


Decoding Deception: Understanding Automatic Speech Recognition Vulnerabilities in Evasion and Poisoning Attacks

Aravindhan G 

AIShield, Bosch Global Software
Technologies Pvt. Ltd.
Bangalore, India
aravindhan.g@in.bosch.com

Yuvaraj Govindarajulu 

AIShield, Bosch Global Software
Technologies Pvt. Ltd.
Bangalore, India
govindarajulu.yuvaraj@in.bosch.com

Parin Shah 

AIShield, Bosch Global Software
Technologies Pvt. Ltd.
Bangalore, India
parin.shah@in.bosch.com

Abstract

Recent studies have demonstrated the vulnerability of Automatic Speech Recognition systems to adversarial examples, which can deceive these systems into misinterpreting input speech commands. While previous research has primarily focused on white-box attacks with constrained optimizations, and transferability based black-box attacks against commercial Automatic Speech Recognition devices, this paper explores cost efficient white-box attack and non transferability black-box adversarial attacks on Automatic Speech Recognition systems, drawing insights from approaches such as Fast Gradient Sign Method and Zeroth-Order Optimization. Further, the novelty of the paper includes how poisoning attack can degrade the performances of state-of-the-art models leading to misinterpretation of audio signals. Through experimentation and analysis, we illustrate how hybrid models can generate subtle yet impactful adversarial examples with very little perturbation having Signal Noise Ratio of 35dB that can be generated within a minute. These vulnerabilities of state-of-the-art open source model have practical security implications, and emphasize the need for adversarial security.

CCS Concepts

• **Computing methodologies** → **Speech recognition**; • **Security and privacy**;

Keywords

Speech Recognition, Adversarial attacks, Adversarial AI Security.

1 Introduction

Automatic Speech Recognition (ASR) systems have witnessed remarkable advancements, revolutionizing human-computer interactions through voice-enabled technologies. However, alongside these advancements comes the growing concern of security vulnerabilities, particularly in the face of adversarial attacks. Recent studies have unveiled the potential threats posed by adversarial examples to ASR systems, highlighting their susceptibility to manipulation and exploitation by malicious actors. While much attention has been devoted to understanding and mitigating adversarial attacks in other domains like image processing [33], the specific vulnerabilities and implications of such attacks on ASR systems remain less explored.

The complexity of ASR systems, characterized by intricate pre-processing, feature extraction, and model-based prediction stages, presents unique challenges in safeguarding against adversarial attacks. Unlike image recognition systems, ASR systems operate in

the domain of continuous audio signals, requiring specialized techniques to craft and detect adversarial examples. Furthermore, the proliferation of commercial ASR devices, such as Google Home [26], Amazon Echo, and Microsoft Cortana, introduces additional complexities due to the proprietary nature of their underlying models, hindering efforts to assess and mitigate potential security risks effectively.

Adversarial attacks include various domains starting from stealing targeted model to poisoning the targeted model. Model extraction attacks [34] is a popular technique where the adversary steal the mathematical functionality of the model by carefully curating queries and thus forming a surrogate dataset and training a offline model of his own. Another popular technique called model evasion that involves fooling the targeted model leading to wrong prediction with high confidence [22]. Further technique involves injecting malicious samples into training data resulting in degradation of model training and creating a backdoor for adversaries to exploit the model [13].

Major significant area of concern is the emergence of white-box and black-box attacks, where adversaries seek to exploit ASR systems with/without access to internal model parameters or architecture. The Zeroth-Order Optimization (ZOO) attack in black-box setting, introduced by Y. Chen et. al [12], represents a paradigm shift in adversarial attacks by enabling adversaries to generate imperceptible adversarial examples using only query access to the target model. Building upon this, the Devil's Whisper paper [14] further explores the feasibility of black-box attacks on commercial ASR devices, demonstrating the effectiveness of hybrid approaches that combine local and white-box models.

Poisoning attack introduced by L. González et. al [23] leverages gradient based procedure to optimize the poisoning points an forming poisoned data. These poisoned data are used later in deep learning algorithms for training resulting in infection of model parameters.

Building upon recent advancements in adversarial attack methodologies, such as Zeroth-Order Optimization (ZOO), evasion attacks and gradient based poisoning attack on images, this paper aims to address this gap on ASR systems. We investigate the potential for crafting robust and imperceptible adversarial examples capable of evading and poisoning ASR systems.

Through comprehensive experimentation and analysis, we aim to shed light on the complex interplay between adversarial attacks and ASR system resilience, ultimately advancing our understanding of the evolving threat landscape in voice-controlled computing environments. By elucidating the challenges and opportunities inherent in defending against adversarial manipulation, we contribute to the

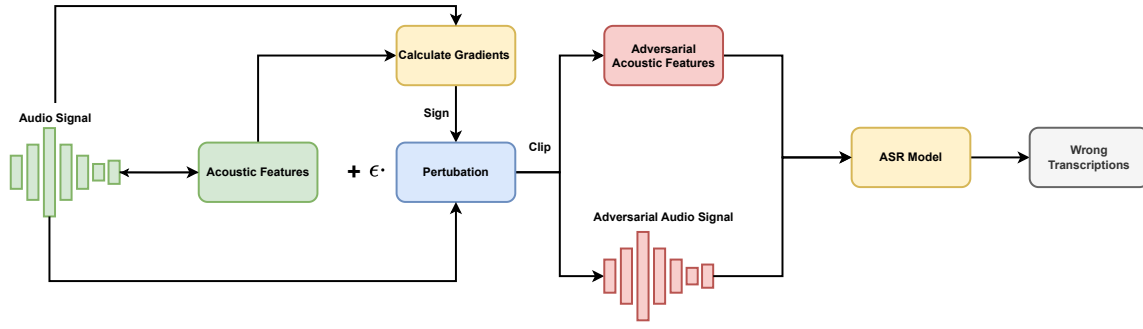


Figure 1: Attack on ASR Systems using Audio/MFCC Features as Input

development of more robust and trustworthy ASR systems capable of withstanding emerging security threats. We summarize our main contributions as follows:

- To the best of our knowledge, this is the first work to speak upon ASR systems threat against cost effective evasion attack using Fast Gradient Sign Method with minimum Signal Noise Ratio ranging from 15-35 dB.
- We demonstrate vulnerability of the current state-of-the-art distil whisper large-v3 against targeted and untargeted evasion attack.
- We propose an adapted version of zeroth-order-optimization evasion attack in black-box setting which achieves Word Error Rate of 50% with Signal Noise Ratio ranging from 1.5-4 dB.
- By incorporating gradient based poisoning method in ASR systems we discuss for the first time how poisoning of data can result in significant degradation of model performance.

2 Related Work

In recent years, the research landscape surrounding adversarial attacks on ASR systems has witnessed significant development. This section provides an overview of relevant literature, categorizing existing approaches and highlighting their contributions to understanding the vulnerabilities of ASR technology.

Advancements in AI technology have brought about significant breakthroughs, but they also raise concerns regarding adversarial attacks. These attacks manipulate AI systems by providing deceptive input, thereby compromising their decision-making processes. Biggio et al. [8] explores the progress in adversarial AI and highlights the susceptibility of AI models, particularly deep networks, to intentional input perturbations aimed at exploiting their weaknesses. These attacks, which exploit vulnerabilities in AI systems, can take various forms and target different aspects such as data, models, or infrastructure. To effectively identify potential security threats and develop defense mechanisms, a threat model is essential. This model defines the capabilities and objectives of attackers under realistic assumptions. Adversarial attacks are typically categorized into Black Box [6], Grey Box [7], and White Box Attacks [10], based on the extent of the attacker's knowledge regarding the targeted AI system's inner workings and components.

Previous studies have explored the vulnerability of third-party applications and skills for IVC (Intelligent Voice Control) systems,

revealing potential misinterpretation attacks. Kumar et al. [19] conducted an empirical analysis of interpretation errors on Amazon Alexa [1], uncovering the possibility of skill squatting attacks. Similarly, Zhang et al. [37] demonstrated how malicious skills with similar pronunciations could impersonate benign skills, posing security risks to IVC systems.

Researchers have identified vulnerabilities in ASR systems that can be exploited through signal manipulation. H. Abdullah et al. [3] explores vulnerabilities in speech and speaker recognition systems, highlighting their susceptibility to manipulated inputs. Kasmi et al. [18] discovered that intentional electromagnetic interference (IEMI) of headset cords could inject voice commands into FM signals, compromising smartphone-based ASR systems. The Dolphin Attack [36] exploited hardware vulnerabilities in microphone circuits to interpret inaudible ultrasonic signals as malicious commands, affecting devices like Apple Siri [2] and Google Now.

Obfuscation-based attacks focus on manipulating feature extraction processes to deceive ASR systems. Demonstration on the inversion of Mel-Frequency Cepstral Coefficients (MFCC) to create malicious audio samples, which could be misinterpreted as commands by ASR systems are proved to be effective. Carlini et al. [9] proposed hidden voice commands embedded in background noise to improve the efficacy of attacks on ASR systems, highlighting the challenges of defending against obfuscated inputs.

Adversarial example-based attacks involve crafting inputs that closely resemble legitimate audio but are misinterpreted by ASR systems. Yuan et al. [35] introduced the CommanderSong attack, embedding malicious commands into normal songs to deceive ASR models. Carlini et al. [9] demonstrated the generation of imperceptible adversarial samples against end-to-end ASR platforms like Mozilla DeepSpeech, highlighting the vulnerability of deep learning-based systems to adversarial inputs. Y. Qin et al. [27] continued Carlini work and extend by creating adversarial inputs that are imperceptible to human ears by masking perturbations using psycho-acoustic models. Oliver et al. [24] showcased how the current state-of-the-art Whisper [28] are vulnerable to adversarial attacks by utilizing techniques involving constrained optimizations.

Drawing upon insights from seminal works such as the ZOO and Devil's Whisper papers, we have identified the need for a deeper understanding of adversarial vulnerabilities in commercial ASR devices and the development of robust defense mechanisms against such attacks. Our contributions in this paper lie in bridging

this gap by investigating the feasibility and implications of cost effective evasive and poisoning adversarial attacks on commercial ASR systems and leveraging novel techniques and insights, we aim to uncover vulnerabilities, propose effective countermeasures, and enhance the security posture of ASR technologies in real-world applications.

3 Methodology

We begin by defining any threat model $f : \mathcal{X} \mapsto \mathcal{Z}$ which takes raw audio signal X and outputs transcription \mathcal{Z} . Generally these model are available online as a service or open-sourced by many providers. To the defined threat model, we do extensive experiments that showcases the risk it possess.

The paper is designed as follows : We begin with the evasion attack under white-box setting and slowly move towards black-box. Later we shift our focus towards gradient based data poisoning attack.

3.1 Model Evasion Attack

Preliminary : Given an raw audio signal X and ground truth transcription y , the goal of evasion attack is to generate adversarial audio signal \tilde{X} close to original signal X which outputs into different transcript \tilde{y} as given in Equation 1. Evasion attacks can be targeted and untargeted attacks. Untargeted attack focuses on misprediction of audio signal and targeted attack leads to prediction of targeted transcript.

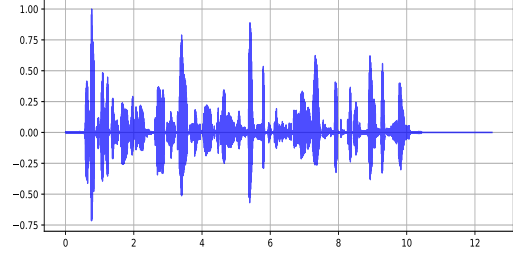
Figure 1 illustrates the process of an audio evasion attack. Given an audio sample attack takes places either in audio signal or at the extracted audio features. The attack involves calculating gradients with respect to input and perturbing it linearly to generate adversarial samples which fool’s ASR systems.

$$\begin{aligned} y &\rightarrow f(X) \\ \tilde{y} &\rightarrow f(\tilde{X}) \mid (f(X) \neq f(\tilde{X})) \wedge (X \sim \tilde{X}) \end{aligned} \quad (1)$$

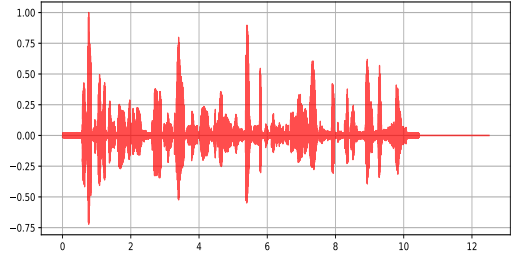
Fast Gradient Sign Method . The Fast Gradient Sign Method (FGSM) [16] is a popular technique for generating adversarial examples in the field of images. It makes use of gradient to craft malicious perturbation’s δ in the direction of gradients that can exploit an AI models into making incorrect predictions. FGSM creates adversarial examples that imperceptible to humans. FGSM is suitable for crafting evasion attacks in untargeted method. It is know for its cost effective successful method.

$$\begin{aligned} \tilde{X} &= X + \epsilon \cdot \text{sign}(\delta) \\ \delta &= \nabla_x J(\theta, X, y) \end{aligned} \quad (2)$$

We adapt FGSM for ASR systems on the acoustic features (MFC) extracted from audio signals. Then sign of the Gradients ∇_x in FGSM are calculated with respect to input X using loss function $J(\theta, X, y)$ as given in Equation 2, where θ corresponds to models internal parameters. For ASR systems input can be raw audio signal X or an MFC $G(X)$ (extracted acoustic feature of the raw signal). The amount of perturbation added is controlled by the parameter ϵ . Lower epsilon corresponds to minimal change of input in both positive and negative direction and higher epsilon corresponds



(a) Audio Signal



(b) Adversarial Signal

Figure 2: Evasion Attack on Audio Signals

Algorithm 1 ZOO-ADAM: Zeroth Order Stochastic Coordinate Descent with Coordinate-wise ADAM

Require: Model f , Input samples X , Original Transcription y
Require: Step size η , ADAM states $M \in \mathbb{R}^p$, $v \in \mathbb{R}^p$, $T \in \mathbb{Z}^p$, ADAM hyper-parameters $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-8}$, Embedding E , $\epsilon = 10^{-8}$
Ensure: Adversarial sample \tilde{X}

- 1: $M \leftarrow 0$, $v \leftarrow 0$, $T \leftarrow 0$
- 2: **while** not converged **do**
- 3: $\hat{y} \leftarrow f(X)$
- 4: $\vec{e} \leftarrow E(y)$, $\vec{\hat{e}} \leftarrow E(\hat{y})$
- 5: Calculate $(1/\cos\text{Sim}(\vec{e}, \vec{\hat{e}}) + \epsilon)$ using Equation (6)
- 6: Randomly pick a coordinate $i \in \{1, \dots, p\}$
- 7: Estimate \hat{g}_i using Equation (5) using $\cos\text{Sim}$
- 8: $T_i \leftarrow T_i + 1$
- 9: $M_i \leftarrow \beta_1 M_i + (1 - \beta_1) \hat{g}_i$, $v_i \leftarrow \beta_2 v_i + (1 - \beta_2) \hat{g}_i^2$
- 10: $\hat{M}_i = \frac{M_i}{1 - \beta_1^{T_i}}$, $\hat{v}_i = \frac{v_i}{1 - \beta_2^{T_i}}$
- 11: $\delta^* = -\eta \frac{\hat{M}_i}{\sqrt{\hat{v}_i + \epsilon}}$
- 12: Update $x_i \leftarrow x_i + \delta^*$
- 13: **end while**

noticeable change (refer Figure 1 for more details)

Projected Gradient Descent. Projected Gradient Descent (PGD) attack is another evasion method that iteratively adjusting input data based on the model’s gradients, aiming to maximize prediction error. It’s effective in generating adversarial examples, perturbed

inputs crafted to deceive the model while appearing similar to the original data. This iterative process enhances the attacker’s ability to find imperceptible alterations that significantly alter the model’s output and works better on both targeted and untargeted attacks.

We optimize δ under the following constrained objective given in Equation 3.

$$\max_{\|\delta\|_2 < \epsilon} L(f(X + \delta), y) \quad (3)$$

To keep δ in the L_2 -ball of radius ϵ , the optimization algorithm is projected gradient descent for n steps: at each step, we run one gradient update, then if δ is too large we project it back onto the ball. PGD can run targeted attacks by simply replacing the objective as in Equation 4 where y_t is the target transcription.

$$\min_{\|\delta\|_2 < \epsilon} L(f(X + \delta), y_t) \quad (4)$$

Zeroth Order Optimization using ADAM. Zeroth Order Optimization using ADAM (ZOO-Adam) is a stochastic coordinate descent evasion attack in black-box setting. It estimates gradient $\frac{\partial f(X)}{\partial X_i}$ (defined as \hat{g}_i) using forward difference approach as given in Equation 5, where h is small constant and e_i are stochastic coordinates. The estimated gradients are then updated to random coordinates using Adaptive Moment Estimator.

$$\hat{g}_i := \frac{\partial f(X)}{\partial X_i} \approx \frac{f(X + he_i) - f(X - he_i)}{2h} \quad (5)$$

ASR system black-box estimation are of two kinds: 1) Score-based attack [21, 29], 2) Decision-based attack [11]. Score-based makes use of logits/probabilities to estimate gradients. Decision-based are pure black-box which only accepts the transcribed output given. The defined black-box attack is based on decision-based (see Algorithm 1 for details) in untargeted method. Given the output transcriptions we transform them into embedding space by leveraging embedding method E and calculate one upon the similarity as given in Equation [6].

$$\text{Cosine Similarity} = \frac{\sum_{i=1}^n A_i \times B_i}{\sqrt{\sum_{i=1}^n A_i^2} \times \sqrt{\sum_{i=1}^n B_i^2}} \quad (6)$$

3.2 Data Poisoning

Data Poisoning [15] attack involves adding malicious adversarial perturbations to the input with the intention of degrading the performance of the model. The key idea is that an input contains little useful information about the original class, which makes it difficult to extract valuable features. In ASR data poisoning, adding a small amount of poisoned data results in a change in words/character predicted on whole.

Gradient Based Poisoning . Gradient Based Poisoning, adversarial perturbations are generated based on first order derivatives. The calculated perturbations are then added to inputs to generated poisoned data. We perform poisoning attack on direct raw audio signals. The gradients are calculated with respect to audio signals using loss function and perturbed linearly to audio signal. The amount of perturbation added is controlled by ϵ . For Whisper

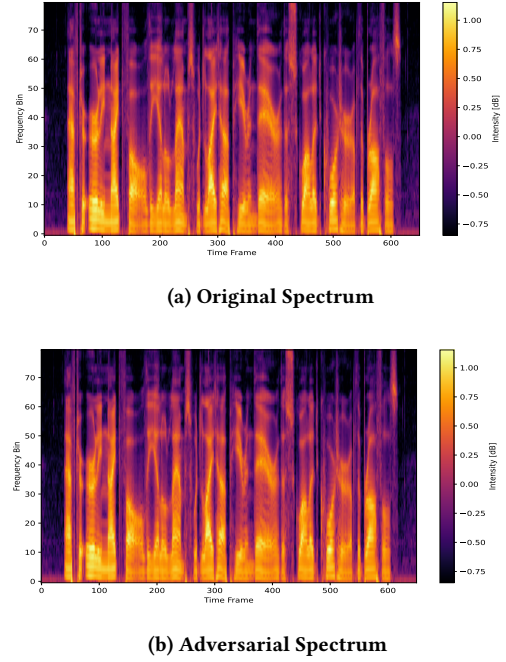


Figure 3: Evasion Attack on Log-Mel Spectrogram

model we make use of Categorical Cross-Entropy loss function and Connectionist Temporal Classification [17] for Wav2Vec and DeepSpeech models .

We make use of FGSM attack explained in the above section to access the effect of poisoned data against ASR systems (how much degradation can occur).

4 Experimental Analysis

In this section, we discuss the data set and the preprocessing required, together with the setup of the experiments performed. In addition to this, we showcase the final results with evaluation metrics

4.1 Dataset Description and Pre-processing

To benchmark the performance of attack we make use of clean test set of Librispeech corpus [25]. It includes five hours of audio data in English with labeled transcript sampled at a rate of 16 kHz. It involves multiple speakers at varying pitch making it suitable for ASR models. To implement the attack raw audio signals are converted into Mel spectrograms or Mel-frequency cepstral coefficients (MFCC) based on the input required. Further of targeted attack we make use of IVC devices commands and attack sensitive words.

4.2 Evaluation Metrics

The success of the attack on ASR systems are evaluated using the following metrics:

Word Error Rate . Word Error Rate (WER) is a metric commonly used to evaluate the performance of automatic speech recognition (ASR) systems. It measures the difference between the recognized

Table 1: Evasion results on Whisper [Tiny/Distill Large-3] (Log-Mel Spectrum), Wav2Vec (Raw audio waveform) and DeepSpeech (Mel Spectrum) in White-Box

Model	Epsilon (ϵ)	Test-Clean (WER/CER)	Adversarial (WER/CER)	SNR (Mean, SD) dB
Whisper (WER)	0.001	5.60%	5.66%	34.81 \pm 2.89
	0.01	5.60%	10.25%	25.27 \pm 2.89
	0.03	5.60%	26.74%	19.24 \pm 2.89
	0.06	5.60%	64.80%	14.81 \pm 2.89
Wav2Vec (WER)	0.001	3.28%	3.89%	41.56 \pm 2.36
	0.01	3.28%	15.37%	32.02 \pm 2.36
	0.03	3.28%	31.38%	25.99 \pm 2.36
	0.06	3.28%	45.37%	21.56 \pm 2.36
DeepSpeech (CER)	0.001	4.54%	10.84%	41.58 \pm 2.37
	0.01	4.54%	18.41%	32.04 \pm 2.37
	0.03	4.54%	24.19%	26.02 \pm 2.37
	0.06	4.54%	51.35%	21.58 \pm 2.37
D.Whisper L-V3 (WER)	0.001	2.10%	2.77%	34.81 \pm 2.89
	0.01	2.10%	3.83%	25.27 \pm 2.89
	0.03	2.10%	6.37%	19.24 \pm 2.89
	0.06	2.10%	37.72%	10.76 \pm 2.89

Table 2: Poisoning results on Whisper, Wav2Vec, and DeepSpeech models

Model	Epsilon (ϵ)	Test-Clean (WER/CER)	Adversarial (WER/CER)	Posioned	SNR (Mean \pm Std)
Whisper (WER)	0.0005	5.66%	6.60%	23.09	40.83 (\pm 2.89)
	0.001	5.66%	7.20%	30.46	34.81 (\pm 2.89)
	0.005	5.66%	11.49%	51.26	20.83 (\pm 2.89)
	0.008	5.66%	14.34%	62.14	16.75 (\pm 2.89)
	0.01	5.66%	16.49%	67.18	14.81 (\pm 2.89)
	0.02	5.66%	31.44%	85.31	8.79 (\pm 2.89)
Wav2Vec (WER)	0.001	3.28%	3.89%	11.95	41.56 (\pm 2.36)
	0.003	3.28%	4.03%	14.01	32.02 (\pm 2.36)
	0.006	3.28%	4.27%	17.25	25.99 (\pm 2.36)
	0.01	3.28%	4.59%	19.96	21.56 (\pm 2.36)
	0.02	3.28%	6.69%	30.31	15.54 (\pm 2.36)
	0.06	3.28%	31.38%	53.7	5.99 (\pm 2.36)
DeepSpeech (CER)	0.001	4.54%	10.84%	94.35	41.58 (\pm 2.37)
	0.003	4.54%	14.27%	96.87	32.04 (\pm 2.37)
	0.006	4.54%	16.40%	97.75	26.02 (\pm 2.37)
	0.01	4.54%	18.41%	98.21	21.58 (\pm 2.37)
	0.02	4.54%	24.19%	99.2	15.56 (\pm 2.37)
	0.06	4.54%	51.35%	99.77	6.02 (\pm 2.37)

text output by the ASR system and the reference or ground truth text. WER is calculated as the ratio of the total number of insertions (I), deletions (D), and substitutions (S) required to transform the recognized text into the reference text, divided by the total number of words in the reference text as given in Equation 7. WER is typically expressed as a percentage, with lower values indicating better ASR performance.

$$\text{WER} = \frac{S + D + I}{N} \quad (7)$$

Signal Noise Ratio. The Signal Noise Ratio (SNR) is a measure used to quantify the level of a signal compared to the level of background noise present in the signal. It's commonly expressed in decibels (dB) and calculated as the ratio of the power of the signal to the power of the noise as given in Equation 8. A higher SNR indicates a stronger, more distinguishable signal relative to the noise.

$$\text{SNR} = 10 \log_{10} \left(\frac{P_{\text{signal}}}{P_{\text{noise}}} \right) \quad (8)$$

Table 3: Targeted model transcriptions on the proposed techniques

Method	Technique	Model	Ground Truth	Adversarial Prediction	SNR (dB)
White Box	FGSM (Untargeted)	Whisper	Then he comes to the beak of it.	Then he comes to the peak of it.	24
			Hypocrite a horse dealer.	Epicrit, a horse-dealer.	28
			Hello Stephanos here comes the Dedalus.	Now I will still have a note here comes the battle.	18
		Wav2Vec	Words was it their colours.	PTO Tetole	26
			A voice from beyond the world was calling.	A boy a beyond the world e falling.	31
			Tied to a woman.	Tie poor woman.	42
		DeepSpeech	So it seems to me.	Wu his thought zeems to me.	22
			Gloves said the young man.	Loves said the young man wo.	40
			Cotton she paused.	Cadenn she wast.	27
	PGD (Targeted)	D.Whisper L-V3	Stuff it into you his belly counselled him.	Google mark. My calender.	18
			A cold, lucid indifference reigned in his soul.	Google cancel my schedule.	15
			Okay google, call 911.	okay google, call 999.	31
			Hey alexa.	Hey roger.	30
			Okay Google, open Youtube.	Okay Google, uninstall Youtube.	22
Black box	Zoo - Adam	Whisper	Stephen's heart began slowly to fold and fade with fear like a withering flower.	Steven sartre then slowly defiled and failed with fear like a wooden flower.	3.8
			A great saint saint francis xavier.	Great to speak from xavier.	3
			A voice from beyond the world was calling.	I am always on the road i am calling.	2.6
			He knows them both.	He lives in the gulf.	4
			Angor pain painful to hear.	Andor hane thankful to you.	3.2

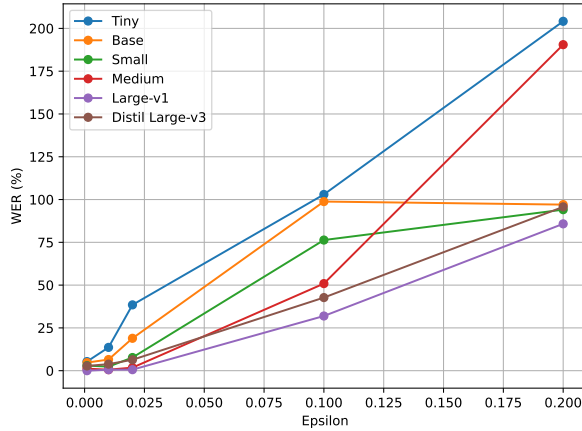


Figure 4: Effect of Epsilon against WER for all versions of Whisper in LibriSpeech test-clean dataset

4.3 Experimental Setup

To conduct the experiments on the LibriSpeech dataset, we utilize state-of-the-art open-source models, namely OpenAI’s Whisper [28], Facebook’s Wav2Vec [5] and DeepSpeech [4]. Whisper and DeepSpeech accepts Log-Mel Spectrograms as input, and Wav2Vec accepts raw audio waveforms as input. All models require audio files sampled at 16 kHz.

The hyper-parameters for the forward difference approach m (random direction) and ϵ (perturbation magnitude) were carefully chosen within the range of 15 – 35 and 0.001 – 0.06 respectively. Additionally, the percentage of poisoned data was selected from 15% – 60%. For PGD n iters was selected as 350 and learning rate of 0.01. This selection was made to maximize WER and SNR.

4.4 Results

Model Evasion. In Table 1 we present the results of four target models, Whisper-tiny, Wav2Vec, DeepSpeech and Distil Whisper Large-V3 under various adversarial conditions. The models are evaluated based on their performance in terms of WER / Character Error Rate (CER) and Signal-to-Noise Ratio (SNR), with different perturbation magnitudes represented by epsilon (ϵ).

For Whisper, as the epsilon value increases from 0.001 to 0.06, the WER on the adversarial data increases substantially, indicating that the model’s performance degrades significantly under higher levels of perturbation. Additionally, the SNR starting from 35dB shows a gradual decrease with increasing epsilon values, suggesting that the perturbations introduce more adversarial sound into the system, further affecting the model’s performance negatively. We also observe that WER jumps from 2.10% to 38% at minimum epsilon of 0.06 with an SNR value of 11dB for distil version of whisper larger-3.

In contrast, Wav2Vec and DeepSpeech exhibits a similar trend where higher epsilon values lead to increased WER / CER and decreased SNR. However, compared to Whisper, Wav2Vec generally

maintains a lower WER reaching upto 45% and a higher SNR of reducing to 22dB across all perturbation levels.

Attacks proposed by Oliver et al. [24] for all version whisper model on average takes 2 minutes (on one A100) to generate adversarial sample in untargeted method, where the proposed technique for untargeted method takes less <10 seconds to generate adversarial sample while maintain good SNR. Additionally targeted method in Oliver’s attacks makes use of CW technique which requires 25 minutes for whisper medium where PGD method require 5-10 minutes with SNR ranging from 15-32dB.

For black box attack, we maintained the minimum WER of 50% and considered attack has success once the minimum WER criteria has reached and were able to achieve 100% success rate with SNR of 4dB. Sample transcriptions are given below in Table 3. We find that all ASR models can be fooled by proposed white box and black-box techniques while maintaining WER of minimum 45% with SNR of 25dB, but for bigger multilingual model like distil whisper large-3 we find significant increase in WER at cost of SNR drop to 10dB. Refer Figure 4 for consolidated results of all Whisper versions.

Data Poisoning. In Table 3 we report the degradation of Whisper, Wav2Vec and DeepSpeech models performance with the amount of poisoned data. For Whisper, as the epsilon value increases, adversarial WERs increase significantly, indicating deterioration of performance under higher levels of perturbation. The SNR also shows a gradual decrease with increasing epsilon values, suggesting that the introduced perturbations lead to higher levels of adversarial audio in the ASR system. Moreover, the percentage of poisoned data increases substantially as the perturbation level rises, indicating a higher proportion of data being manipulated to generate adversarial examples.

In contrast, Wav2Vec exhibits a similar trend where higher epsilon values result in increased original and adversarial WERs and decreased Signal-to-Noise Ratios. However, compared to Whisper, Wav2Vec generally maintains lower WERs and higher SNRs across all perturbation levels, highlighting its relatively higher robustness against adversarial attacks. Additionally, the percentage of poisoned data is also lower for Wav2Vec compared to Whisper under similar perturbation levels, indicating a lesser vulnerability to data poisoning. Audio Signals and MFCC of original and adversarial are represented in Figure 3a and Figure 3b respectively.

4.5 Mitigation Strategies

Research work to overcome adversarial audio attacks are still not explored as extensive as in image domain. To mitigate and protect ASR we discuss how the most popular defense strategy from the adversarial image can be adapted in the audio domain.

Robust Training. Robust training involves training the model using perturbed samples generated by adversarial algorithms. This approach has demonstrated greater success in adversarial images. Essentially, it enhances the decision boundary, either by making it resistance to attacks or by making it more challenging for adversaries to create effective perturbations. Exploiting such an adversarial trained model would require attackers to either extend the duration of their attack algorithms or introduce more significant distortions to the adversarial inputs. However, it’s important to note

that adversarial training can lead to a decrease in the model’s accuracy, a phenomenon referred to as label leaking [20]. In this case, while the adversarial trained model exhibits improved resilience against adversarial samples, it comes at the expense of reduced accuracy when dealing with legitimate samples.

Detection Mechanism. Detection mechanism involves distinguishing between benign and malicious audio samples. This method involves training a detector capable of detecting malicious samples even at very little distortion from benign ones. These work involves training an ML model [30–32] as part of pipeline. The process involves extracting acoustic features, such as Mel-Frequency Cepstral Coefficients (MFCCs), from the audio samples and using them as input to train a binary classifier model.

Table 4 summarizes the performance of the Wav2Vec Classifier Model, trained on the LibriSpeech Test-Clean dataset with adversarial samples generated using the FGSM method at 0.05 Epsilon (ϵ). The model effectively detects adversarial samples for epsilon values ranging from 0.1 to 0.8 and accurately predicts unseen data, including benign samples with added sine waves and white noise.

4.6 Conclusion

In this work, we propose how ASR systems such as Whisper, Wav2Vec and DeepSpeech are vulnerable against adversarial attacks despite its robustness to naturalness. We display how easy it is to generate audio adversarial samples in targeted and untargeted method with very little perturbations that result in high misclassified words in both white-box and black-box setting.

We also elaborate how poisoning of audio can result in compromise of ASR system’s prediction emphasizing the importance of incorporating benign audio samples during system training. Finally we propose possible mitigation strategies to overcome against adversarial attacks.

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Table 4: Performance of Wav2Vec Classifier as Defense Model on Adversarial Attacks Detection

Epsilon (ϵ)	Class	Performance Metrics			
		Precision	Recall	F1-Score	Accuracy
0.05	0	0.99	1	1	1
	1	1	0.99	1	1
0.1	0	0.99	1	1	1
	1	1	0.99	1	1
0.2	0	0.99	1	1	1
	1	1	0.99	1	1
0.5	0	0.98	1	0.99	0.99
	1	1	0.98	0.99	0.99
0.8	0	0.98	1	0.99	0.99
	1	1	0.98	0.99	0.99
0.05 (Unseen Data)	0	0.99	1	1	1
	1	1	0.99	1	1
Unseen - White Noise		-	-	-	1
Sinusoidal Hz-440, amplitude - 0.1		1	0.99	0.99	0.99

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