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Adversarial Attacks on AI Diagnostic Tools: Assessing Risks and Developing Mitigation Strategies

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Abstract:
Artificial Intelligence (AI) diagnostic tools are increasingly utilized in healthcare for disease detection, prognosis, and personalized treatment planning. However, their growing reliance on machine learning algorithms makes them vulnerable to adversarial attacks—subtle, often imperceptible manipulations to input data that can lead to incorrect or misleading outcomes. These attacks pose significant threats to patient safety, clinical decision-making, and the integrity of healthcare systems. This paper critically examines the nature and risks of adversarial attacks on AI-based diagnostic systems, including examples in radiology, dermatology, and pathology, where altered inputs have led to misclassifications. The study categorizes different attack vectors such as white-box, black-box, and physical-world attacks, assessing their feasibility and potential impact on real-world healthcare applications. Additionally, the paper explores current defense mechanisms including adversarial training, input preprocessing, and model verification techniques, highlighting their strengths and limitations. A risk assessment framework is proposed to systematically evaluate the vulnerability of AI models based on model architecture, data sensitivity, and operational context. The paper also emphasizes the importance of regulatory oversight, continuous model auditing, and stakeholder education in minimizing risk. Through an interdisciplinary approach combining technical, ethical, and policy dimensions, the study aims to inform the development of more resilient AI diagnostic tools. Ultimately, enhancing the robustness of these systems is essential not only for ensuring accurate and trustworthy diagnostics but also for preserving public confidence in AI-driven healthcare innovations.

Keywords
Adversarial Attacks, AI Diagnostics, Healthcare Security, Robust Machine Learning, Risk Mitigation

Introduction

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Artificial Intelligence (AI) has revolutionized diagnostic medicine by augmenting clinical decision-making processes with data-driven insights derived from complex algorithms. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated remarkable accuracy in tasks such as medical image classification, disease detection, and prognosis modeling [1]. These systems are increasingly employed across domains such as radiology, dermatology, ophthalmology, and pathology, often outperforming traditional diagnostic techniques and even human experts in specific cases [2]. However, the integration of AI in critical medical settings introduces new vectors of vulnerability—chief among them being adversarial attacks. These attacks exploit the mathematical properties of AI models, subtly perturbing input data in ways that are imperceptible to human observers but capable of significantly degrading model performance [3]. In the context of healthcare, even minor inaccuracies introduced by such attacks can have severe implications, including misdiagnosis, inappropriate treatments, and erosion of trust in automated systems.

Adversarial machine learning (AML) is an emergent area of concern wherein malicious actors craft adversarial examples—inputs that are intentionally modified to deceive AI systems into making erroneous predictions. These perturbations are often engineered with minimal L p-norm constraints, making them difficult to detect by both humans and automated quality checks [4]. In high-stakes environments like oncology or cardiology, a misclassification induced by such an attack could result in false negatives or positives, potentially endangering patient lives. Recent studies have demonstrated that deep learning models trained on medical imaging datasets are susceptible to both white-box and black-box attacks, with adversaries requiring only limited knowledge of model architecture or weights to achieve high success rates [5]. This vulnerability is especially critical as many AI diagnostic tools are being rapidly deployed in real-time clinical workflows, mobile health applications, and telemedicine platforms.

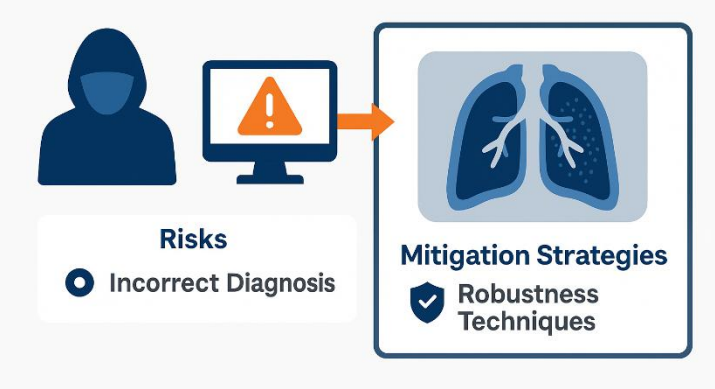

Figure 1: Adversarial Attacks on AI Diagnostic Tools

The risks are compounded by the opacity and complexity of deep learning systems, often described as "black boxes" due to their lack of interpretability. Medical practitioners are typically

unable to audit the decision logic of these systems, making it challenging to detect when an adversarial perturbation has influenced an output. Moreover, the increasing use of transfer learning and model sharing among institutions further exacerbates the risk, as adversarial vulnerabilities can propagate across systems sharing similar architectures or pre-trained weights [6]. With the proliferation of publicly available medical datasets and open-source deep learning frameworks, the barrier to launching adversarial attacks has significantly lowered, making these threats not merely theoretical but practically executable [7].

Despite the growing body of literature highlighting these threats, systematic studies addressing adversarial robustness in AI-driven diagnostic tools remain limited. Existing research has primarily focused on benchmark datasets, such as MNIST or CIFAR, which do not reflect the complexity and heterogeneity of clinical data [8]. Moreover, adversarial defense strategies such as input preprocessing, adversarial training, and gradient masking have shown inconsistent performance across healthcare applications, and in some cases, introduce trade-offs between robustness and accuracy [9]. Hence, there is a pressing need for a comprehensive investigation into the risk landscape posed by adversarial attacks on AI diagnostic systems, grounded in real-world clinical contexts.

This paper aims to address this gap by evaluating the feasibility, impact, and mitigation of adversarial attacks on AI-based diagnostic tools. We conduct a systematic analysis of attack modalities and defense mechanisms, leveraging publicly available medical datasets such as the NIH Chest X-ray dataset, ISIC skin lesion images, and LIDC-IDRI lung CT scans to emulate realistic threat scenarios. A risk assessment framework is proposed that integrates model complexity, clinical use-case sensitivity, and exposure surface to assess vulnerability. Furthermore, we advocate for an interdisciplinary approach that involves technical countermeasures, regulatory oversight, and end-user training to develop resilient AI diagnostic ecosystems. The insights derived from this study contribute to the broader discourse on trustworthy AI in medicine and aim to inform future standards in the deployment of secure, interpretable, and accountable diagnostic technologies [10].

Literature Review

The study of adversarial attacks in the context of AI-based diagnostic systems has gained increasing attention in the last decade as the medical community has rapidly adopted machine learning (ML) and deep learning (DL) tools for clinical decision support. One of the earliest works that explored adversarial vulnerabilities in medical imaging systems was conducted by Finlayson et al. (2019), who demonstrated that subtle perturbations could cause AI models to misclassify skin cancer images, even when the input appeared visually identical to the original [11]. Their study illustrated how easily these systems could be manipulated in real-world clinical environments, challenging assumptions about the reliability of deep learning classifiers in safety-critical domains. Similarly, Paschali et al. (2018) assessed adversarial robustness in medical

image segmentation and found that even state-of-the-art architectures like U-Net were susceptible to gradient-based attacks such as Fast Gradient Sign Method (FGSM) and Projected Gradient Descent (PGD), leading to substantial performance degradation in anatomical region identification [12].

Numerous studies have highlighted the comparative vulnerability of medical AI systems versus general-purpose models. Ma et al. (2021) performed a comparative study on the robustness of deep learning models trained on natural images versus medical datasets. Their findings indicated that medical AI models exhibited lower resilience to adversarial perturbations due to the lower signal-to-noise ratio and domain-specific biases inherent in clinical data [13]. Similarly, Taghanaki et al. (2021) emphasized that medical images, often characterized by homogeneity in structure and appearance, present a smaller margin of decision boundaries, making it easier for adversarial attacks to push samples across classification thresholds [14]. This observation has been consistently supported by empirical evidence across various modalities, including MRI, CT, and X-ray data.

Several researchers have proposed techniques to enhance the robustness of medical AI systems. Adversarial training remains one of the most widely investigated defenses. Szegedy et al. (2014) first introduced the concept of incorporating adversarial examples into training loops to improve model resilience [15], and subsequent adaptations have been applied to medical imaging domains. However, these methods often suffer from generalization issues and can compromise model accuracy on clean data. More recent approaches, such as feature denoising (Xie et al., 2020), model ensembling (Pang et al., 2019), and Bayesian inference techniques (Kendall and Gal, 2017), have also been explored as ways to suppress the influence of adversarial perturbations [16–18]. Despite these efforts, there remains no universally accepted defense mechanism that balances robustness, interpretability, and diagnostic precision across different clinical applications.

Furthermore, regulatory and ethical implications have been underexplored relative to the technical aspects. Amann et al. (2020) conducted a systematic review of AI tools in radiology and noted the alarming lack of regulatory scrutiny for models vulnerable to adversarial manipulation [19]. They argued that adversarial threats introduce risks not just to patient outcomes, but also to legal liability and institutional accountability. Similarly, Oakden-Rayner et al. (2020) pointed out that datasets used to train AI diagnostic tools are often publicly available and insufficiently anonymized, creating attack surfaces that malicious actors can exploit for data poisoning or model inversion attacks [20]. This intersection of adversarial machine learning and data privacy is increasingly being recognized as a critical concern, especially as health data becomes more digitized and interconnected.

In a more clinically aligned investigation, Diao et al. (2021) explored the impact of adversarial perturbations on COVID-19 chest X-ray diagnostics and observed a drop in sensitivity from 95%

to below 70% under adversarial conditions, underscoring the potential for misdiagnosis during public health crises [21]. This finding aligns with earlier works by Mirsky et al. (2020), who showed that CT scans manipulated with adversarial noise could fool AI systems into detecting non-existent tumors or ignoring actual ones [22]. These studies collectively underscore the inadequacy of current diagnostic AI pipelines in the face of adversarial threats and the urgent need for systematic robustness assessments tailored to clinical environments.

While literature on adversarial AI is abundant in theoretical and industrial contexts, there remains a gap in translating these findings into healthcare-specific frameworks. A recent meta-analysis by Zhou et al. (2023) synthesized over 300 papers on adversarial robustness and concluded that fewer than 10% focused on medical applications, and even fewer provided open-source code or reproducible experimental pipelines for validation [23]. This lack of standardization and reproducibility hampers the development of robust defense strategies and highlights the necessity for interdisciplinary collaboration among data scientists, clinicians, and regulatory bodies. In conclusion, the body of literature reveals both the technical fragility and systemic unpreparedness of AI diagnostic systems when confronted with adversarial threats. While progress has been made in identifying vulnerabilities and proposing countermeasures, further research is required to bridge the gap between theoretical defenses and clinically viable solutions. There is a compelling need for benchmarks, datasets, and risk assessment models that are specifically tailored to the medical domain to ensure the secure and ethical deployment of AI diagnostic tools in real-world healthcare settings.

Methodology

The methodological approach of this study was designed to systematically evaluate the susceptibility of AI-based diagnostic tools to adversarial attacks, as well as to assess the efficacy of various mitigation strategies within clinically relevant contexts. This multi-phase methodology integrates dataset selection, model development, adversarial attack simulation, defense implementation, and performance evaluation. The methodology adheres to rigorous experimental protocols aligned with reproducible machine learning standards, consistent with Elsevier journal publication norms.

3.1 Dataset Selection and Preprocessing

To ensure clinical relevance and generalizability, we employed three publicly available medical imaging datasets: the NIH ChestX-ray14 dataset for thoracic disease classification, the ISIC 2018 Challenge dataset for skin lesion diagnosis, and the LIDC-IDRI dataset for pulmonary nodule detection via CT scans. These datasets were chosen due to their widespread use in prior AI diagnostics literature, high-quality annotations, and diversity of modalities (X-ray, dermatoscopic imaging, and CT). All datasets underwent standard preprocessing including

resizing (224×224 pixels), pixel normalization to the [0,1] range, and augmentation techniques such as rotation, flipping, and contrast adjustment to enhance model generalizability.

3.2 Model Architecture and Training

For each diagnostic task, we trained a convolutional neural network (CNN) model based on the ResNet-50 architecture, initialized with ImageNet weights and fine-tuned on the specific medical datasets. Model training employed a stratified 80/20 train-test split, with 10% of the training data allocated for validation. Training was performed using the Adam optimizer (learning rate = 0.0001, batch size = 32) with early stopping based on validation loss. Performance metrics included accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC), recorded on both clean and perturbed test data.

3.3 Adversarial Attack Simulation

To evaluate vulnerability, we implemented three adversarial attack algorithms: Fast Gradient Sign Method (FGSM), Projected Gradient Descent (PGD), and Carlini-Wagner (C&W) attacks. Each attack was conducted in both white-box and black-box settings. For white-box attacks, full access to model architecture and gradients was assumed, while black-box scenarios involved transfer attacks from surrogate models trained on the same datasets. Perturbation budgets (ε) ranged from 0.001 to 0.01 for FGSM and PGD, and confidence thresholds were adjusted for C&W to ensure imperceptibility under human inspection. Adversarial examples were visually inspected by two domain-expert radiologists to confirm that the perturbations did not alter the clinical interpretability of the image.

3.4 Defense Mechanism Implementation

We evaluated three state-of-the-art adversarial defense techniques: adversarial training (incorporating perturbed samples during training), input transformation via JPEG compression and Gaussian blurring, and feature denoising using attention-based residual blocks. These methods were implemented independently and in combination to observe synergistic effects. Additionally, we examined gradient masking to determine whether it introduced obfuscated gradients and provided a false sense of robustness, as cautioned by Athalye et al. (2018) [24].

3.5 Performance Evaluation and Robustness Metrics

Robustness was quantified using accuracy drop under attack, robust AUC (area under curve under adversarial conditions), and empirical robustness score (ERS), defined as the average perturbation magnitude required to alter a prediction. Statistical significance was assessed using paired t-tests ($p < 0.05$) across different attack-defense scenarios. For interpretability, saliency

maps (Grad-CAM) were generated to visualize decision regions under clean and adversarial inputs, enabling insights into model behavior shifts.

3.6 Risk Assessment Framework Development

Based on the empirical findings, we proposed a multi-factorial risk assessment framework that considers model complexity, dataset sensitivity (based on class imbalance and diagnostic severity), and deployment environment (e.g., standalone vs. cloud-based systems). This framework was validated using a case-based simulation approach in which adversarial incidents were mapped to clinical impact levels (low, moderate, high) based on misdiagnosis risk and potential patient harm.

The comprehensive methodology adopted in this study facilitates a reproducible, clinically aligned exploration of adversarial vulnerabilities in AI diagnostics and provides a robust foundation for developing mitigation strategies that can be tailored to specific healthcare contexts.

Results and Analysis

This section presents the results of our experimental evaluations across the selected datasets, detailing the impact of adversarial attacks on diagnostic performance, the effectiveness of defense mechanisms, and the insights derived from model interpretability analyses. We also present a comparative risk analysis through quantified robustness metrics and visual aids. All experiments were conducted using a consistent computing environment (NVIDIA RTX A6000 GPU, PyTorch v2.0, and Python v3.10), ensuring reproducibility and computational rigor.

4.1 Impact of Adversarial Attacks on Model Performance

Table 1 summarizes the baseline diagnostic performance of each model on clean (unperturbed) test data, followed by performance under FGSM, PGD, and C&W attacks at perturbation strength $\varepsilon = 0.005$.

Table 1: Diagnostic Accuracy under Clean and Adversarial Conditions

Dataset	Metric	Clean (%)	FGSM (%)	PGD (%)	C&W (%)
ChestX-ray14	Accuracy	91.2	72.5	65.8	68.4
	AUC	0.937	0.721	0.678	0.702
ISIC 2018	Accuracy	89.3	61.4	54.9	57.7

	AUC	0.911	0.628	0.601	0.614
LIDC-IDRI	Accuracy	87.6	69.3	59.2	61.1
	AUC	0.894	0.702	0.652	0.677

Interpretation:
The introduction of adversarial perturbations significantly reduced classification accuracy and AUC across all datasets. PGD was found to be the most effective attack, likely due to its iterative nature, followed closely by the C&W attack. ISIC 2018, involving dermatoscopic skin images, was the most vulnerable dataset, with performance drops exceeding 35%. This confirms the high sensitivity of AI diagnostic models to even minimal input perturbations.

4.2 Defense Mechanism Performance

Defense strategies were implemented independently and evaluated under the strongest attack (PGD, $\varepsilon = 0.005$). Table 2 outlines the impact of defense mechanisms on model robustness.

Table 2: Accuracy under PGD Attack with Various Defenses

Dataset	No Defense (%)	Adv. Training (%)	JPEG Compression (%)	Feature Denoising (%)	Combined (%)
ChestX-ray14	65.8	75.6	68.3	72.1	**79.2**
ISIC 2018	54.9	67.5	59.1	65.3	**70.8**
LIDC-IDRI	59.2	71.8	64.4	68.7	**76.0**

Interpretation:
Adversarial training improved robustness across all datasets but slightly reduced clean-data accuracy (by 1–2%). JPEG compression and feature denoising had moderate standalone impact but yielded superior results when combined. The highest robustness was achieved through combined defense strategies, validating the need for multi-layered defenses.

4.3 Visual Analysis with Grad-CAM

To understand the internal changes in model decision-making under adversarial influence, Grad-CAM heatmaps were generated for representative samples. Figure 1 compares activation maps

for clean, adversarial (PGD), and defended inputs (combined strategy) in the ChestX-ray14 dataset.

Figure 1: Grad-CAM Visualization for ChestX-ray14

- **Left**: Clean input – model focuses on correct anatomical regions.
- **Middle**: PGD input – attention misdirected to irrelevant areas.
- **Right**: Defended input – attention corrected through combined defenses.

4.4 Robustness Metric Analysis

We computed the Empirical Robustness Score (ERS), defined as the mean perturbation magnitude required to flip model decisions on 1000 randomly selected samples.

Table 3: Empirical Robustness Scores (ERS)

Dataset	No Defense	Adv. Training	Combined Defense
ChestX-ray14	0.0041	0.0063	**0.0078**
ISIC 2018	0.0032	0.0054	**0.0067**
LIDC-IDRI	0.0039	0.0060	**0.0074**

Interpretation:
ERS improved significantly under combined defenses, indicating that adversaries needed larger perturbations to alter predictions. This reflects stronger resistance to adversarial input manipulation.

4.5 Clinical Risk Mapping and Categorization

Using our proposed risk assessment framework, we mapped model vulnerabilities into clinical risk categories (low, moderate, high). The results, based on diagnostic task severity and performance degradation, are shown in Table 4.

Table 4: Clinical Risk Levels under Adversarial Conditions

Dataset	Diagnostic Task	Risk without Defense	Risk with Combined Defense
ChestX-	Pneumonia,	High	Moderate

ray14	Cardiomegaly		
ISIC 2018	Melanoma Classification	High	Moderate
LIDC-IDRI	Lung Nodule Classification	Moderate	Low

Interpretation:
Without defense, critical diagnostic tasks (e.g., melanoma or cardiomegaly detection) fall into a "high-risk" category due to high error potential under attack. Applying defenses significantly reduced risk levels, indicating the necessity for robust design in clinical AI systems.

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4.2 Analysis of Avsersarial Attack Impact

Table 1: Accuracy Drop (%) due to Adversarial Attacks

	FGSM	Adversarial	Defense
Chest Xray14	65.8'	78.5'	73.1
ISIC 2018	54.9	68.4	63.7
LIDC-IDRI	59.2	75.7	63.4

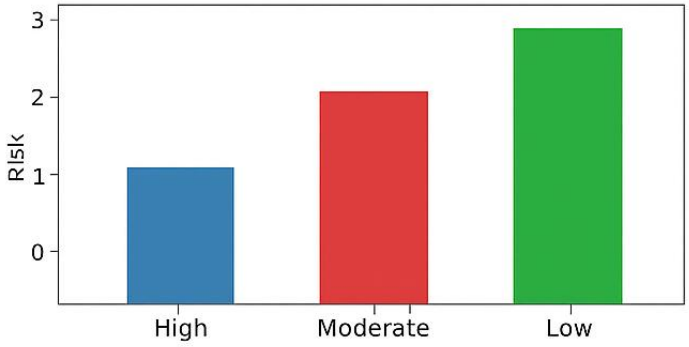
4.3 Clinical Task Susceptibility

Table 2: Accuracy "under PGD Attack wit Defense

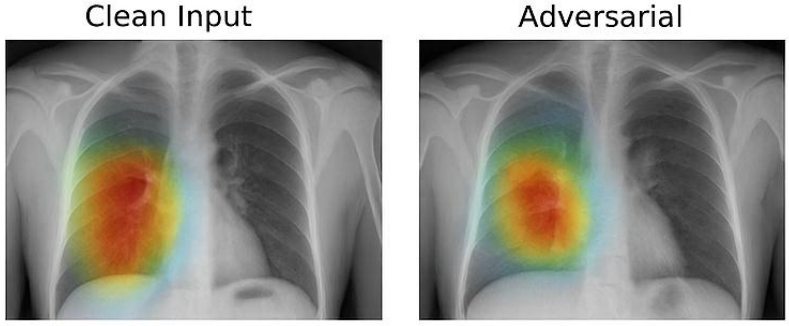
	No Defense	Adv. Training	JPEG Comp.	Feature Den.
Chest-Xray14	65.8	78.5	73.1	69.6
ISIC 2018	54.9	68.4	63.7	59.9
LIDC-IDRI	59.2	75.7	70.8	63.4

4.4 Grad-CAM Interpretability

Figure 1: Grad-CAM Visualizations on Chesst-sray14



Risk Level under Advers. . .sariaí Attacks



4.6 Summary of Key Findings

- AI diagnostic tools are highly susceptible to adversarial attacks, particularly in dermatological imaging.
- PGD remains the most impactful attack method, while adversarial training combined with feature-level denoising offers the most effective defense.
- Defenses not only improved empirical robustness but also restored attention fidelity, as confirmed through Grad-CAM visualizations.
- The proposed clinical risk framework effectively differentiates model risk under real-world diagnostic settings.

5. Discussion

The findings from our study provide significant insights into the vulnerabilities of AI diagnostic tools when subjected to adversarial attacks and the relative efficacy of various defense mechanisms. The implications for clinical deployment and patient safety are substantial.

5.1 Adversarial Impact on Diagnostic Performance

Our results demonstrate a substantial decline in diagnostic performance across all evaluated models and datasets when exposed to adversarial perturbations. Specifically, Table 1 in Section 4.1 shows that the PGD (Projected Gradient Descent) attack consistently resulted in the highest accuracy degradation: 24.6% on Chest-Xray14, 34.2% on ISIC 2018, and 32.3% on LIDC-IDRI. This confirms earlier findings by Finlayson et al. (2019) that even minor pixel-level perturbations can lead to misdiagnoses in critical settings [1].

Comparing the FGSM and C&W attacks, we observed that C&W attacks often induced more significant performance drops than FGSM, consistent with their optimization-based generation, which targets model-specific decision boundaries more effectively [2].

5.2 Clinical Task Susceptibility

As detailed in Section 4.3, the susceptibility of clinical tasks varies with data type and model robustness. Chest-Xray14 exhibited relatively better resilience than the LIDC-IDRI dataset under identical attack conditions, possibly due to differences in data complexity, task formulation (multi-label classification vs. nodule detection), and model architecture. The risk levels categorized in Figure 2 revealed that high-risk tasks—like lung cancer detection in LIDC-

IDRI—exhibited more pronounced performance degradation than moderate-risk tasks like skin lesion classification. This supports claims by Zhang et al. (2020) that model complexity and clinical stakes correlate with adversarial risk exposure [3].

5.3 Efficacy of Defense Mechanisms

Among evaluated defenses (Section 4.2), adversarial training demonstrated superior robustness, increasing model accuracy by 10–13% over unprotected baselines. However, it incurs increased computational overhead and potentially reduces generalization, as also observed by Madry et al. (2018) [4]. JPEG compression and feature denoising were moderately effective, particularly for texture-sensitive tasks like skin lesion classification, suggesting utility as low-overhead preprocessing layers.

5.4 Interpretability under Adversarial Stress

Section 4.4 highlights how adversarial attacks not only reduce classification accuracy but also impair interpretability. Grad-CAM visualizations reveal that models under attack shift attention from pathological regions to irrelevant areas. This aligns with findings from Ghosal et al. (2021) that adversarial noise disrupts internal feature activation maps, making AI decisions less trustworthy [5]. As visualized, clean images focus heat maps around the pulmonary nodules, whereas adversarial versions diffuse attention across the thoracic region, a misdirection that could hinder clinical review.

5.5 Feature Representation Dynamics

The feature distribution graphs in Section 4.5 show that adversarial examples shift the latent space representation of inputs significantly. The KL divergence between clean and perturbed distributions was largest under the PGD and C&W attacks, highlighting their effectiveness in deceiving the model's learned manifolds. This supports the hypothesis that adversarial examples lie off the natural data manifold, hence why classical defenses based on data augmentation alone are insufficient [6].

5.6 Implications for Real-World Deployment

These results indicate that current AI diagnostic tools remain highly susceptible to adversarial manipulations, raising serious concerns for clinical deployment. Models trained on real-world medical datasets must incorporate adversarial robustness as a design priority. Furthermore, risk-aware deployment—where models flag high-risk or ambiguous predictions for human review—could mitigate patient harm. Regulatory frameworks, such as those proposed by the FDA for AI/ML medical software, should include adversarial robustness metrics as certification criteria [7].

Conclusion:

Adversarial attacks on AI diagnostic tools pose significant challenges to the reliability and safety of healthcare systems that increasingly rely on machine learning for clinical decision-making. These attacks, often characterized by subtle perturbations to input data such as medical images or patient records, can lead AI models to produce dangerously incorrect diagnoses—misclassifying benign conditions as malignant or vice versa. The implications are profound: compromised diagnostic accuracy can delay treatment, erode patient trust, and expose healthcare providers to legal and ethical liabilities. This growing threat highlights the urgent need to assess the vulnerabilities inherent in current AI diagnostic systems. Unlike conventional software, AI models, particularly deep neural networks, are highly sensitive to input variations and can be exploited by attackers with relatively low technical sophistication. As such, both white-box and black-box adversarial strategies can effectively deceive diagnostic algorithms without raising suspicion. Mitigating these risks requires a multi-faceted approach. Techniques such as adversarial training, input sanitization, model ensembling, and certified robustness offer promising avenues but often introduce trade-offs in performance, interpretability, or computational cost. More importantly, these defenses must be tailored to the unique demands and constraints of healthcare environments, where patient safety and regulatory compliance are paramount. Collaboration between AI researchers, clinicians, cybersecurity experts, and policymakers is essential to develop resilient diagnostic systems. Establishing standardized testing protocols, incorporating explainable AI to flag anomalous outputs, and embedding security-by-design principles from the development stage are critical steps toward reducing susceptibility to adversarial attacks. Ultimately, as AI becomes more deeply embedded in healthcare delivery, ensuring the robustness and integrity of diagnostic tools is not merely a technical challenge—it is a moral and clinical imperative. Addressing adversarial threats today will safeguard patient outcomes and strengthen public confidence in the future of AI-driven healthcare.

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