alpha}_n)}\boldsymbol{\epsilon}, \boldsymbol{\epsilon} \sim \mathcal{N}(0, \mathbf{I})$, and the optimization objective is:

$$\theta^\star = \arg\max_\theta \sum_{n=1}^{N} \lambda_n \mathbb{E}_{\mathbf{x}(0)} \left\| \boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_n}\mathbf{x}_0 + \sqrt{(1-\bar{\alpha}_n)}\boldsymbol{\epsilon}, n) \right\|_2^2 \tag{6}$$

where λ_n is the weighting coefficient (Ho et al., 2020).

According to Song et al. (2021b), as $N \to \infty$, DDPM becomes VP-SDE, a continuous-time formulation of diffusion models. Particularly, the forward SDE is formulated as:

$$\mathrm{d}\mathbf{x} = -\frac{1}{2}\beta(t)\mathbf{x}\mathrm{d}t + \sqrt{\beta(t)}\mathrm{d}\mathbf{w}. \tag{7}$$

where $t \in [0, 1]$, $\mathrm{d}t$ is an infinitesimal positive time step, $\mathbf{w}$ is a standard Wiener process, $\beta(t)$ is the continuous-time noise schedule. Similarly, the reverse SDE can be defined as:

$$\mathrm{d}\mathbf{x} = -\frac{1}{2}\beta(t)[\mathbf{x} + 2\nabla_{\mathbf{x}} \log p_t(\mathbf{x})]\mathrm{d}t + \sqrt{\beta(t)}\mathrm{d}\bar{\mathbf{w}}, \tag{8}$$

where $\mathrm{d}t$ is an infinitesimal negative time step, and $\bar{\mathbf{w}}$ is a reverse-time standard Wiener process.

3.2 AudioPure: a plug-and-play defense for acoustic systems

To standardize the formulation of the defense, as suggested by Nie et al. (2022), we use the continuous-time formulation defined by Eq. 7 and Eq. 8. Note that since the existing pretrained DiffWave models (Kong et al., 2021) are based on DDPM, we will use their equivalent VP-SDE.

If we use the Euler-Maruyama method to solve the VP-SDE and the step size $\Delta t = \frac{1}{N}$, the sampling of the reverse-time SDE will be equivalent to the reverse sampling of DDPM (detailed proofs can be found in Song et al. (2021b)). Under this prerequisite, we have $t = \frac{n}{N}$ where $n \in \{1, \ldots, N\}$. We define $\beta(\frac{n}{N}) := \beta_n$, $\bar{\alpha}(\frac{n}{N}) := \bar{\alpha}_n$, $\tilde{\beta}(\frac{n}{N}) := \tilde{\beta}_n$, and $\mathbf{x}(\frac{n}{N}) := \mathbf{x}_n$. Given an adversarial example x_{adv} as the input at $t = 0$, *i.e.* $\mathbf{x}_0 = \mathbf{x}_{adv}$, we first run the forward SDE from $t = 0$ to $t^\star = \frac{n^\star}{N}$ by solving Eq. 7 (it is equivalent to running n^* DPPM steps), which yields:

$$\mathbf{x}(t^\star) = \sqrt{\bar{\alpha}(t^\star)}\mathbf{x}_{adv} + \sqrt{1 - \bar{\alpha}(t^\star)}\mathbf{z}, \qquad \mathbf{z} \sim \mathcal{N}(0, \mathbf{I}), \tag{9}$$

Next, we run the truncated reverse SDE from $t = t^\star$ to $t = 0$ by solving Eq. 8. Similar to Nie et al. (2022), we define an SDE solver $\mathbf{sdeint}$ that uses the Euler-Maruyama method, and sequentially takes in six inputs: initial value, drift coefficient, diffusion coefficient, Wiener process, initial time, and end time. The reverse output $\hat{\mathbf{x}}(0)$ at $t = 0$ can be formulated as:

$$\hat{\mathbf{x}}(0) = \mathbf{sdeint}(\mathbf{x}(t^\star), f_{rev}, g_{rev}, \bar{\mathbf{w}}, t^\star, 0). \tag{10}$$

where the drift and diffusion coefficients are:

$$f_{rev}(\mathbf{x}, t) := -\frac{1}{2}\beta(t)[\mathbf{x} + 2\mathbf{s}_\theta(\mathbf{x}, t)], \qquad g_{rev}(t) := \sqrt{\tilde{\beta}(t)}. \tag{11}$$

Note that we use a diffusion coefficient different from Nie et al. (2022) for the purpose of cleaner output (see the detailed explanation in the Section 3.3). Next, we use the discrete-time noise estimator $\epsilon_\theta(\mathbf{x}_n, n)$ to compute the continuous-time score estimator $s_\theta(\mathbf{x}, t)$. By defining $\tilde{\epsilon}_\theta(\mathbf{x}(t), t) := \epsilon_\theta(\mathbf{x}(\frac{n}{N}), n) = \epsilon_\theta(\mathbf{x}_n, n)$ with $t := \frac{n}{N}$, the score function in the reverse VP-SDE can be estimated as:

$$\mathbf{s}_\theta(\mathbf{x}, t) = -\frac{\tilde{\epsilon}_\theta(\mathbf{x}, t)}{\sqrt{1 - \bar{\alpha}(t)}} \approx \nabla_{\mathbf{x}} \log p_t(\mathbf{x}). \tag{12}$$

Accordingly, $\hat{\mathbf{x}}(0)$, the purified output of the adversarial input $\mathbf{x}(0) = \mathbf{x}_{adv}$, is fed into the later stages of the acoustic system to make predictions. The whole purification operation can be denoted as a function $\mathbf{Purifier} : \mathbb{R}^d \times \mathbb{R} \to \mathbb{R}^d$:

$$\mathbf{Purifier}(\mathbf{x}_{adv}, n^\star) = \mathbf{sdeint}\left(\sqrt{\bar{\alpha}(\frac{n^\star}{N})}\mathbf{x}_{adv} + \sqrt{1 - \bar{\alpha}(\frac{n^\star}{N})}\mathbf{z}, f_{rev}, g_{rev}, \bar{\mathbf{w}}, \frac{n^\star}{N}, 0\right) \tag{13}$$

The acoustic systems are usually built on the features extracted from the raw audio. For example, the system can extract Mel spectrogram as the features: 1) it first applies short-time Fourier transformation (STFT) on the time-domain waveform to get linear-scale spectrogram, and 2) it then rescales the frequency band to the Mel-scale. We denote this process as Wave2Mel : $\mathbb{R}^d \to \mathbb{R}^m \times \mathbb{R}^n$, which is a differentiable function. Then the classifier $F : \mathbb{R}^m \times \mathbb{R}^n \to \mathbb{R}^c$ (usually a convolutional network) takes the Mel spectrogram as the input and gives predictions.

Since both the time domain waveform and time-frequency domain spectrogram go through the pipeline, the purifier can be applied in either the time domain or time-frequency domain. If the purifier is applied in time domain, the whole defended acoustic system $\mathbf{AS} : \mathbb{R}^d \times \mathbb{R} \to \mathbb{R}^c$ can be formulated as:

$$\mathbf{AS}(\mathbf{x}_{adv}, n^\star) = F(\text{Wave2Mel}(\mathbf{Purifier}(\mathbf{x}_{adv}, n^\star))) \tag{14}$$

where the waveform $\mathbf{Purifier}$ is based on DiffWave.

Meanwhile, if we want to purify the input adversarial examples in the time-frequency domain, we can choose a diffusion model used for image synthesis, and apply it to the output spectrogram of Wave2Mel. We denote this purifier as $\mathbf{Purifier}_{spec} : \mathbb{R}^m \times \mathbb{R}^n \times \mathbb{R} \to \mathbb{R}^m \times \mathbb{R}^n$. In this scenario, the whole defended acoustic system will be:

$$\mathbf{AS}(\mathbf{x}_{adv}, n^\star) = F(\mathbf{Purifier}_{spec}(\text{Wave2Mel}(\mathbf{x}_{adv})), n^\star) \tag{15}$$

The architecture of the whole pipeline is illustrated in Figure. 1. For the purification in the time-frequency domain spectrogram, we use an Improved DDPM (Nichol & Dhariwal, 2021) trained on the Mel spectrograms of audio data and denote it as *DiffSpec*. We compare these two purifiers and discover that the purification in the time domain waveform is more effective to defend against adversarial audio. Detailed experimental results can be found in Sec. 4.2.

3.3 TOWARDS EVALUATING AUDIOPURE

Adaptive attack For the forward diffusion process formulated as Eq. 9, the gradients of the output $\mathbf{x}(t^\star)$ *w.r.t.* the input $\mathbf{x}(0)$ is a constant. For the reverse process formulated as Eq. 10, the adjoint method (Li et al., 2020) is applied to compute the full gradients of the objective function $\mathcal{L}$ *w.r.t.* $x(t^\star)$ without any out-of-memory issues, by solving another augmented SDE:

$$\begin{pmatrix} \mathbf{x}(t^\star) \\ \frac{\partial \mathcal{L}}{\partial \mathbf{x}(t^\star)} \end{pmatrix} = \mathbf{sdeint}\left(\begin{pmatrix} \mathbf{x}(0) \\ \frac{\partial \mathcal{L}}{\partial \mathbf{x}(0)} \end{pmatrix}, \begin{pmatrix} f_{rev} \\ \frac{\partial f_{rev}}{\partial \mathbf{x}}\mathbf{z} \end{pmatrix}, \begin{pmatrix} g_{rev}\mathbf{1} \\ \mathbf{0} \end{pmatrix}, \begin{pmatrix} -\mathbf{w}(1-t) \\ -\mathbf{w}(1-t) \end{pmatrix}, 0, t^\star \right) \tag{16}$$

where $\mathbf{1}$ and $\mathbf{0}$ represent the vectors of all ones and all zeros, respectively.

SDE modifications for clean output We observe that directly applying the framework of Nie et al. (2022) to the audio domain will cause the performance degradation. That is, when converting the discrete-time reverse process of DiffWave (Kong et al., 2021) to its corresponding reverse VP-SDE in Eq. 8, the output audio still contains much noise, resulting in lower classification accuracy. We identify two influencing factors and solve this problem with by modifying the SDE formulation.

The first factor is the diffusion error due to the mismatch of the reverse variance between the discrete and continuous cases. Ho et al. (2020) observed that both $\sigma_\theta^2 = \tilde{\beta}_t$ and $\sigma_\theta^2 = \beta_t$ get similar results experimentally in the image domain. However, we find that it is not the case in the audio modeling with diffusion models. For audio synthesis using DiffWave trained with $\sigma_\theta^2 = \tilde{\beta}_t$, if we switch the reverse variance schedule to $\sigma_\theta^2 = \beta_t$, the output audio becomes noisy. Thus, in Sec. 3.2 we define $\tilde{\beta}(\frac{n}{N}) = \tilde{\beta}_n$ and use the diffusion coefficient $g_{rev} = \sqrt{\tilde{\beta}(t)}$ in Eq. 11 instead of $g_{rev} = \sqrt{\beta(t)}$ to match the variance $\tilde{\beta}_t$ in DiffWave.

The second factor is the inaccuracy from the continuous-time noise schedule $\beta(t) = \beta_0 + (\beta_N - \beta_0)t$ and $\tilde{\alpha}(t) = e^{-\int_0^t \beta(s)\mathrm{d}s}$ used by Nie et al. (2022). The impact of the difference between $\beta(t) = \beta_0 + (\beta_N - \beta_0)t$ and β_{Nt} cannot be negligible, especially when N is not large enough (*e.g.* $N = 200$ for the pretrained DiffWave model we use). Besides, when t is close to 0, $\tilde{\alpha}(t) = e^{-\int_0^t \beta(s)\mathrm{d}s}$ is not a good approximation of $\bar{\alpha}_{Nt}$ any more. Thus, we define the continuous-time noise schedule directly based on the discrete schedule, namely, $\beta(\frac{n}{N}) := \beta_n$ and $\bar{\alpha}(\frac{n}{N}) := \bar{\alpha}_n$, for the purpose of better denoised output and more accurate gradient computation.

4 EXPERIMENTS

In this section, we first introduce the detailed experimental settings. Then we compare the performance of our method and other defenses under strong white-box adaptive attack where the attacker has full knowledge about the defense and black-box attacks. To further show the robustness of our method, we also evaluate the certified accuracy via randomize smoothing Cohen et al. (2019), which provides a provable guarantee of model robustness against $\mathcal{L}_2$ norm bounded adversarial perturbations.

4.1 EXPERIMENTAL SETTINGS

Dataset: Our method is evaluated on the task of speech command recognition. We use the Speech Commands dataset (Warden, 2018), which consists of 85,511 training utterances, 10,102 validation utterances, and 4,890 tests utterances. Following the setting of Kong et al. (2021), we choose the utterances which stand for digits $0 \sim 9$ and denote this subset as SC09.

Models: We use DiffWave (Kong et al., 2021) and DiffSpec (based on Improved DDPM (Nichol & Dhariwal, 2021)) as our defensive purifiers, which are representative diffusion models on the waveform domain and the spectral domain respectively. We use the unconditional version of Diffwave with the official provided pretrained checkpoints. Since the Improved DDPM model does not provide the pretrain checkpoint for audio, we train it from scratch on the Mel spectrograms of audio from SC09. The training details and hyperparameters are in the appendix A.

For the classifier, we use ResNeXt(Xie et al., 2017) for spectrogram representation and M5 Net(Dai et al., 2017) for waveform except the experiments for ablation studies.

Table 1: We use a pre-trained ResNeXt-29-8-64 as the classifier (Xie et al., 2017), and compare AudioPure with other different defense methods under adaptive $\mathcal{L}_\infty$-PGD attacks, $\mathcal{L}_2$-PGD attacks, and FAKRBOB (Chen et al., 2021a) which is a $\mathcal{L}_\infty$-norm black-box attack designed for acoustic systems. We use the attack budget $\epsilon = 0.002$ for all the $\mathcal{L}_\infty$ attacks. For $\mathcal{L}_2$ attacks we set $\epsilon = 1$. AudioPure shows much stronger robustness under different attacks. Even under the strongest $\mathcal{L}_2$-PGD$_{100}$, AudioPure can keep 60% robust accuracy, while adversarial training virtually fails to get any robustness.

Defense	Clean	$\mathcal{L}_\infty$ white-box						$\mathcal{L}_2$ white-box					$\mathcal{L}_\infty$ black-box
		PGD$_{10}$	PGD$_{20}$	PGD$_{30}$	PGD$_{50}$	PGD$_{70}$	PGD$_{100}$	PGD$_{10}$	PGD$_{20}$	PGD$_{30}$	PGD$_{50}$	PGD$_{100}$	FAKEBOB
None	**100**	3	1	1	1	1	1	1	0	0	0	0	21
AS (Yang et al., 2019)	**100**	4	2	1	1	1	1	4	0	0	0	0	24
MS (Yang et al., 2019)	**100**	6	3	2	1	1	1	1	0	0	0	0	21
DS (Yang et al., 2019)	99	2	1	1	1	1	1	0	0	0	0	0	16
LPF (Rajaratnam & Alshemali, 2018)	**100**	5	2	1	1	1	1	1	0	0	0	0	20
BPF (Rajaratnam & Alshemali, 2018)	99	5	1	1	1	1	1	3	0	0	0	0	18
AdvTr (Madry et al., 2018)	**100**	45	28	24	23	23	22	8	5	3	3	1	**76**
AudioPure	96	**84**	**77**	**76**	**77**	**72**	**72**	**77**	**69**	**69**	**65**	**60**	74

For white-box attacks, we use PGD (Madry et al., 2018) with different iteration steps from 10 to 100. The attack budget is set to $\epsilon = 0.002$ for $\mathcal{L}_\infty$-norm constraint except the ablation study. For black-box attacks, we apply query-based attack, FAKEBOB (Chen et al., 2021a) and set the iteration steps to 200, NES samples to 200, and the confidence coefficient $\kappa = 0.5$. For adversarial training, we use $\mathcal{L}_\infty$-based adversarial attack with 10 PGD step size and also constrain the attack budget to $\epsilon = 0.002$.

Baselines. We compare our method with two types of baselines including: (1) transformation-based defense (Yang et al., 2019; Rajaratnam & Alshemali, 2018) including average smoothing (AS), median smoothing (MS), downsampling (DS), low-pass filter (LPF), and band-pass filter (BPF), and (2) adversarial training based defense (AdvTr) (Madry et al., 2018).

4.2 Main results

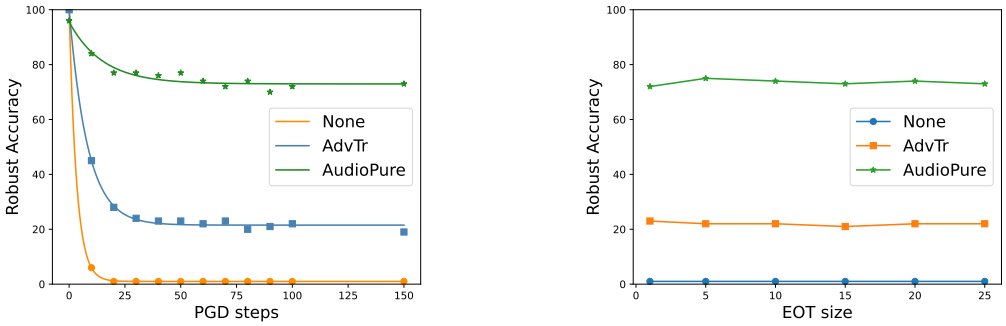
We evaluate AudioPure under adaptive attacks, assuming the attacker obtains full knowledge of AudioPure . We use the adaptive attack algorithm described in previous section so that attacker is able to accurately compute the full gradients for attacking. The results are shown in Table 1. We find that the baseline transformation-based defenses (Yang et al., 2019; Rajaratnam & Alshemali, 2018), including average smoothing (AS), median smoothing (MS), downsampling (DS), low-pass filter (LPF), and band-pass filter (BPF), are virtually broken through by white-box attacks with up to 4% robust accuracy. For the adversarial training-based method (AdvTr) trained on $\mathcal{L}_\infty$-norm adversarial examples, it achieves a slightly high 22% robust accuracy against $\mathcal{L}_\infty$-based adversarial examples. But the improvement is so insignificant compared to its counterpart in the image domain. It shows that the domain difference contributes to significantly different results. Furthermore, such the method does not work on other types of adversarial examples (i.e., $\mathcal{L}_2$-based method), achieving 1% robust accuracy under $\mathcal{L}_2$-based PDG$_{100}$ attack. Compared with all baselines, AudioPure can obtain a much higher robust accuracy, 50% improvements on average, on $\mathcal{L}_\infty$-based adversarial examples and is also effective against $\mathcal{L}_2$-based white-box attacks, achieving 60% robust accuracy.

We also evaluate on black-box attacks including: FAKEBOB (Chen et al., 2021a) and transferability-based attacks. The results of FAKEBOB are shown in Table 1. The attack success of FAKEBOB is lower than the adaptive attacks. The results on the transferability-based attack are in the appendix B. They draw the same conclusion. These results further verify the effectiveness of our method. All results indicate that AudioPure can work under attacks with different types of constraints, while adversarial training has to apply different training strategies, making it a less universal defense manner than our method.

4.3 ablation study

PGD steps To ensure the effectiveness of PGD attacks, we test different iteration steps from 10 to 150. As Figure. 2a illustrates, the robust accuracy converges after iteration steps $n \geq 70$.

Effectiveness against Expectation over transformation (EOT) attack. Besides, since the diffusion and reverse process of AudioPure consist of many randomized sampling operations, we apply



(a) robust accuracy with different PGD steps

(b) robust accuracy with different EOT size

Figure 2: The performance of baseline (no defense, denoted as None), adversarial training (denoted as AdvTr), and AudioPure under attacks with different iteration steps and EOT size. (a) indicates the step of convergence, and the attack is almost optimal when iterating over 70 steps. (b) shows that increasing EOT size can barely affect the robustness of our method.

Table 2: The robust accuracy under different attack budget ϵ when using different reverse steps $n^\star$. Larger ϵ requires larger $n^\star$ to ensure better robustness.

Attack Budget	Diffusion Steps						
	$n^\star = 0$	$n^\star = 1$	$n^\star = 2$	$n^\star = 3$	$n^\star = 5$	$n^\star = 7$	$n^\star = 10$
$\epsilon = 0.002$	3	**94**	90	89	84	77	67
$\epsilon = 0.004$	0	76	**89**	86	83	74	66
$\epsilon = 0.008$	0	27	70	**85**	84	74	68
$\epsilon = 0.016$	0	0	21	53	**69**	57	63

Table 3: Ablation studies among different model architectures. The robust accuracy is evaluated under $\mathcal{L}_\infty$-PGD$_{100}$. Our method is effective on various models with different architectures.

Defense	ResNeXt-29-8-64		VGG-19-BN		WideResNet-28-10		DenseNet-BC-100-12		M5	
	Clean	Robust	Clean	Robust	Clean	Robust	Clean	Robust	Clean	Robust
None	100	1	100	2	100	1	100	5	94	12
AudioPure	96	72	94	67	94	71	93	69	89	64

the expectation over transformation (EOT) attack to evaluate the effectiveness of AudioPure with different EOT sample sizes. Figure 2b demonstrates the result. We find that AudioPure is effective among different EOT sizes.

Attack budget ϵ. We evaluate the effectiveness of our method among different ϵ including $\epsilon = \{0.002, 0.004, 0.008, 0.016\}$. Since the diffusion steps $n^\star$ are the hyperparameters for AudioPure , we conduct experiments among different $n^\star$. As shown in Table 2, if $n^\star$ is larger than 2, AudioPure will show strong effectiveness among different ϵ. When ϵ increases, it requires a larger $n^\star$ to achieve the optimal robustness since a larger adversarial perturbation requires a large noise from the forward process of the diffusion model to override the adversarial perturbations and the corresponding larger step to recover purified audio. However, if the $n^\star$ is too large, it will override the original audio information as well so that the recovered audio from the diffusion model will lose the original audio information, contributing to the performance drop.

Architectures. Moreover, we apply AudioPure to different classifiers, including spectrogram-based classifier: VGG-19-BN(Simonyan & Zisserman, 2015), ResNeXt-29-8-64(Xie et al., 2017), WideResNet-28-10(Zagoruyko & Komodakis, 2016) DenseNet-BC-100-12(Huang et al., 2017) and wave-form based classifier: M5 (Dai et al., 2017). Table 3 shows that our method is effective for various neural network classifiers.

Audio representations Audio has different types of representations including raw waveforms or time-frequency representations (e.g., Mel spectrogram). We conduct an ablation study to show the effectiveness of diffusion models by using different representations, including *DiffWave*, a diffusion

Table 4: Ablation studies among different audio representations. We implement AudioPure using two different diffusion models as purifiers, DiffWave and DiffSpec, that respectively process the representations in the time domain and time-frequency domain.

Defense	Clean	$\mathcal{L}_\infty$ white-box						$\mathcal{L}_2$ white-box				
		PGD_{10}	PGD_{20}	PGD_{30}	PGD_{50}	PGD_{70}	PGD_{100}	PGD_{10}	PGD_{20}	PGD_{30}	PGD_{50}	PGD_{100}
DiffWave	96	**84**	**77**	**76**	**77**	**72**	**72**	**77**	**69**	**69**	**65**	**60**
DiffSpec	**100**	80	76	67	64	60	57	50	45	42	37	34

Table 5: Certified accuracy for different methods. For each noise level σ, we add the same level of noise to train the classifier and apply it to RS-Gaussian.

Method	Noise level	Certified radius ($\mathcal{L}_2$)						
		0	0.25	0.50	0.75	1.0	1.25	1.50
RS-Vanilla	$\sigma = 0.5$	30	21	12	6	4	3	3
	$\sigma = 1.0$	8	8	8	7	4	3	3
RS-Gaussian	$\sigma = 0.5$	**49**	39	33	23	14	6	3
	$\sigma = 1.0$	18	15	11	10	5	5	4
AudioPure	$\sigma = 0.5$	45	**40**	**35**	**27**	**21**	**17**	**13**
	$\sigma = 1.0$	**27**	**22**	**16**	**15**	**12**	**11**	**8**

model for waveforms (Kong et al., 2021) and *DiffSpec*, a diffusion model for spectrogram based on the original image model (Nichol & Dhariwal, 2021). The results are shown in Table 4. We find that the *DiffWave* consistently outperforms *DiffSpec* against $\mathcal{L}_2$ and $\mathcal{L}_\infty$-based adversarial examples. Moreover, compared with *DiffWave*, despite *DiffSpec* achieve higher clean accuracy, it only achieves 34% robust accuracy, a significant 26% performance drop against $\mathcal{L}_2$-based adversarial examples. We think the potential reason is that the short-time Fourier transform (STFT) is an operation of information compression. The spectrogram contains much less information than the raw audio waveform. This result shows that directly applying the image domain method can lead to suboptimal result for audio. It also verifies the crucial design of AudioPure for adversarial robustness.

4.4 Certified robustness

In this section, we evaluate certified robustness of AudioPure via randomized smoothing(Cohen et al., 2019). Here we draw $N = 100,000$ noise samples and select noise levels $\sigma \in \{0.5, 1.0\}$ for certification. Note that we follow the same setting from Carlini et al. (2022) and choose to use one-shot denoising method. The detailed implementation of our method could be found in Appendix C.

We compare our results with randomized smoothing using the vanilla classifier and Gaussian augmented classifier, denoted RS-Vanilla and RS-Gaussian respectively. The results are shown in Table 5. We also provide a certified robustness with different L_2 perturbation bound with different Gaussian noise $\sigma = \{0.5, 1.0\}$ in Figure A of Appendix C. By observing our results, we find that our method outperforms baselines for a better certified accuracy except $\sigma = 0.5$ at 0 radius. We also notice that the performance of our method will be even better when the input noise gets larger. This may due to AudioPure can still recover the clean audio with a large L_2-based perturbation while Gaussian augmented model could even not be converged when training with such large noise.

5 Conclusion

In this paper, we propose an adversarial purification-based defense pipeline for acoustic systems. To evaluate the effectiveness of AudioPure , we design the adaptive attack method and evaluate our method among adaptive attack, EOT attack and black-box attacks. Comprehensive experiments indicate that our defense is more effective than existing methods (including adversarial training) among the diverse type of adversarial examples. We show AudioPure achieves a better certifiable robustness via Randomized Smoothing than other baselines. Moreover, our defense can be a universal plug-and-play method for classifiers with different architectures.

Limitations. By adding the diffusion model, the inference of AudioPure will take more time and computational resources. How to compress the size and accelerate the sampling of diffusion models is an important future work.

ETHICS STATEMENT

Our work proposes a defense pipeline for protecting acoustic systems from adversarial audio examples. In particular, our study focuses on speech command recognition, which is closely related to keyword spotting systems. Such systems are well known to be vulnerable to adversarial attacks. Our pipeline will enhance the security aspect of such real-world acoustic systems and benefit the social beings. The Speech Commands dataset used in our study are released by others and has been publicly available for years. The dataset contains various voices from anonymous speakers. To the best of our knowledge, it does not contain any privacy-related information for these speakers.

REPRODUCIBILITY STATEMENT

We tried our best to include necessary details (e.g., hyperparameters, steps) for reproducing our results. More importantly, we upload our experimental code in the supplementary material. Once the paper is accepted, we will open-source the code and release the pre-trained models to the public.

REFERENCES

Hadi Abdullah, Muhammad Sajidur Rahman, Washington Garcia, Kevin Warren, Anurag Swarnim Yadav, Tom Shrimpton, and Patrick Traynor. Hear" no evil", see" kenansville"*: Efficient and transferable black-box attacks on speech recognition and voice identification systems. In *2021 IEEE Symposium on Security and Privacy (SP)*, pp. 712–729. IEEE, 2021.

Dario Amodei, Sundaram Ananthanarayanan, Rishita Anubhai, Jingliang Bai, Eric Battenberg, Carl Case, Jared Casper, Bryan Catanzaro, Qiang Cheng, Guoliang Chen, et al. Deep speech 2: End-to-end speech recognition in english and mandarin. In *International conference on machine learning*, pp. 173–182. PMLR, 2016.

Maksym Andriushchenko, Francesco Croce, Nicolas Flammarion, and Matthias Hein. Square attack: a query-efficient black-box adversarial attack via random search. In *European Conference on Computer Vision*, pp. 484–501. Springer, 2020.

Nicholas Carlini and David Wagner. Towards evaluating the robustness of neural networks. In *2017 ieee symposium on security and privacy (sp)*, pp. 39–57. Ieee, 2017.

Nicholas Carlini and David Wagner. Audio adversarial examples: Targeted attacks on speech-to-text. In *2018 IEEE security and privacy workshops (SPW)*, pp. 1–7. IEEE, 2018.

Nicholas Carlini, Florian Tramer, J Zico Kolter, et al. (certified!!) adversarial robustness for free! *arXiv preprint arXiv:2206.10550*, 2022.

Guangke Chen, Sen Chenb, Lingling Fan, Xiaoning Du, Zhe Zhao, Fu Song, and Yang Liu. Who is real bob? adversarial attacks on speaker recognition systems. In *2021 IEEE Symposium on Security and Privacy (SP)*, pp. 694–711. IEEE, 2021a.

Guoguo Chen, Carolina Parada, and Georg Heigold. Small-footprint keyword spotting using deep neural networks. In *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 4087–4091. IEEE, 2014.

Nanxin Chen, Yu Zhang, Heiga Zen, Ron J Weiss, Mohammad Norouzi, and William Chan. Wavegrad: Estimating gradients for waveform generation. In *International Conference on Learning Representations*, 2021b.

Jeremy Cohen, Elan Rosenfeld, and Zico Kolter. Certified adversarial robustness via randomized smoothing. In *International Conference on Machine Learning*, pp. 1310–1320. PMLR, 2019.

Francesco Croce and Matthias Hein. Reliable evaluation of adversarial robustness with an ensemble of diverse parameter-free attacks. In *International conference on machine learning*, pp. 2206–2216. PMLR, 2020.

Wei Dai, Chia Dai, Shuhui Qu, Juncheng Li, and Samarjit Das. Very deep convolutional neural networks for raw waveforms. In *2017 IEEE international conference on acoustics, speech and signal processing (ICASSP)*, pp. 421–425. IEEE, 2017.

Prafulla Dhariwal and Alexander Nichol. Diffusion models beat gans on image synthesis. *Advances in Neural Information Processing Systems*, 34:8780–8794, 2021.

Tianyu Du, Shouling Ji, Jinfeng Li, Qinchen Gu, Ting Wang, and Raheem Beyah. Sirenattack: Generating adversarial audio for end-to-end acoustic systems. In *Proceedings of the 15th ACM Asia Conference on Computer and Communications Security*, pp. 357–369, 2020.

Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. In *International Conference on Learning Representations*, 2015.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770–778, 2016.

Jonathan Ho, Ajay Jain, and Pieter Abbeel. Denoising diffusion probabilistic models. *Advances in Neural Information Processing Systems*, 33:6840–6851, 2020.

Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. Densely connected convolutional networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 4700–4708, 2017.

Zhifeng Kong, Wei Ping, Jiaji Huang, Kexin Zhao, and Bryan Catanzaro. Diffwave: A versatile diffusion model for audio synthesis. In *International Conference on Learning Representations*, 2021.

Juncheng Li, Shuhui Qu, Xinjian Li, Joseph Szurley, J Zico Kolter, and Florian Metze. Adversarial music: Real world audio adversary against wake-word detection system. *Advances in Neural Information Processing Systems*, 32, 2019.

Xuechen Li, Ting-Kam Leonard Wong, Ricky TQ Chen, and David Duvenaud. Scalable gradients for stochastic differential equations. In *International Conference on Artificial Intelligence and Statistics*, pp. 3870–3882. PMLR, 2020.

Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu. Towards deep learning models resistant to adversarial attacks. In *International Conference on Learning Representations*, 2018.

Alexander Quinn Nichol and Prafulla Dhariwal. Improved denoising diffusion probabilistic models. In *International Conference on Machine Learning*, pp. 8162–8171. PMLR, 2021.

Weili Nie, Brandon Guo, Yujia Huang, Chaowei Xiao, Arash Vahdat, and Anima Anandkumar. Diffusion models for adversarial purification. In *International conference on machine learning*. PMLR, 2022.

Yao Qin, Nicholas Carlini, Garrison Cottrell, Ian Goodfellow, and Colin Raffel. Imperceptible, robust, and targeted adversarial examples for automatic speech recognition. In *International conference on machine learning*, pp. 5231–5240. PMLR, 2019.

Krishan Rajaratnam and Basemah Alshemali. Speech coding and audio preprocessing for mitigating and detecting audio adversarial examples on automatic speech recognition. `http://cs.uccs.edu/~jkalita/work/reu/REU2018/07Rajaratnam.pdf`, 2018.

Mirco Ravanelli and Yoshua Bengio. Speaker recognition from raw waveform with sincnet. In *2018 IEEE Spoken Language Technology Workshop (SLT)*, pp. 1021–1028. IEEE, 2018.

Mirco Ravanelli, Titouan Parcollet, and Yoshua Bengio. The pytorch-kaldi speech recognition toolkit. In *ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 6465–6469. IEEE, 2019.

Douglas A Reynolds, Thomas F Quatieri, and Robert B Dunn. Speaker verification using adapted gaussian mixture models. *Digital signal processing*, 10(1-3):19–41, 2000.

Hadi Salman, Mingjie Sun, Greg Yang, Ashish Kapoor, and J Zico Kolter. Denoised smoothing: A provable defense for pretrained classifiers. *Advances in Neural Information Processing Systems*, 33:21945–21957, 2020.

Ali Shafahi, Mahyar Najibi, Mohammad Amin Ghiasi, Zheng Xu, John Dickerson, Christoph Studer, Larry S Davis, Gavin Taylor, and Tom Goldstein. Adversarial training for free! *Advances in Neural Information Processing Systems*, 32, 2019.

Jonathan Shen, Patrick Nguyen, Yonghui Wu, Zhifeng Chen, Mia X Chen, Ye Jia, Anjuli Kannan, Tara Sainath, Yuan Cao, Chung-Cheng Chiu, et al. Lingvo: a modular and scalable framework for sequence-to-sequence modeling. *arXiv preprint arXiv:1902.08295*, 2019.

Changhao Shi, Chester Holtz, and Gal Mishne. Online adversarial purification based on self-supervised learning. In *International Conference on Learning Representations*, 2021.

Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. In *International Conference on Learning Representations*, 2015.

David Snyder, Daniel Garcia-Romero, Gregory Sell, Daniel Povey, and Sanjeev Khudanpur. X-vectors: Robust dnn embeddings for speaker recognition. In *2018 IEEE international conference on acoustics, speech and signal processing (ICASSP)*, pp. 5329–5333. IEEE, 2018.

Jiaming Song, Chenlin Meng, and Stefano Ermon. Denoising diffusion implicit models. In *International Conference on Learning Representations*, 2021a.

Yang Song and Stefano Ermon. Generative modeling by estimating gradients of the data distribution. *Advances in Neural Information Processing Systems*, 32, 2019.

Yang Song, Jascha Sohl-Dickstein, Diederik P Kingma, Abhishek Kumar, Stefano Ermon, and Ben Poole. Score-based generative modeling through stochastic differential equations. In *International Conference on Learning Representations*, 2021b.

Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian Goodfellow, and Rob Fergus. Intriguing properties of neural networks. In *International Conference on Learning Representations*, 2014.

Florian Tramer and Dan Boneh. Adversarial training and robustness for multiple perturbations. *Advances in Neural Information Processing Systems*, 32, 2019.

Florian Tramer, Nicholas Carlini, Wieland Brendel, and Aleksander Madry. On adaptive attacks to adversarial example defenses. *Advances in Neural Information Processing Systems*, 33:1633–1645, 2020.

Pete Warden. Speech commands: A dataset for limited-vocabulary speech recognition. *arXiv preprint arXiv:1804.03209*, 2018.

Eric Wong, Leslie Rice, and J Zico Kolter. Fast is better than free: Revisiting adversarial training. In *International Conference on Learning Representations*, 2020.

Saining Xie, Ross Girshick, Piotr Dollár, Zhuowen Tu, and Kaiming He. Aggregated residual transformations for deep neural networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1492–1500, 2017.

Zhuolin Yang, Bo Li, Pin-Yu Chen, and Dawn Song. Characterizing audio adversarial examples using temporal dependency. In *International Conference on Learning Representations*, 2019.

Jongmin Yoon, Sung Ju Hwang, and Juho Lee. Adversarial purification with score-based generative models. In *International Conference on Machine Learning*, pp. 12062–12072. PMLR, 2021.

Sergey Zagoruyko and Nikos Komodakis. Wide residual networks. In *British Machine Vision Conference 2016*. British Machine Vision Association, 2016.

Dinghuai Zhang, Tianyuan Zhang, Yiping Lu, Zhanxing Zhu, and Bin Dong. You only propagate once: Accelerating adversarial training via maximal principle. *Advances in Neural Information Processing Systems*, 32, 2019a.

Hongyang Zhang, Yaodong Yu, Jiantao Jiao, Eric Xing, Laurent El Ghaoui, and Michael Jordan. Theoretically principled trade-off between robustness and accuracy. In *International conference on machine learning*, pp. 7472–7482. PMLR, 2019b.

APPENDIX

A DETAILS ON TRAINING THE IMPROVE DDPM.

We train an Improved DDPM using the official repository (https://github.com/openai/improved-diffusion). For UNet model, we set $image_size = 32$, $num_channels = 3$ and $num_res_blocks = 128$. For diffusion flags, we set $N = 200$, $\beta_1 = 0.0001$, $\beta_N = 0.02$ and use the linear variance schedule. For the model training, we set the learning rate to $1e{-}4$ and batch size to 230. The training loss has converged after 80,000 training steps, and we use this checkpoint to build our purifier.

B ADDITIONAL EXPERIMENTS OF TRANSFER-BASED ATTACK

We additionally evaluate our method under transfer-based attack, where we assume the attacker can only get the output logits of the acoustic system but have no knowledge about the used defense.

We use model functional stealing to train a surrogate model. Specifically, we first feed input examples into the acoustic system consisting of DiffWave and a ResNeXt classifier and get the output logits. Then we use these output logits of the acoustic system as labels and train a new surrogate ResNeXt model, which has the same architecture as the classifier in the acoustic system. The results are shown in Table A. The *Stealing Acc.* denotes the accuracy of the surrogate classifier using the predictions of the defended acoustic system as ground truth. The *Transfer to Vanilla* and *Transfer to Defended* represent the undefended vanilla classifier and the defended acoustic system. The surrogate classifier is attacked to generate adversarial examples, and these adversarial examples are transferred to evaluate the robustness of the undefended vanilla classifier and the defended acoustic system.

Table A: Diffusion purification on different models

Stealing Target	Stealing Acc.	Transfer to Vanilla		Transfer to Defended	
		Clean	Robust	Clean	Robust
AudioPure($n^\star = 1$)	100	100	22	100	99
AudioPure($n^\star = 5$)	98	100	58	96	94

C DETAILS ABOUT CERTIFIED ROBUSTNESS

Randomized smoothing (Cohen et al., 2019) provides a provable robustness guarantee in $\mathcal{L}_2$-norm by evaluating models under noise. Usually, the performance of the vanilla classifier will degrade when feeding the Gaussian perturbed inputs. To alleviate this problem, we can re-train a new network or fine-tune a pretrained network on Gaussian augmented data. However, both of them could take a lot of time on training. Another way is to apply a denoiser before the vanilla classifier, named denoised smoothing (Salman et al., 2020). Since the reverse process of diffusion model can be seen as a good denoiser, we can use a pretrained diffusion model as a plug-and-play method to make any model certifiably robust. For a given noise level σ, we can compute the corresponding diffusion step $t^\star$ which adds the same level of noise to the input examples. The diffusion process can be reformulated as:

$$\mathbf{x}_n = \sqrt{\bar{\alpha}_n}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\mathbf{z} = \sqrt{\bar{\alpha}_n}(\mathbf{x}_0 + \sqrt{\frac{1-\bar{\alpha}_n}{\bar{\alpha}_n}}\mathbf{z}), \qquad \mathbf{z} \sim \mathcal{N}(0, \mathbf{I}), \tag{S17}$$

while the noisy input $\hat{\mathbf{x}}$ of randomized smoothing is

$$\hat{\mathbf{x}} = \mathbf{x}_0 + \sqrt{\sigma}\mathbf{z}, \qquad \mathbf{z} \sim \mathcal{N}(0, \mathbf{I}). \tag{S18}$$

So we can obtain $n^\star$ *s.t.* $\frac{1-\bar{\alpha}_n}{\bar{\alpha}_n} = \sigma$ after multiplying a rescale coefficient $\sqrt{\bar{\alpha}_n}$ on the input $\hat{\mathbf{x}}$.

According to Carlini et al. (2022), a single reverse step is able to recover an image with a high accuracy for the classifier and can largely save computational time by directly recovering the data

through $\mathbf{x}_0 = \frac{1}{\sqrt{\bar{\alpha}_n}}(\mathbf{x}_n - \sqrt{1-\bar{\alpha}_n}\boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_n}\hat{\mathbf{x}}, n))$. So we can just apply one-shot denoising instead of running full steps in our reverse process.

Figure A shows certified accuracy of AudioPure compared with RS-Gaussian and RS-Vanilla. The results show that certified robustness of our method is consistently better than baselines except at small certified radius when $\sigma = 0.50$.

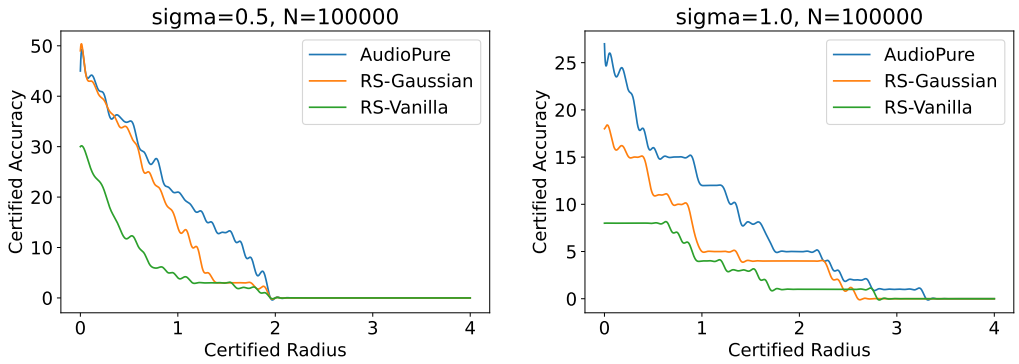


Figure A: Certified robustness (L_2) with different input noise level σ. Larger σ ensures better robustness under larger perturbations, but the performance for benign inputs will be degraded.