IMPROVING DIAGNOSTIC ACCURACY IN CHEST X-RAYS USING AI-BASED IMAGE ENHANCEMENT: A MACHINE LEARNING APPROACH

This research systematically investigates how AI-based image enhancement (traditional and GAN-based) influences chest X-ray (CXR) diagnosis. It compares these techniques' impact on classification performance and visual interpretability across both traditional machine learning and deep learning models. The study employs methods like Grad-CAM for interpretability, intending to derive actionable insights for creating more transparent and effective AI diagnostic systems

CLINICAL PROBLEM & RESEARCH MOTIVATION

Chest X-rays (CXRs) are essential for diagnosing pulmonary diseases, yet their diagnostic reliability is often compromised by low contrast, anatomical overlap, and inter-reader variability. These challenges are especially acute in high-throughput or resource-constrained settings, where subtle abnormalities are frequently missed.

While AI models, particularly deep learning, have shown promise in improving detection, their performance is highly sensitive to input quality. This research is motivated by the need to systematically investigate how AI-based image enhancement can improve diagnostic accuracy and trustworthiness in both traditional and deep learning pipelines.



RESEARCH GAP & PROPOSED SOLUTION

Despite growing interest in AI for chest X-ray diagnosis, most studies apply image enhancement heuristically i.e. without systematically evaluating how these techniques influence classification performance or interpretability across different model types. This lack of methodological rigor limits clinical translation.

To address this gap, my study proposes a structured, comparative evaluation of traditional and GAN-based enhancement pipelines across both classical ML and deep learning architectures. The goal is to generate actionable insights for developing more effective, interpretable, and trustworthy AI diagnostic systems.

RESEARCH QUESTION & OBJECTIVES

To what extent do AI-based image enhancement

techniques improve the classification accuracy and visual

interpretability of machine learning models for chest X-

Compare the classification performance of ML and

Assess how enhancement methods affect model

• Evaluate whether image enhancement reduces

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classification errors in low-contrast or diagnostically

focus and interpretability using Grad-CAM and

DL models when trained on original versus enhanced

RESEARCH QUESTION:

rays?

OBJECTIVES:

CXR datasets.

ambiguous cases.

Score-CAM visualizations.

AFFILIATIONS

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PROPOSED METHODOLOGY

This research adopts a structured, multi-phase pipeline to investigate how image enhancement influences classification performance and interpretability in chest X-rays (CXRs).

Phase 1: Data Curation

We use the NIH ChestX-ray14 dataset, from which a stratified, class-balanced subset of 5,000–10,000 images is curated. Only images labeled as Pneumonia, Infiltration, or Normal are retained, with multi-label or uncertain cases excluded.

Phase 2: Image Enhancement

Three enhancement strategies are applied in parallel:

- CLAHE and Gamma Correction (Traditional methods)
- Conditional GAN-based Augmentation (Deep enhancement)

Phase 3: Model Training

Two model categories are evaluated:

- Classical ML: Random Forest, XGBoost
- Deep Learning: Fine-tuned CNNs (ResNet50, DenseNet121)

Phase 4: Evaluation

Models are assessed using AUC, class-wise recall, and F1-score. Interpretability is quantified using Grad-CAM and Score-CAM, focusing on attention shifts in low-contrast and diagnostically ambiguous cases.



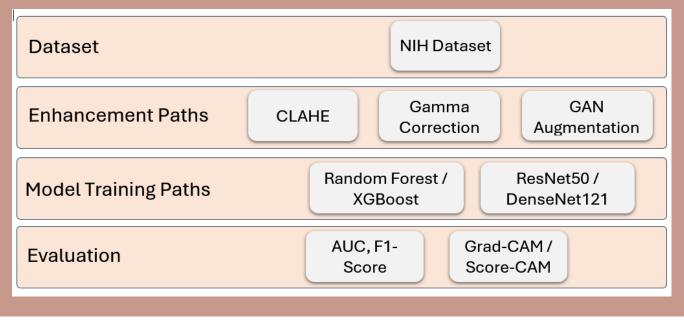


This study hypothesizes that image enhancement will significantly improve both diagnostic accuracy and visual interpretability in chest X-ray (CXR) classification across machine learning (ML) and deep learning (DL) models.

I anticipate the following outcomes:

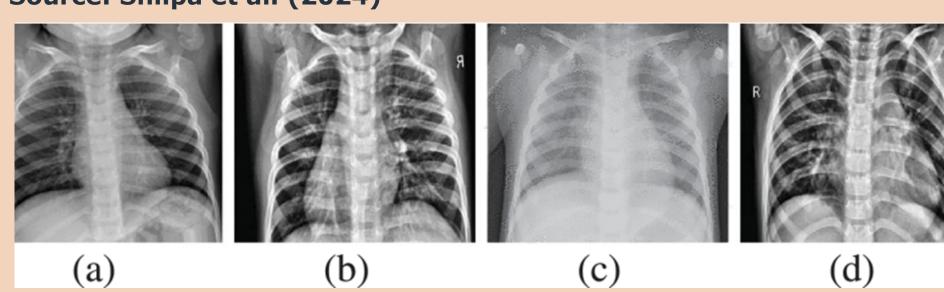
- Improved classification performance (AUC, F1-score) when models are trained on enhanced images versus raw data.
- Greater anatomical alignment in Grad-CAM attention maps, especially for enhanced deep learning models, indicating improved model focus.
- GAN-based augmentation will yield stronger gains in DL models than in classical ML models, particularly for low-contrast or diagnostically challenging cases.

Visual 2: Planned Flowchart



Visual 1: A clear before-and-after comparison of X-ray images enhanced using CLAHE

Source: Shilpa et al. (2024)



X-Ray Images of

(a) Normal (b) CLAHE enhanced image of Normal sample (c) Pneumonia (d) CLAHE enhanced image of Pneumonia.

IMPLICATIONS & FUTURE IMPACT

This research will offer a reproducible, comparative framework for assessing how image enhancement influences diagnostic performance and interpretability in AI-driven medical imaging systems. By systematically comparing enhancement techniques across ML and DL models, the study addresses a critical methodological gap in CXR analysis.

Clinically, the findings aim to support the development of transparent and trustworthy AI tools that are better suited for deployment in low-resource or high-risk environments, where interpretability and diagnostic reliability are paramount. Broadly, this project demonstrates how advanced data science techniques can be applied to solve real-world healthcare challenges, reinforcing the importance of interdisciplinary training and rigorous evaluation in the design of next-generation clinical AI systems.

