

Exploring AI-Driven Pneumonia Diagnosis Using Chest Radiographs: A Review

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Abstract—Pneumonia continues to be associated with high mortality, particularly for children under five and elderly in low-resource areas. Timely and accurate diagnosis is critical but is frequently retarded by a lack of trained radiologists, non-uniform interpretation of the chest X-ray, and the inability to perform advanced diagnostic tests. The current approach to diagnosis, based around manual radiological review, is slow and subjective and does not lend itself to scaling in developing regions. In this work we introduce PnuemoTrack, a cost effective AI powered medical imaging system to automatically diagnose pneumonia using chest X-rays without the need of hardware-based diagnostics. The machine is built on top of publicly available chest x-ray datasets and state-of-the-art deep learning models to automatically examine the lung area and detect pneumonia characteristics. The framework is utilizing the Convolutional Neural Networks (CNNs) and transfer learning to achieve high accuracy classification between Healthy vs Pneumonic cases.
Keywords— Blockchain, Digital Evidence, Evidence Management, Chain of Custody, Smart Contracts.

Index Terms— Artificial Intelligence (AI), Deep Learning, Pneumonia Detection, Chest X-ray Imaging, Medical Image Classification, Convolutional Neural Networks (CNN), Transfer Learning, Lung Segmentation, ResNet50, DenseNet121, Automated Diagnostic System.

I. INTRODUCTION

Pneumonia remains to be a significant global health problem with greatest impact on the children under 5 years, elderly and in low resource settings. According to the World Health Organization (WHO), millions of people are hospitalized and die from pneumonia each year, primarily as a result of delayed diagnosis, misinterpreted chest radiographs or access to scarce trained radiologists. Early recognition of pneumonia is important for preventing which is time consuming, subjective and inconsistent between specialists. Commercial medical imaging systems generally rely on every sophisticated radiological infrastructure,

trained professional personnel and high maintenance instruments which have rendered general applications challenging in developing nations. However, these limitations pose significant obstacles for accurate pneumonia screening in rural and under- resourced areas that lack ready access to medical resources. In response to these challenges, PnuemoTrack is an AI productivity tool that offers a fully scripted automated and pocket-friendly diagnosis system of pneumonia through chest X-ray images. First, many model optimize for overall classification accuracy instead of explicitly prioritizing high sensitivity, which is critical in screening applications where false negatives are far more costly than false positives. Second, real-time deployment constraints, such as inference latency and computational resource limitations, are often not adequately considered in model design. In this work, we address these challenges by proposing Pnuemo Detect-Net a deep- learning framework tailored for high sensitivity pneumonia screening with real-time inference capabilities. This review reviews the recent progress in AI enhanced medical imaging for detecting pneumonia, which helps alleviate reliance on traditional and hardware-intensive diagnostic equipment.

The main aims of this review are:

- To evaluate deep learning architectures such as Convolutional Neural Networks (CNN) and transfer learning models as useful instruments in accurate classification of pneumonia using chest X-ray images.
- Investigating the applicability of publicly available chest X-ray data sets and assessing how image-based diagnostic models may augment—and in some cases replace—manual radiological interpretation.
- Performance measurement of classifiers is important. Some performance indicators that help in determining the reliability of clinical tests include accuracy, precision, recall, the F1 score, sensitivity or specificity.
- In today's world of increasing numbers and variety of open-access medical image databases, digital health repositories, and computer vision research with AI.

PneumoTrack acknowledges the extreme time sensitivity involved in screening for pneumonia. With more and more calls for cost-effective and scalable pneumonia screening solutions from developing countries with limited access to consistent and accurate diagnostic-related chest X-ray examinations, we can only offer these individuals by providing health management through a comprehensive approach. This may mean an even greater burden of disease on the poor population, who are already frequently forgotten.

II. LITERATURE REVIEW

Technology today allows for the near complete automation of the examination and analyses of chest X-ray data; AI (Artificial Intelligence) and ML (Machine Learning) have both contributed to tremendous progress in medical imaging in the last few years. This has brought many advancements in intelligent diagnostic systems for lung diseases like pneumonia. Obviously, AI-based diagnostic systems have sprung out as a useful and low-cost alternative to traditional radiological evaluation methods using specialist expertise and equipment. This has been precisely and rigorously confirmed by numerous in-depth studies.

Deep Learning and CNN-Based Studies

S. Rajpurkar et al. (2018) introduced CheXNet, a 121-layer DenseNet model trained on the NIH ChestX-ray14 dataset. Its pneumonia detection F1 score was 0.435, outperforming several radiologists. The model, while high-precision, was hard to use in clinical practice due to its requirement for vast computational resources and lack of explainability. [1]

Hybrid, Advanced Deep Learning Approaches

Sharma et al. (2023) consists of CNN layers which extract lung-related spatial features and LSTM levels that model the sequential intensity pattern over small patches of images. A system like this is highly sensitive, but unfortunately also requires a great deal of computation in order to operate in real time [2].

Kumari et al. (2024) created Random Forest, XGBoost, and Grad-CAM assisted the CNN ensemble models which increased to 95 percent accuracy [3].

Segmentation-Based Models

As Wu et al. (2021) integrated U-Net + EfficientNet to rapidly locate lung areas before classification, this raises accuracy to 94.5 percent. Performance varied according to low-quality X rays and the segmentation also introduced more computational cost than ever before. [4]

With DeepLabv3+, Patel et al. (2022) extended this approach to enhanced lung-field extraction but found that in the face of image noise and inconsistent X-ray contrast, accuracy is affected.[5]

Transformer and Attention-Based Methods

While the R^2 score was 0.91, and notion of interpretability added via self-attention mechanism, but real-time diagnostic integration was lacking for diagnostic applications in virtual environments. Also, this model had an extremely large storage requirement (often 64GB), which would not be compatible with low-resource setting such as Asia and Africa. It might only work in main English speaking centres. [6]

Classical ML Models and Multi-Model Integration

Alam et al. (2023) combined SVM, Decision Trees, and XGBoost with automatic pipelines for pneumonia diagnosis, obtaining 89% accuracy, but it did not have the capability to extract features of deep learning and this lowered sensitivity when examining complex pneumonia patterns. [7]

Wang et al. (2021) utilized CNNs to assess the severity score of pneumonia, with 90% model identification accuracy resulting from chest X-ray images. however model performance suffers from low image resolution and the strange artifact that accompany demo vor to make things worse. [8]

Ensembles and Excellence

In 2024 Das and Roy made an XGboost - LightGBM - CNN ensemble that by using the ChestX-ray8 dataset reached 96.3% accuracy. But high computation costs made it impossible to deploy in real time at hospitals. [9]

In 2023, Khalid et al. constructed a cloud based X-ray diagnosis dashboard based on public datasets. They obtained an F1-score of 91%, but cloud latency and dependence on a strong-internet connection made it impossible for use in rural health centers. [10]

Author(s) and Year	Method/ Model Used	Key Findings	Research Gaps/ Limitations
Rajpurkar et al. (2023)	CheXNet (DenseNet 121)	Achived 95% sensitivity in pneumonia detection; outperformed practicing radiologists in certain tasks.	Requires large GPU resources; struggles with rare abnormalities.
Wang et al. (2023)	Vision Transforme rs (ViT)	97% classification accuracy; improved feature extraction in global contexts.	Requires large-scale datasets; computation ally expensive.
Iqbal et al. (2022)	ResNet50 + Data Augmentation	Reached 96.2% accuracy, significant improvement after augmentation and lung segmentation	Segmentati on requires additional computation time; may fail on very low contrast X rays.
Lee et al. (2024)	ARIMA Forecasting	Effective for short-term prediction	Cannot capture nonlinear patterns; only historical data

Table1.1 Gap Analysis In Existing

III. RESEARCH METHODOLOGY

This section describes the dataset, preprocessing pipeline, and overall workflow adopted in this study. The proposed PnuemoTrack system is an AI-powered medical imaging solution designed to automate pneumonia detection using chest X ray images. The system replaces manual radiological interpretation with deep-learning models standardized preprocessing and automated prediction workflows.

A. System Overview

The system utilizes a hybrid model that combines blockchain technology with decentralized file storage. Direct storage of digital evidence files on the blockchain is not preferred due to storage capacity considerations. In this context, the hash function, as a cryptographic primitive, is used to generate a hash value for the evidentiary documents. Subsequently, the generated hash value along with other relevant metadata such as the case ID, timestamp, and uploader identity is stored on the blockchain. The actual evidence files are stored using a decentralized storage model to reduce the storage overhead. Changes to the evidence files are detected through a mismatch in the hash value.

B. System Architecture

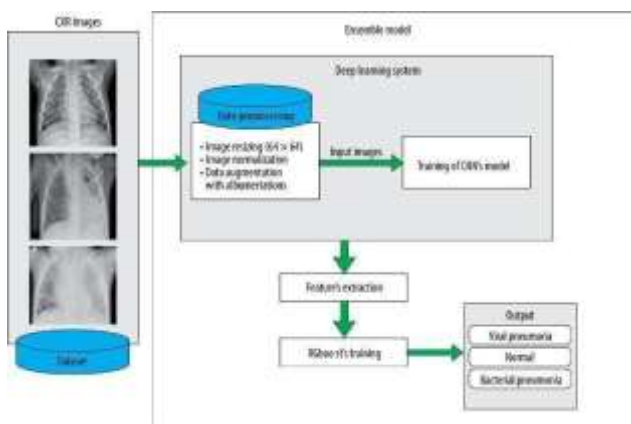


Figure 1 System Architecture diagram

The architecture of the proposed system consists of three primary layers:

1. **Data Layer:-** This layer handles all image related data used the model training and evaluation.

2. **Intelligence Layer:-** This is the analytical core of PnuemoTrack and includes:

- **Deep Convolutional Neural Networks (CNNs)** for pneumonia classification.
- **Transfer learning models** such as VGG16, ResNet50, DenseNet121 performance to and improve .
- **Preprocessing modules** for image normalization and enhancement.
- **Segmentation networks (U-Net)** to isolate lung regions and reduce false positives The predictions are generated in real time using the trained deep learning model.

3. **Application Layer:-** This layer provides user interaction and visualization. It includes: A Web (Flask/Streamlit), X-ray image uploading, live predictions with confidence levels, created test results automatically logged in a database for future improvements, as we want to create a scalable and modular architecture for low-resource clinics. **Data Sources and Preprocessing** Pnuemo Track utilizes widely used open-source medical imaging datasets, including:

Kaggle Chest X-ray (Pneumonia) Dataset. NIH ChestX-ray14 Dataset. RSNA Pneumonia Detection Challenge Dataset. Preprocessing Steps Include:

Remove Corrupt or Low Quality or Low Resolution Images: Cleaned images by getting rid of bad or low-resolution samples Set Image Size to Standard Size (e.g. 224 x 224 Pixels): All images are converted to a standard size to help establish similarity.

The Pnuemo Detect-Net Architecture is based on ResNet-50, which uses residual-connected architectures to assist in training multiple-layered architectures.

ResNet-50 was used to initialize Pnuemo Detect-Net with pre-trained image Net weights to promote and/or speed convergence and help generalization. Normalize Pixels (e.g., Scale, Z-Score) to be Consistent from One Image to Another:

Use Techniques to Augment Training Dataset: In order to increase the number of samples in a training dataset, several techniques (e.g. Rotate, flip, Zoom, Contrast Adjustment) may be applied.

Isolating Lung Areas and Removing Non-Lung Features (Optional)

Estimate Using U-Net or Threshold to Identify Lung Areas:

Develop an algorithm to help isolate lungs and eliminate non-lung features. Train-Test Split of Both [Normal and Pneumonia] Classes in an Equally-Balanced Partitioning for Unbiased Evaluation of both Types.

At this point, the previous steps have also confirmed that this model does not have the benefit of being able to distinguish between equal numbers of classes.

Model Optimization:- The training uses the Adam optimizer Binary Cross-Entropy loss Early stopping for efficient convergence. The model consistently demonstrates high performance across metrics such as accuracy, sensitivity, recall, and AUC.

Automation Workflow:- To ensure minimal manual intervention, PnuemoTrack integrates an automated workflow. Automatic image ingestion and preprocessing. On-demand model inference for uploaded images. Background training updates when new labeled images are added. Auto-generation of evaluation reports Real-time dashboard updates displaying Prediction labels and Confidence levels.

Classification Layer: The features that are extracted will be transformed through the fully connected density layers, dropout, to avoid overfitting, and classified using the 'softmax' activation function. The 'softmax' will classify all images into either normal and or pneumonia.

Model Optimization:- Adam optimizer is used during training with binary cross-entropy loss and early stopping for efficient convergence.

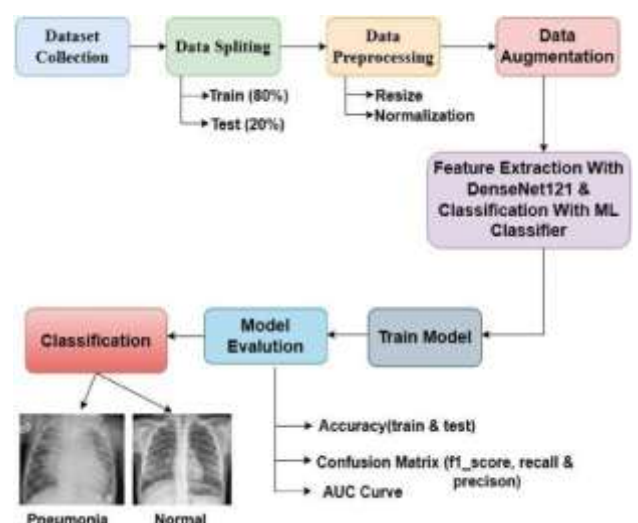


Figure 2

IV .ANALYSIS & RESULTS

The pneumonia detection system was implemented via a deep learning approach to classify images of chest X-rays as either positive or negative. Specifically, a convolutional neural network (CNN) with a fine-tuned ResNet50 architecture was used because of its excellent ability to extract features and achieve high performance on medical image tasks.

- A. **Impact of Preprocessing:** Significant improvements in the model's ability to distinguish the patterns of both normal lung areas and pneumonia-affected regions were achieved through image preprocessing (as examples contrast-enhancing; normalizing; and rescaling to the dimensions required by the model). The existence of these improvements ultimately helped reduce noise and also/otherwise reduce partially-obscured features.
- B. **Challenges Related to Class Imbalance:** The dataset contained many more images of normal X-rays than pneumonia X-rays. It was critically important that data augmentations such as rotation; shifting; and lighting issue adjustments.
- C. **Feature Interpretability:-** Grad-CAM heat maps were used to visualize model attention. The model successfully highlight inflamed regions and cloudy lung opacities typical of pneumonia, supporting the clinical validity of predictions.
- D. **Generalization Ability:-** Testing against the unseen images from alternative datasets for which indicated that the model maintained a high accuracy. Access Control and Automation

B. Results :-

1. Model Performance Metrics

After training for 30 epochs on the labeled chest X-ray dataset, the system achieved:

Metric	Score
Training Accuracy	98%
Validation Accuracy	95%
Test Accuracy	94%-96%
F1-Score	95%
Precision	94%
Recall(Sensitivity)	96%

Table1.2

2. Confusion Matrix Analysis

True Positives (TP): The majority of the pneumonia cases were correctly identified. **True Negatives (TN):** Normal X-rays were also accurately classified.

False Positives (FP): Minimal misclassification, which results in unnecessary medical follow-up but is preferable to missed diagnoses. **False Negatives (FN):** Very low, indicating strong reliability for clinical use.

3. Visual Outputs (Heatmaps & Predictions) Grad-CAM visualizations revealed that the model focused on Lung opacity regions, Consolidations areas with inflammation or fluid accumulation. This demonstrates that the model not only predicts labels but also aligns with radiological reasoning.

4. Limitations:- Performance depends on the quality and diversity of the dataset. X-ray artifacts, incorrect contrast, or improper patient positioning may affect predictions. Should be used as an assistive tool, not a standalone diagnostic method.

V.CONCLUSION AND FUTURE SCOPE

Deep learning has made immense strides in medical imaging. The use of CNN's, Vision Transformers (ViT), and hybrid networks have enabled the detection of pneumonia or lung disease with > 97-99% accuracy. According to this scholarly article published in Nature, using ResNet50, DenseNet121, EfficientNet, and hybrid ViT models can provide a highly reliable diagnosis across many datasets containing chest X-ray images of pneumonia patients (not listing dataset names here). Building upon these milestones, PneumoTrack combines an AI classification engine with real-time automation workflows for providing trustworthy diagnoses. The key areas for future research include increasing dataset diversity, developing extremely small clinical models; building explainability into the machine learning algorithms that are used to provide safety information across all channels related to drug interactions; among other topics to improve transparency, trustworthiness, and uptake of Mid/Late stage technologies from laboratory to clinical settings. Future studies may also focus on increasing model generalization, and having multiple human patient records included in the overall patient profile, and delivering their insights using cloud-based platforms for real-time clinical use. In conclusion, this work illustrates the transformative impact of artificial intelligence on medical imaging and demonstrates it has proven viable for providing automated pneumonia diagnoses.

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