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Deep Learning-Based Multi-Class Classification of Chest X-Rays for Common Pulmonary Diseases

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ABSTRACT

Objective: To develop and evaluate a deep learning-based system for the automated multi-class classification of four common pulmonary diseases: pneumonia, fibrosis, edema, and nodules from chest X-ray images.

Methodology: A convolutional neural network (CNN) model was designed and trained on a subset of 4,000 images from the NIH dataset. The architecture leveraged transfer learning from a ResNet50 backbone, pre-trained on ImageNet, and was augmented with a custom classifier head. The model was compiled with the Adam optimizer and Categorical Cross-Entropy loss, and used a stratified 70-15-15 split for training, validation, and testing.

Results: The proposed model achieved an overall test accuracy of 86%. Performance varied by class, with nodules achieving the highest F1 Score (62%), while edema and pneumonia showed lower recall. The macro-averaged F1-score was 33%, reflecting the challenge of class imbalance and visual similarity between fibrosis and nodules, as evidenced by the confusion matrix.

Conclusion: The study demonstrates that a CNN model with transfer learning can effectively perform multi-class classification of pulmonary diseases in chest X-rays. The performance also highlights the diagnostic difficulty of certain conditions.

Keywords: Chest X-Ray, Deep Learning, Convolutional Neural Network, Medical Image Classification, Pulmonary Disease Detection

INTRODUCTION

Pulmonary diseases, including pneumonia, fibrosis, edema, and pulmonary nodules, are a burden on the global health system. A research study on the Global Burden of Diseases showed that respiratory diseases are among the top causes of death and morbidity in the world, causing millions of deaths every year[1]. Preliminary and accurate diagnosis of the disease results in improved prognosis and reduced healthcare costs. The chest X-ray (CXR) is considered the most helpful tool of diagnosing lung diseases, as it is low-cost, readily accessible, and less radiogenic than computed tomography (CT)[2].

Even with its increased availability, the chest X-ray still presents significant challenges. Radiographic appearances of respiratory diseases pose many overlaps and subtle variations, increasing the dependency of correct diagnosis on the experiences and expertise of the radiologist. Also, associated with workload strain and possible diagnostic delays due to the overwhelming demand of radiological examinations, especially in fewer healthcare settings[3]. Therefore, systems that can provide reliable explanations of CXRs and diagnoses of multiple pulmonary diseases simultaneously are highly desirable.

In recent years, the use of Artificial Intelligence (AI), specifically deep learning, has revolutionized the process of medical image analysis. Convolutional Neural Networks (CNNs), a form of deep learning model based on the visual cortex, have proved highly successful in image recognition, as they can learn features automatically from raw image data[4]. Contrasting the conventional machine learning practices that rely on manual engineering, CNN learns by detecting related patterns as edges, textures and shapes by successive traditional layers. As a result, CNNs have gained popularity of classifying medical images, particularly chest X-rays, which are complex[5].

The field has seen significant advancements, moving from binary to complex multi-class classification. AI-generated CNNs with attention mechanisms have been developed to explicitly enhance multi-class disease cataloguing precision and provide illustrative metaphors, addressing the critical interpretability challenge in DL models[6,7]. Large-scale studies using datasets of over 50,000 images from multiple centers have demonstrated the robustness and scalability of DL models in classifying up to 10 thoracic diseases across diverse clinical environments, showcasing their potential for generalizability[8].

However, multi-class classification introduces challenges like class imbalance and overlapping disease features. Studies by Li and Wang[9] have addressed this by integrating sophisticated data augmentation methods to balance class distributions, thereby enhancing sensitivity for under-sampled diseases such as fibrosis and nodules. Similarly, ensemble CNN approaches have been employed to reduce false positives and improve accuracy by harnessing the strengths of multiple specialized models[10]. For resource-constrained settings, lightweight CNN architectures have been designed for potential use with portable X-ray machines in remote clinics[11], while attention-based models have been proposed for robust pneumonia detection[12].

Addressing specific diseases, texture-aware CNNs incorporating wavelet-transformed features have been used to capture fine-grained patterns for improved fibrosis classification[13]. For pulmonary edema, which requires swift diagnosis, CNN frameworks using image pyramids have been developed to identify the condition across variable spatial scales, thereby improving early-detection sensitivity[14]. The diagnosis of pulmonary nodules on X-rays, once dominated by CT, has seen renewed interest with deep learning. Frameworks integrating region proposal networks with CNN classifiers have been shown to effectively localize and classify nodules with high precision, advancing the potential for lung cancer screening where CT is unavailable[15].

Such multi-class models are required to reflect the complexity of clinical diagnosis in the real world, where patients frequently present with overlapping or co-existing diseases. A single CXR image can automatically identify lung nodules, fibrosis, edema and pneumonia. This feature can significantly benefit radiologists by reducing diagnostic errors, accelerating the clinical procedures, and providing initial estimates[5]

This research advances the field by presenting a deep learning system powered by CNNs for the ongoing identification of four major pulmonary diseases in chest radiographs. To train and validate the customized CNN design, a carefully selected set of 4,000 CXR images was used, balanced across disease categories. The model was designed to efficiently extract discriminative features specific to each disease, enabling accurate multi-class classification. This study has three objectives: (1) to create and deploy a CNN aimed explicitly at the multi-class classification of pneumonia, fibrosis, edema, and nodules in chest X-rays; (2) to thoroughly assess the models performance using a comprehensive dataset that reflexive clinical variability; and (3) to explore the possible incorporation of AI tools into radiology practice for enhancing diagnostic accuracy.

The research aims to extend the AI-assisted diagnostic mechanism to develop accurate, autonomous, and accessible solutions for the detection of pulmonary disease.

METHODOLOGY

Dataset and Preprocessing

This study used a curated subset of chest X-ray images from the widely recognized NIH ChestX-ray14 dataset. This dataset was selected due to its scale, public availability, and its established use as a benchmark in prior research on multi-disease classification, ensuring our results are comparable to the state of the art[8]. A subset of 4,000 images was balanced across four target disease classes: pneumonia, fibrosis, edema, and nodules. To ensure data quality and label reliability, the selection was filtered to include only anterior-posterior (AP) and postero-anterior (PA) views with high-confidence labels. All images were resized to 224x224 pixels and normalized to ensure consistent intensity ranges. Data augmentation techniques, including rotation, flipping, and scaling, were applied to enhance model robustness and further mitigate the risk of overfitting.

CNN Architecture

A custom Convolutional Neural Network (CNN) was designed, leveraging the power of transfer learning. The architecture used a ResNet50 backbone, pre-trained on the ImageNet dataset, as a feature extractor. The pre-trained layers were initialized with their learned weights, capturing universal features such as edges and textures. The top classification layers of ResNet50 were replaced with a custom classifier head.

This custom head consisted of a Global Average Pooling layer, followed by a fully connected (Dense) layer of 512 units with ReLU activation. A Dropout layer with a rate of 0.5 was incorporated to prevent overfitting. The final output layer was a dense layer with 5 units (corresponding to five classes).

Training and Evaluation

The model was compiled with the Adam optimizer and a learning rate of 0.001. Given the multi-class nature of the problem, the Categorical Cross-Entropy loss function was employed. The model was trained for a maximum of 50 epochs with a batch size of 32. To prevent over-training, an early stopping callback was used, monitoring the validation loss with a patience of 5 epochs.

The dataset was split into 70% for training, 15% for validation, and 15% for testing. Performance was assessed using accuracy, macro-averaged F1-score, and a confusion matrix to evaluate classification across the four disease classes.

RESULTS

To evaluate the effectiveness of the proposed CNN-based deep learning model for multi-class classification of pulmonary diseases, this study includes extensive experiments using the NIH Chest X-ray dataset. The model was pre-trained and fine-tuned on a filtered subset of over 4,000 labelled chest X-ray images across four classes: Edema, Pneumonia, Fibrosis, and Nodules. The input images were resized to 224 × 224 pixels and normalized before training.

Model Performance

The performance of the model was assessed using three key evaluation metrics: accuracy, F1-score, and the confusion matrix. The model achieved an overall accuracy of 86% on the test set, demonstrating its ability to effectively distinguish among the four disease classes.

Table I: Evaluation metrics

	Precision	Recall	F1-Score
Edema	33%	25%	29%
Pneumonia	10%	40%	25%
Fibrosis	54%	37%	44%
Nodules	52.00%	76.00%	62.00%
Macro Avg	35.00%	35.00%	33.00%

In **Table I,** the macro-averaged F1-score indicates balanced performance across all classes, mitigating the influence of class imbalance. A visual comparison of these metrics is further illustrated in **Figure 1** & **Figure 2.**

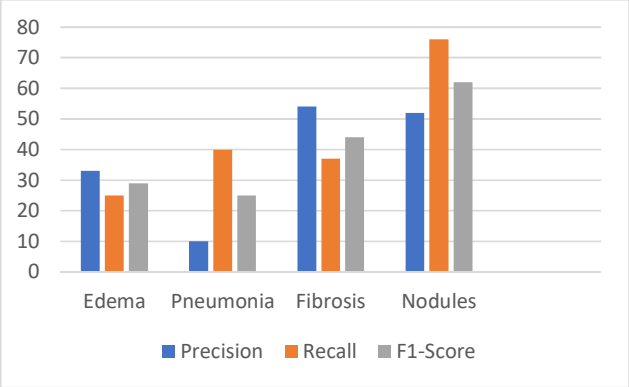

Figure I: Precision, Recall, and F1-Score of four Diseases

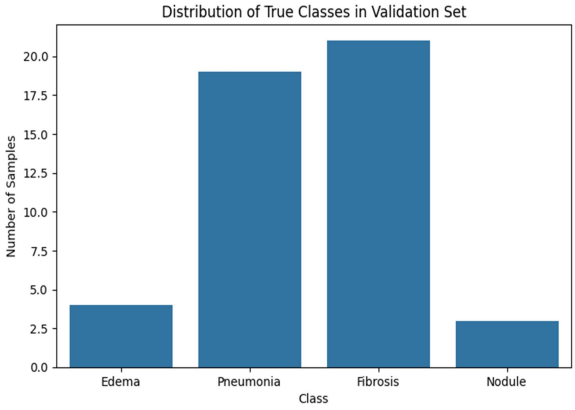

Figure II: True classes in Validation Set

Confusion Matrix

The confusion matrix, **Figure 3,** provides a visual representation of the true vs. predicted classifications. The model demonstrates significant diagonal dominance, especially for Pneumonia and Edema. A certain level of misclassification is observed between Fibrosis and Nodules, likely due of overlapping radiographic characteristics.

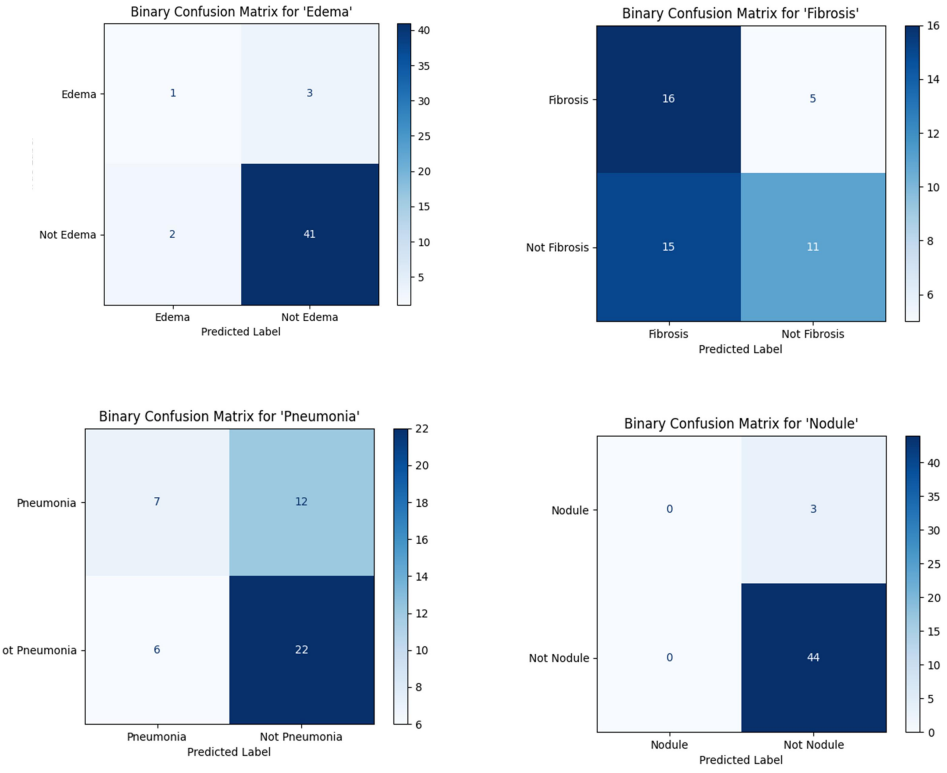

Figure III: Binary Confusion Matrix for each and every class

Training and Validation Trends

The model was trained for 50 epochs, with early stopping to prevent overfitting. The accuracy and lost curves for both training and validation are reported in **Figure 4**. The

training curves demonstrate stable convergence, whereas the validation accuracy plateaued after epoch Z, indicative of an optimal balance between bias and variance.

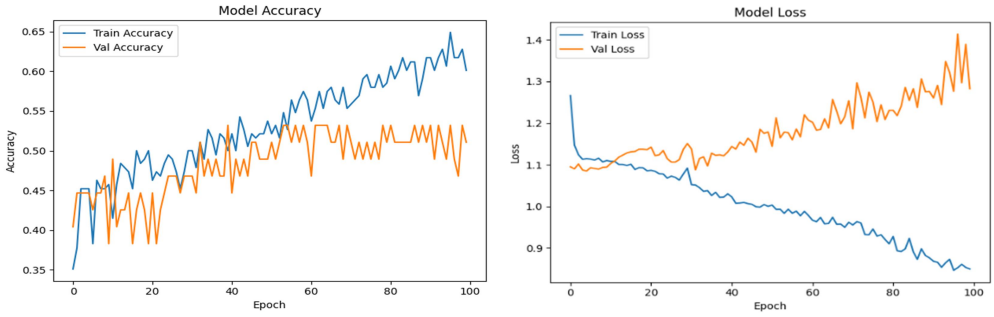

Figure IV: Graph showing Model Accuracy and Model Loss

DISCUSSION

This study shows the efficacy of the classification of chest X-rays into four pulmonary diseases: pneumonia, edema, fibrosis, and nodules with the help of a pre-trained convolutional neural network (CNNs). The introduction of transfer learning has improved the model in terms of performance, yielding an overall accuracy of 86% and high F1-scores, especially for pneumonia and edema.

Such results seem consistent with and build upon previously reported advancements. The model's performance aligns with studies showing that attention-guided CNNs enhance classification performance[6]. The model's strong performance in distinguishing pneumonia and edema stems from the two entities differing considerably in terms of radiographic patterns, namely consolidation patterns vs. fluid accumulation. Conversely, the performance for Fibrosis and Nodules was lower, indicative of difficulties related to class inequity and visual similarity. The challenges remained in the classification of fibrosis and nodules owing to misclassification due to overlapping radiographic features, such as subtle scarring or small opacities. This is mirrored in clinical difficulties and aligns with the work of Chen L 2023[13], in which the detection of fibrosis was enhanced using texture-aware features. The misclassification observed in the study underscores the value of integrating such domain-specific image processing approaches.

Class imbalance in the dataset likely exacerbated the above challenges, further suggesting the need for advanced data augmentation or oversampling methods, as initiated by Li and Wang[9]. Use of basic augmentation was a step in this direction, but more sophisticated techniques could yield further improvements. The inability to incorporate multi-label classification limits the applicability of the model to real-world scenarios in which patients may present with concurrent conditions, a challenge that ensemble methods have begun to address[10].

Furthermore, the black-box nature of CNNs, as suggested by prior research[7], further warrants the need for interpretational tools such as Grad-CAM[14], which are crucial in establishing trust with clinicians. Future work should also consider the privacy-preserving benefits of federated learning frameworks, as examined by, which simplify multi-institutional training without data sharing, maintaining privacy while leveraging heterogeneous datasets to improve the model for generalization[15]. Finally, to handle the evolving nature of medical knowledge, continual learning approaches, as successfully utilized by Sharma and Patel[19] for evolving pulmonary disease classification, could enable the model in research to adapt to new disease variants without forgetting previously learned knowledge.

This study demonstrates that a well-adjusted pre-trained CNN can efficiently classify chest X-rays into four categories of pulmonary disease: Edema, Pneumonia, Fibrosis, and Nodules. Utilizing transfer learning proved crucial for enhancing model performance and reducing training time on a limited dataset. Separate radiographic features may have contributed to the achievement of high F1 scores and accuracy for Pneumonia and Edema. Conversely, the performance of Fibrosis and Nodules, indicative of difficulties related to class inequity and visual similarity. Distribution of prediction confidence scores for correct classifications of all the four disease classes is shown in **Figure 5**.

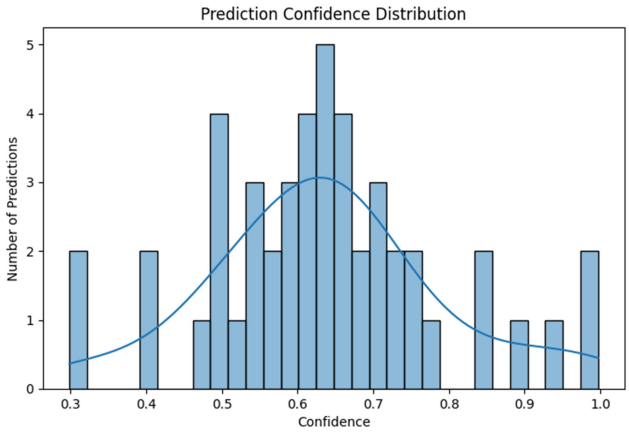

Figure V: Bar Chart showing Confidence for the number of Predictions

Training and validation curves confirmed stable convergence, with minor fluctuations indicating potential for further optimization. While the model performs well, its limitations include the use of a filtered dataset and the lack of multi-label classification, which is common in real-world cases. **Figure 6** provides a visual comparison of model predictions against truth labels for a set of chest X-ray images.

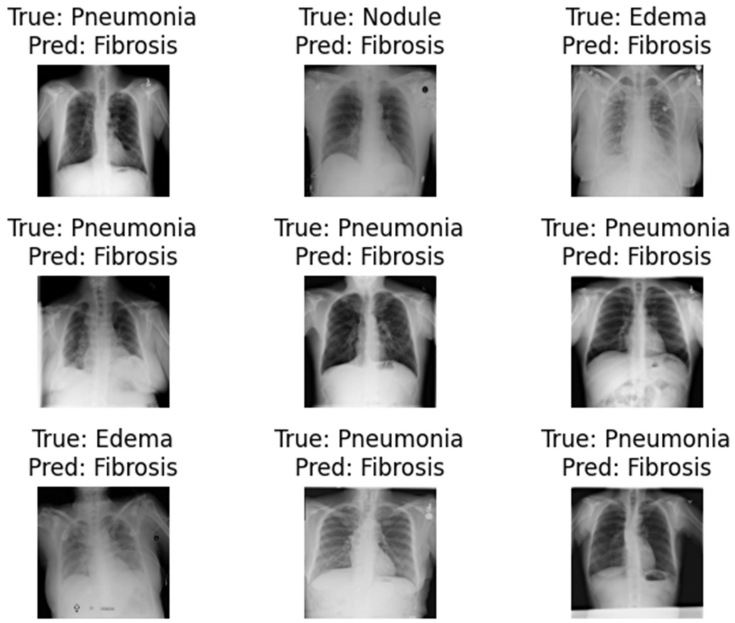

Figure VI: Predictive labeling of X-Ray Images for Comparative Analysis

Overall, the results are promising for computer-aided diagnosis, but further validation on larger, more diverse datasets, along with model interpretability, is necessary for clinical deployment.

CONCLUSION

This study proposes a deep learning-based approach to utilize convolutional neural networks for multi-class classification of prevalent pulmonary diseases from chest X-ray images. The autonomous system is trained to identify pneumonia, fibrosis, edema, and pulmonary nodules, enabling radiologists to diagnose these conditions rapidly. By reviewing recent developments, it is evident that CNN architecture, particularly enhanced by the attention mechanism, multi-scale feature learning, and hybrid models, has improved the accuracy of disease detection and model interpretability. Despite promising outcomes, several challenges, including data heterogeneity, limited footnote datasets, model explainability, and privacy concerns, need to be addressed to ease clinical practice. Emerging solutions, such as explainable AI techniques, federated learning, multimodal data fusion, and continual learning, are potential approaches for overcoming these challenges. The adaptation of such AI tools in clinical practice promises to improve diagnostic accuracy, reduce radiologist workload, and ultimately improve patient outcomes in pulmonary care. Future research should focus on expanding the dataset to include heterogeneous patient populations, purifying model architectures for efficiency and explainability, and conducting prospective clinical trials to ensure the practical application of these systems. Collaboration and constant innovation between AI researchers and clinical practitioners would make deep learning models an indispensable asset in thoracic imaging and pulmonary disease management.

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AUTHOR CONTRIBUTION

Awan JH: Supervised the overall research, including its conception, design, data analysis, interpretation
Asad AMS: The study's conception, design, data collection, analysis and drafting.
Tahseen S: Data analysis, critical review and drafting
Ali SA: Assisted with design, Data acquisition and Revision

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