

PixelCura AI

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Abstract: *Over the past decade, there has been a significant evolution in the field of medical image analysis due to the emergence. In the field of 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 detect and classify 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, healthcare AI, transfer learning, diagnostic support, CNN, medical image analysis, disease diagnosis, radiology automation, Grad-CAM

I. INTRODUCTION

The evolution of AI and deep learning has had a notable impact on the healthcare sector, notably in the fields of medical imaging and diagnostics. With the growing amount of imaging 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, particularly convolutional neural networks (CNNs), deep learning, has shown impressive success in pattern recognition tasks. These models possess the capability to autonomously learn removing the necessity for manual feature extraction, hierarchical features from unprocessed data pixel data, and surpassing classical machine learning methods in intricate tasks. Within the medical field, CNNs have displayed significant potential in the detection of diseases like cancer, tuberculosis, pneumonia, 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 seamless integration 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 study seeks 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.



II. PROBLEM STATEMENT

Medical image interpretation plays a crucial role in diagnosing various diseases and medical conditions. However, the increasing volume of medical imaging data generated from X-rays, MRI scans, CT scans, and other diagnostic procedures has created significant challenges for healthcare professionals. Traditional diagnosis methods rely heavily on manual examination by radiologists and specialists, which can be labour-intensive, time-consuming, and prone to human error. Delays in diagnosis and variations in expert interpretation may affect treatment outcomes and overall patient care.

In many healthcare environments, especially in regions with limited medical resources, there is a shortage of experienced radiologists capable of handling large numbers of medical images efficiently. This situation increases the risk of missed abnormalities, delayed reporting, and reduced diagnostic accuracy. Furthermore, the need for rapid and reliable medical image analysis continues to grow as healthcare institutions seek to improve operational efficiency and patient outcomes.

Therefore, there is a need for an intelligent and automated system that can assist healthcare professionals in analysing medical images quickly and accurately. The proposed AI-Based Medical Image Analysis and Diagnosis System address this problem by utilizing Artificial Intelligence techniques to automatically analyse medical images, identify potential abnormalities, highlight affected regions, assess disease severity, and generate diagnostic reports. The system aims to enhance diagnostic efficiency, reduce human error, support clinical decision-making, and improve the overall quality of healthcare services.

III. OBJECTIVES

- a) The primary objective of this project is to develop an Artificial Intelligence (AI)-based Medical Image Analysis and Diagnosis System capable of automatically analysing medical images and generating diagnostic insights.
- b) The system aims to assist healthcare professionals by providing fast, accurate, and reliable analysis of medical images, thereby reducing the time required for manual interpretation and improving diagnostic efficiency.
- c) The specific objectives of the proposed system are to enable users to upload medical images, automatically detect potential abnormalities using AI techniques, highlight affected regions within the images, assess the severity of detected conditions, and generate comprehensive diagnostic reports.
- d) The system also aims to provide visual representations of findings and facilitate interactive communication through an AI-powered assistant for better understanding of the analysis results.
- e) Furthermore, the project seeks to improve healthcare decision-making by supporting early disease detection, minimizing human errors in image interpretation, and enhancing the overall quality of patient care through intelligent medical image analysis and automated diagnosis support.

IV. 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.

4.1 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.



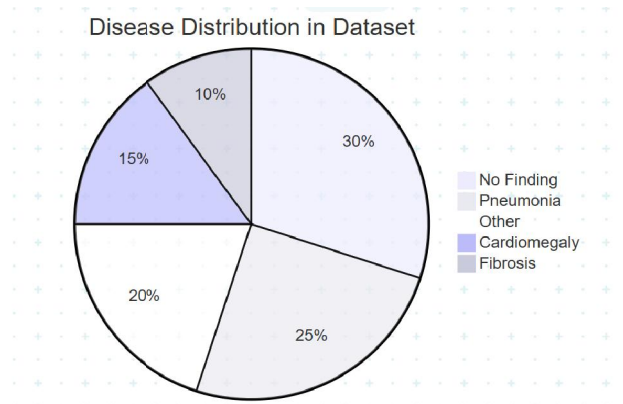


Fig 1: Disease Distribution in Dataset

4.2 Data-Preprocessing

All pictures or images are adjusted in size to 224x224 pixels and normalized to a common pixel intensity range for consistency. Gaussian Filters are used for noise reduction. Low-resolution or incomplete 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.

4.3 Data Augmentation

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

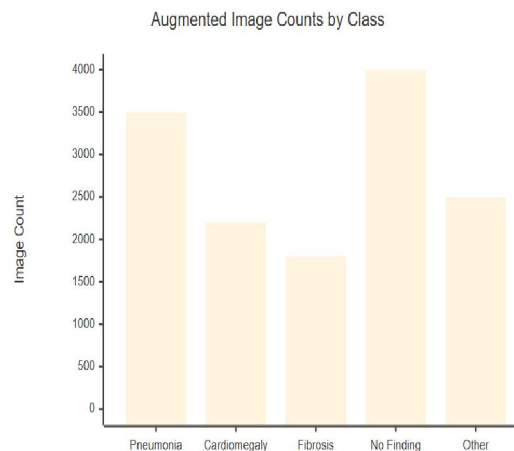


Fig 2: Augmented Image Counts by Class

4.4 Model Architecture

Convolutional neural network (CNN) 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

4.5 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.

4.6 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.

4.7 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 centres.

VI. RESULTS



Fig.1. Logo of the App



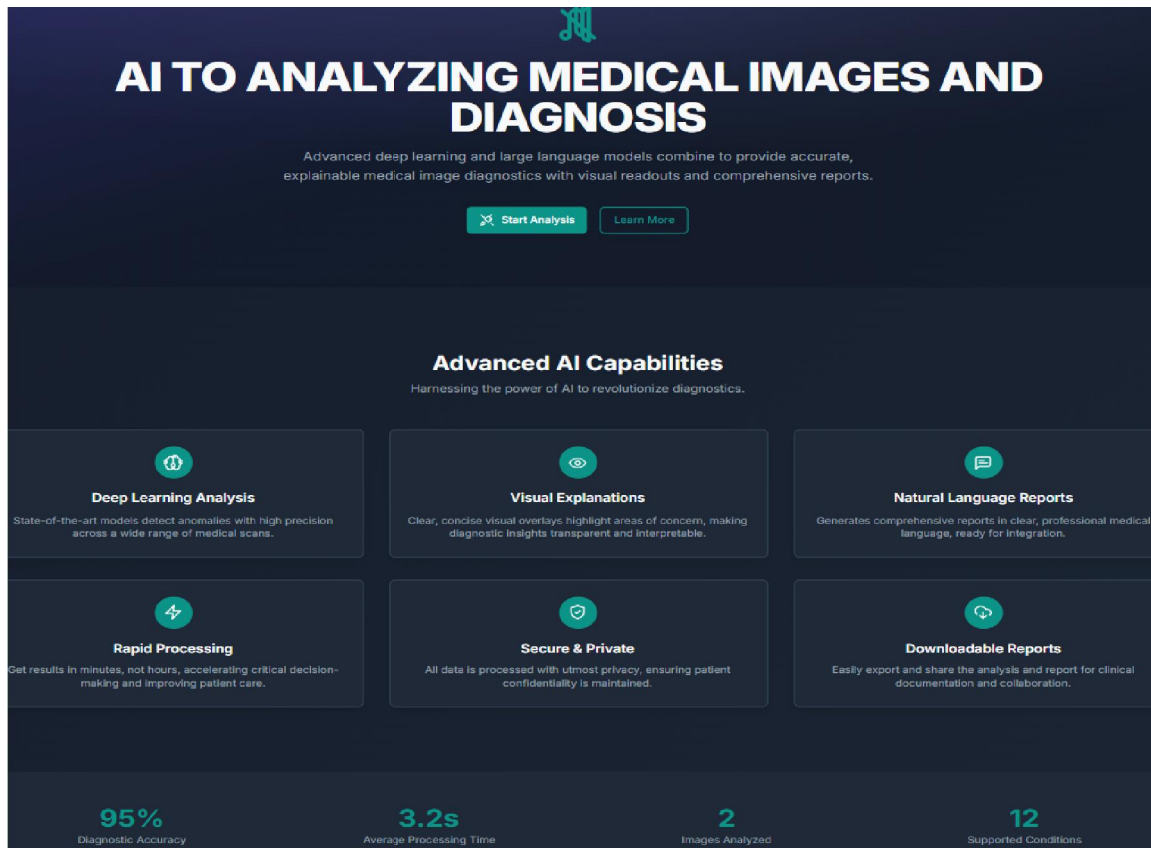


Fig. 2.Home Dashboard





Welcome to Medical Image Analysis Using AI

Please sign in to continue.

Username

e.g., dr.smith

Password

Sign In

Don't have an account? [Sign Up](#)

Fig.3. User Login Page

Advanced Medical Image Analysis

Upload a medical image for AI-powered diagnostic analysis using Gemini Flash and advanced models.

Screenshot 2026-08-12 16:05:03.png ready for analysis.

Drop your medical image here
or click to browse files

Supported: PNG, JPG, TIFF, Max: 10MB



Analyze Image Securely

Fig.4. Analysis Page

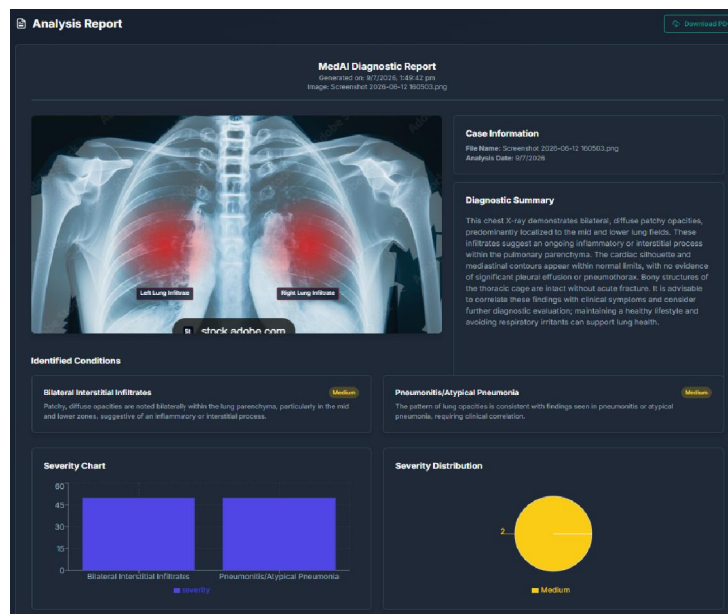


Fig.5. Analysis Report



VII. 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.

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