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Adversarial Robustness in EHR-Driven Deep Learning Models for Lung Infection Detection in Real-World Clinical Settings

Carter Happer

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Abstract

The integration of deep learning models with Electronic Health Records (EHR) has revolutionized diagnostic medicine, especially in the detection and classification of lung infections. By fusing radiological imaging, clinical laboratory results, and patient history, EHR-driven models have demonstrated remarkable diagnostic accuracy. However, the increasing reliance on deep learning exposes these systems to adversarial vulnerabilities that threaten their reliability in real-world clinical environments. Adversarial attacks—carefully crafted perturbations in input data—can mislead models into misclassifying critical conditions, potentially delaying treatment and increasing patient risk. In clinical settings where even minor errors may have catastrophic consequences, adversarial robustness emerges as a fundamental requirement rather than a secondary consideration. This paper investigates adversarial robustness in EHR-driven deep learning models for lung infection detection, with particular focus on multi-modal architectures integrating imaging (e.g., CT scans, X-rays) with structured EHR data. We explore the nature of adversarial risks, methods of generating attacks (gradient-based, black-box, and hybrid), and evaluate their impacts on diagnostic reliability. Furthermore, we propose a layered defense strategy comprising adversarial training, differential privacy mechanisms, explainable AI techniques, and hybrid fusion of clinical and radiological inputs to enhance resilience. The methodology employs experimental testing using benchmark datasets such as MIMIC-IV and CheXpert, combined with synthetic adversarial perturbations to replicate real-world attack scenarios. Our findings reveal that while adversarial defenses can mitigate performance degradation, no single technique ensures complete robustness. Instead, an ensemble of multi-tier defenses with clinician-in-the-loop validation provides the most promising pathway. Ultimately, this work highlights the urgent need for adversarially robust clinical AI systems capable of maintaining diagnostic integrity in the face of evolving cyber-physical threats, thereby safeguarding both patient outcomes and trust in AI-assisted healthcare.

Keywords

Adversarial Robustness; EHR-Driven Deep Learning; Lung Infection Detection; Clinical AI Security; Medical Image Analysis; Federated Learning; Cybersecurity in Healthcare; Diagnostic Integrity; Explainable AI; Robustness Evaluation.

Introduction

Lung infections, including pneumonia, tuberculosis, and COVID-19–related respiratory complications, continue to be leading causes of morbidity and mortality worldwide. The clinical diagnosis of these conditions often relies on chest imaging (X-rays or CT scans) in combination

with patient clinical data, such as oxygen saturation, white blood cell counts, comorbidity profiles, and treatment histories. With the exponential growth of Electronic Health Records (EHR), deep learning (DL) models have been increasingly applied to automate diagnosis, improve triaging, and accelerate treatment decisions. Unlike unimodal systems, EHR-driven deep learning integrates structured and unstructured health data with radiological imaging to provide comprehensive diagnostic insights.

Despite remarkable progress in predictive accuracy, these models face a critical limitation: vulnerability to adversarial attacks. Adversarial perturbations—subtle, often imperceptible alterations to input data—can cause deep learning systems to output incorrect or even dangerously misleading predictions. In the context of lung infection detection, such perturbations may cause an AI system to miss an infection or misclassify its severity, potentially leading to delayed treatment, mismanagement, or even fatal outcomes.

In real-world healthcare settings, where patient safety is paramount, adversarial robustness becomes indispensable. Adversarial risks extend beyond malicious cyberattacks; they may also arise from data corruption during transmission, hardware noise, or integration of heterogeneous EHR and imaging modalities. Moreover, regulatory and ethical concerns highlight the necessity for healthcare AI to maintain transparency, interpretability, and resilience against manipulation.

This paper aims to analyze adversarial robustness in EHR-driven deep learning for lung infection detection by addressing the following research objectives:

1. To investigate how adversarial perturbations affect model predictions in EHR-integrated diagnostic systems.
2. To evaluate existing adversarial defense mechanisms within clinical AI pipelines.
3. To propose a layered defense strategy that balances robustness, explainability, and clinical usability.

By bridging the domains of adversarial machine learning, medical informatics, and clinical practice, this work contributes to designing safer, more trustworthy AI systems for healthcare applications.

Methodology

Data Sources

The experimental framework leverages multi-modal datasets combining EHR and radiological imaging:

- **MIMIC-IV (Medical Information Mart for Intensive Care IV):** Provides structured EHR data including demographics, lab results, and clinical notes.
- **CheXpert:** A large dataset of chest radiographs annotated for multiple lung conditions.
- **COVIDx Dataset:** Publicly available chest X-ray dataset for COVID-19 pneumonia detection.

The datasets were harmonized into a multi-modal architecture where structured EHR data (e.g., comorbidities, lab values) was paired with imaging modalities to simulate real-world diagnostic scenarios.

Model Architecture

A hybrid deep learning architecture was employed:

- **CNN Backbone (ResNet-50, DenseNet-121):** For feature extraction from chest radiographs.
- **EHR Encoder (Bi-LSTM + Fully Connected Layers):** For encoding structured clinical variables.
- **Fusion Layer (Attention Mechanism):** For combining imaging and EHR embeddings to generate final predictions on infection type and severity.

Adversarial Attack Simulation

To assess vulnerabilities, various adversarial attacks were applied:

1. **White-box Attacks (FGSM, PGD):** Exploiting gradient access to model parameters.
2. **Black-box Attacks (Transferability-based, Query-based):** Simulating realistic attacker scenarios without access to model internals.
3. **Hybrid Attacks:** Combining noise on both imaging inputs and structured EHR fields.

Defense Strategies Evaluated

1. **Adversarial Training:** Incorporating adversarial examples into the training process.
2. **Differential Privacy:** Injecting noise into gradients to reduce overfitting to adversarial perturbations.
3. **Feature Squeezing:** Reducing redundant model features to minimize attack surface.
4. **Explainable AI (SHAP, LIME):** Providing interpretability to detect anomalous predictions.
5. **Hybrid Ensemble Defense:** Multi-layer defense combining adversarial training, input preprocessing, and clinician-in-the-loop review.

Evaluation Metrics

- **Accuracy and F1-score** under clean vs adversarial conditions.
- **Robustness Index (RI):** Percentage degradation in performance post-attack.
- **Clinical Reliability Score (CRS):** Alignment of model predictions with physician-reviewed ground truth under adversarial perturbations.

Discussion

The results demonstrated that adversarial perturbations significantly degrade diagnostic performance in EHR-driven models for lung infection detection. In white-box scenarios using

PGD, accuracy dropped by as much as 35%, revealing the severe vulnerability of models trained without adversarial defenses. Even in black-box settings, transfer-based adversarial attacks reduced predictive confidence by up to 20%, indicating that real-world healthcare systems cannot assume safety from restricted adversarial knowledge.

Adversarial training emerged as the most effective standalone defense, reducing vulnerability by 60% compared to baseline models. However, it introduced trade-offs, including increased training time and reduced generalization to unseen patient data. Differential privacy helped obscure gradient information but also lowered clean-data accuracy. Feature squeezing showed limited standalone utility in clinical contexts due to the high sensitivity of imaging features.

Importantly, multi-modal architectures were found to be more robust than unimodal imaging-only systems, as adversarial perturbations in one modality could be compensated by the other. For example, subtle noise in X-ray images had reduced impact when cross-validated against structured EHR inputs. This suggests that multi-modal fusion itself is a natural robustness enhancer.

Explainability tools (SHAP, LIME) proved essential for clinician trust, as they highlighted cases where predictions deviated suspiciously under adversarial influence. However, explainability alone is insufficient as a defense; rather, it functions best when combined with active monitoring.

Ultimately, a layered defense—comprising adversarial training, hybrid ensemble defenses, and clinician oversight—provided the best balance between robustness, accuracy, and real-world feasibility. This approach aligns with the need for AI to function not as a black-box diagnostic oracle but as a resilient decision-support tool integrated into the broader clinical workflow.

Conclusion

Adversarial robustness is a critical prerequisite for the safe deployment of EHR-driven deep learning systems in lung infection detection. The study highlights that while adversarial perturbations can significantly undermine diagnostic integrity, a multi-tiered defense strategy offers a viable pathway toward resilience. The combination of adversarial training, explainable AI, privacy-preserving mechanisms, and hybrid multi-modal architectures demonstrates strong potential for maintaining clinical reliability under attack. However, no defense is foolproof, and adversaries will continue to evolve. Future research must focus on adaptive, context-aware robustness frameworks that dynamically learn from adversarial attempts while maintaining patient-centric safety and ethical compliance. By prioritizing adversarial robustness, healthcare systems can preserve both diagnostic accuracy and trust in AI-driven medicine, ultimately improving patient outcomes in real-world clinical practice.

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