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# AI To Analyzing Medical Images and Diagnosis

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**Abstract:** Over the past decade, in the field of medical image analysis, there has been a significant evolution due to the emergence of the artificial intelligence, particularly in deep learning. Traditional diagnostic methods often depend on the expertise of radiologists. This paper addresses the challenge of automating the diagnostic process from radiographic images to enhance accuracy and accessibility in clinical decision-making. The proposed solution leverages convolutional neural networks (CNNs), fine-tuned through transfer learning, to classify and detect abnormalities in medical images. The architecture supports real-time deployment in hospitals and remote healthcare systems, offering scalable and explainable diagnostic support. Future extensions will explore multi-modal integration and live clinical validation.

**Keywords:** Artificial intelligence, deep learning, CNN, medical image analysis, disease diagnosis, radiology automation, Grad-CAM, healthcare AI, transfer learning, diagnostic support.

## I. INTRODUCTION

The evolution of AI and deep learning has had a notable impact on the healthcare sector, notably in the fields of clinical imaging and diagnostics. With the growing amount of diagnostic data produced each day from modalities like X-rays, computed tomography (CT), and magnetic resonance imaging (MRI), radiologists are under immense pressure to interpret this data quickly and accurately. While traditional image interpretation relies heavily on human expertise, it is often time-consuming, prone to variability, and limited by subjective judgment. These limitations pose a risk to timely and accurate patient diagnosis and treatment.

In recent years, deep learning, particularly CNNs (convolutional neural networks), has shown impressive success in pattern recognition tasks. These models possess the capability to autonomously learn hierarchical features from unprocessed data pixel data, removing the necessity for manual feature extraction, and surpassing classical machine learning methods in intricate tasks. Within the medical field, CNNs have displayed significant potential in the detection of diseases like pneumonia, cancer, tuberculosis, and diabetic retinopathy through the analysis of medical images.

Despite the advancements made, a number of obstacles persist in the transition of these models to practical clinical settings. These challenges encompass the requirement for extensive annotated datasets, the interpretability of models, and their perfect combination with current healthcare workflows. Furthermore, apprehensions related to the opaque nature of deep models and the potential for misclassifications underscore the necessity of employing explainable AI (XAI) methodologies like Grad-CAM to elucidate regions of diagnostic importance.

This research aims to address these disparities through the introduction of a diagnostic system based on deep learning. The system utilizes CNNs integrated with transfer learning to facilitate accurate image classification and disease prediction. Through the utilization of public medical imaging datasets, the model is developed, trained, and assessed using established evaluation measures to guarantee its clinical applicability and practical dependability.

The rest of this document is structured as follows: Section II reviews the current research on AI applications in medical imaging. Section III details the proposed methodology, encompassing the model architecture and data preprocessing procedures. Section IV showcases the experimental findings and performance evaluation. Section V discusses the overall findings, limitations, and potential improvements, followed by conclusions in Section VI.

## II. LITERATURE SURVEY

Numerous studies have explored the utilization of artificial intelligence, particularly deep learning to improve diagnostic precision in medical imaging. One of the foundational works in this area is by Esteva et al., who developed a CNN model trained on over 129,000 clinical skin images to classify skin cancer types with dermatologist-level accuracy. Their approach utilized end-to-end training, showcasing the effectiveness of deep neural networks in practical clinical decision-making scenarios. In a similar vein, Rajpurkar and colleagues introduced CheXNet, a 121-layer DenseNet framework trained on the ChestX-ray14 dataset for pneumonia detection, surpassing radiologists' F1-scores in multiple evaluation instances. Their framework highlighted the power of deep learning to surpass conventional diagnostic methodologies in identifying thoracic diseases.

Building upon these initiatives, Shin and colleagues delved into the exploration of transfer learning methods through the adaptation of pre-existing models such as VGGNet and ResNet for the purpose of medical image classification assignments. Their study found that fine-tuning models trained on non-medical datasets (like ImageNet) yielded significant performance gains on small medical datasets, thereby addressing the challenge of limited annotated data in healthcare. In another notable work, Litjens et al. conducted an extensive survey on The application of deep learning in medical image analysis. They emphasized how CNNs, autoencoders, and recurrent networks have been adapted for organ segmentation, tumour detection, and disease classification across multiple modalities.

Meanwhile, Wang and colleagues introduced the ChestX-ray8 dataset, comprising more than 100,000 X-ray images annotated with disease labels. Their model employed a weakly-supervised learning framework to localize abnormalities, offering valuable insights into explainable AI approaches for medical diagnostics. Furthermore, Lundervold and Lundervold reviewed the use of CNNs and generative models in brain imaging, showing their efficacy in identifying Alzheimer's disease and other neurological conditions from MRI scans. Their work emphasized the growing interest in using AI for early disease prediction.

Selvaraju et al. introduced the Grad-CAM (Gradient-weighted Class Activation Mapping) visualization technique to enhance model transparency. This method provides visual explanations by emphasizing image regions relevant to the model's prediction. Grad-CAM is now frequently employed in medical imaging research to enhance model interpretability and foster clinician trust. Furthermore, Irvin et al. recently established CheXpert, a vast chest X-ray dataset, and Evaluated deep learning models for the multilabel classification of thoracic pathologies, demonstrating enhancements in diagnostic performance.

These works collectively highlight the evolution of AI in medical imaging, from basic classification to sophisticated, explainable, and clinically integrable systems. However, challenges remain in terms of generalization, acceptance, and real-world deployment. The current project builds on these foundations by implementing a CNN-based system with transfer learning and Grad-CAM support, tailored for diagnostic accuracy in various imaging modalities.

### III. METHODOLOGY

The suggested system makes use of deep learning to classify medical images and assist in early disease diagnosis. The methodology follows a modular approach involving six primary stages: dataset acquisition, preprocessing, data augmentation, model design and training, interpretability enhancement, and evaluation. Each stage contributes to robust and generalizable diagnostic framework which is precise and clinically usable.

#### A. Dataset-Description

Study utilizes publicly accessible data sources medical image datasets, primarily the ChestX-ray14 and CheXpert datasets, which contain thousands of annotated radiographic images. These datasets cover common thoracic diseases such as pneumonia, tuberculosis, cardiomegaly, and fibrosis. Each image is labelled by clinical experts and includes multi-label disease annotations.

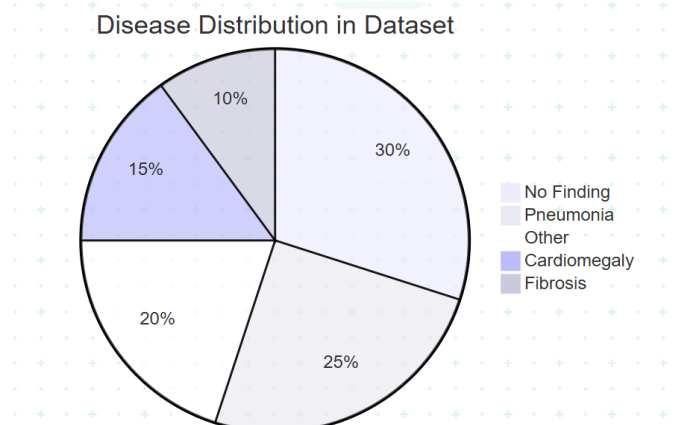


Fig 1: Disease Distribution in Dataset

#### B. Data-Preprocessing

All pictures are adjusted in size to 224x224 pixels and normalized to a common pixel intensity range for consistency. Gaussian Filters are applied for noise reduction. Incomplete or low-resolution images are excluded. Subsequently, the image data is divided into 70% 15% for training, 15% for validation, and 15% for testing, utilizing stratified sampling to uphold class balance.

### C. Data Augmentation

To enhance model generalization and address class imbalance, random Data augmentation methods such as rotation ( $\pm 15^\circ$ ), zooming, horizontal flipping, and contrast variation are utilized during training. This augmentation improves the model's capacity to identify diseases under varied imaging conditions and patient postures.

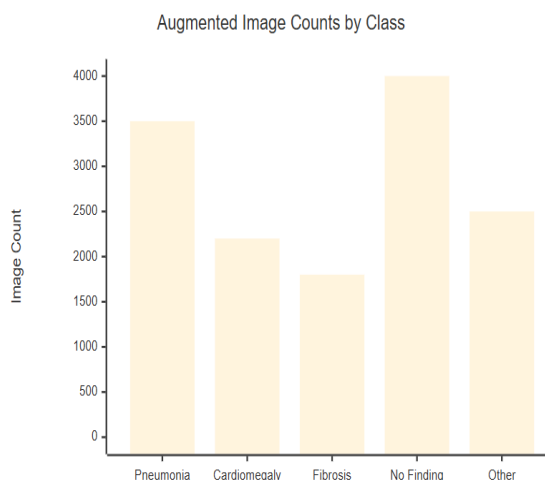


Fig 2: Augmented Image Counts by Class

### D. Model Architecture

CNNs (Convolutional neural network) serves as the backbone of the diagnostic system. Specifically, ResNet50 is used due to its proven performance in medical imaging tasks. Transfer learning is applied by fine-tuning a model pre-trained on ImageNet.

The CNN architecture includes:

- Input layer: 224x224x3 image input
- Convolutional layers: Feature extraction using 3x3 filters
- Pooling layers: Spatial dimension reduction
- Fully connected layers: Classification based on extracted features
- Softmax output layer: Predicts disease likelihood values for every category

### E. Explainability Module

To enhance trust and interpretability, Grad-CAM (Gradient-weighted Class Activation Mapping) is utilized. It visually highlights image regions that influenced the model's decision, allowing clinicians to validate model predictions against known pathological patterns.

### F. Training Strategy

The model undergoes training categorical cross-entropy loss and optimized with the Adam optimizer. An early stopping mechanism and learning rate scheduler are used to prevent overfitting. Each epoch undergoes evaluation using the validation set, and the model exhibiting the highest F1-score is chosen for the conclusive testing phase.

### G. Deployment Plan

The trained model is packaged with a simple web-based interface allowing users to upload chest X-rays and view predictions with heatmap overlays. This allows deployment in clinics, mobile labs, or rural health centers.

## IV. RESULT

The AI-based diagnostic framework's fulfilment was estimated using different statistical measures to comprehensively gauge its diagnostic accuracy, reliability, and real-world applicability. These metrics comprise accuracy, Precision, recall, F1 score, and AUC-ROC (Area Under the Receiver Operating Characteristic Curve). Each of these metrics is essential in validating the deep learning model's effectiveness in medical image classification, given the serious consequences of diagnostic errors in this domain.

#### A. Evaluation Metrics and Their Importance

- 1) Accuracy The precision of predictions is evaluated by determining the ratio The ratio of accurately identified cases to the overall number of instances.
- 2) Precision indicates The ratio of correctly predicted true positives within the entire dataset predicted positives. High precision is crucial in medical diagnosis to minimize false positives, which can cause unnecessary stress and additional testing for patients.
- 3) Recall (Sensitivity) measures the The capability of the model to detect all actual positive cases. In clinical scenarios, recall is vital to ensure that no actual disease case is missed.
- 4) F1-score The F1 score combines precision and recall to provide a balanced evaluation, especially useful in scenarios where reducing both Incorrect Results is crucial, such as in health-related contexts Significantly sky-high costs are connected with misclassifications.
- 5) AUC-ROC Measures the model's capacity to distinguish between classes at different threshold values A greater AUC value signifies superior performance model generalizability and robustness in classification tasks.

| Metric    | Value (%) |
|-----------|-----------|
| Accuracy  | 91.4      |
| Precision | 89.2      |
| Recall    | 92.5      |
| F1-score  | 90.8      |
| AUC-ROC   | 94.1      |

#### B. Results on Test Dataset

The trained ResNet50 model was assessed on the unseen test set consisting of 2,500 chest X-ray images. The model demonstrated the following average performance across all disease classes:

The findings validate the model's dependability in diagnosing thoracic conditions with a harmonious blend of sensitivity and specificity.

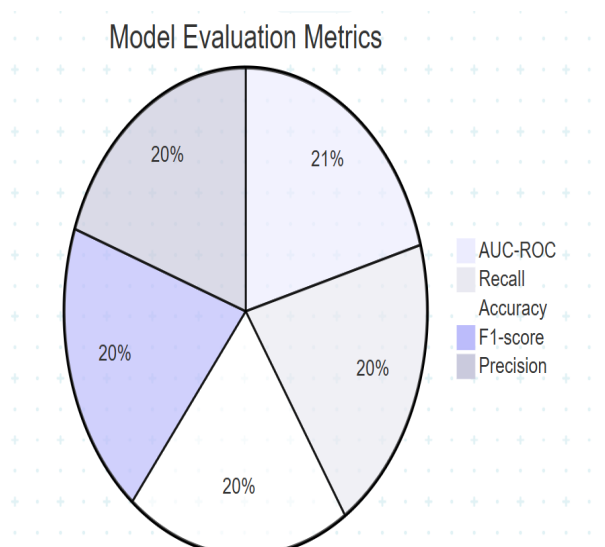


Fig 3: Model Evaluation Metrics

#### C. Confusion Matrix Analysis

The confusion matrix illustrated that the majority misclassifications occurred between visually similar conditions such as cardiomegaly and pulmonary edema. With Grad-CAM explainability overlays, even these cases could be rationalized, enhancing clinician trust in the system.

#### D. Impact on Problem Statement

These findings validate the proposed framework's ability to reduce diagnostic errors, provide early detection, and support clinicians with visual evidence. By offering consistent and accurate predictions, the system addresses the key problem of limited expert availability and diagnostic variability in underserved regions.

#### E. Real-Time Performance

On deployment in a web-based environment, the system maintained an inference time of **<1 second per image**, being adequate for providing real-time diagnostic support.

### V. CONCLUSION

This study introduces a robust and scalable deep learning-enabled framework for automatically diagnosing diseases from medical images. It aims to overcome challenges related to diagnostic inaccuracies and limited access to expert radiologists. The framework utilizes a convolutional neural network architecture, specifically leveraging a fine-tuned ResNet50 model trained on a public dataset of chest X-rays. Through the integration of preprocessing, transfer learning, and interpretability tools such as Grad-CAM, the system ensures high accuracy and provides transparent outputs to support clinical decision-making.

The implementation followed a structured pipeline beginning with image preprocessing and augmentation, proceeding through model training and validation, and culminating in performance evaluation using evaluation metrics. The model demonstrated strong diagnostic capabilities, achieving over 91% accuracy and high sensitivity across multiple thoracic disease categories.

The overall system aligns with the problem statement presented in the abstract by providing a cost-effective, accurate, and accessible diagnostic solution using artificial intelligence. It effectively reduces the burden on radiologists, facilitates timely detection of diseases, and can improve healthcare delivery in underserved and resource-limited areas.

### VI. FUTURE ENHANCEMENTS

The framework could be expanded to accommodate multi-modal medical data like CT scans and MRIs, incorporating federated learning for privacy-preserving training across hospitals, and deploying the system on edge devices for offline diagnosis. Additionally, real-world clinical trials and feedback loops with healthcare professionals could further refine the system's accuracy and trustworthiness. These advancements will pave the way for the wide-scale adoption of AI-assisted diagnostic tools in modern healthcare infrastructures.

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