Pneumonia Detection in X-Ray Chest Images Based on Convolutional Neural Networks and Data Augmentation Methods

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Abstract: Pneumonia, a widespread lung ailment, stands as a leading global cause of mortality, particularly affecting vulnerable demographics such as children under five, the elderly, and individuals with underlying health conditions. Accounting for a significant portion of childhood fatalities, at 18%, pneumonia remains a critical health concern. Despite advancements in imaging diagnostic methods, chest radiographs remain pivotal due to their cost-effectiveness and rapid results. The proposed model, trained on data sourced from a readily available Kaggle database, consists of two primary stages: image preprocessing and feature extraction/image classification. Utilizing a CNN model, the framework achieves remarkable performance metrics, with precision, recall, F1-score, and accuracy reaching 93%, 96%, 94%, and 96%, respectively. These results underscore the CNN model's effectiveness in pneumonia detection, showcasing superior consistency and accuracy compared to other pretrained deep learning models.

1 INTRODUCTION

Pneumonia is a prevalent and potentially life-threatening respiratory infection, particularly affecting vulnerable populations such as children, the elderly, and immunocompromised individuals. Early detection of pneumonia is crucial for timely intervention and treatment to prevent complications and improve patient outcomes. While numerous imaging diagnostic methods exist, many are prohibitively expensive and inaccessible to large segments of the population, especially in low-resource regions Asnake, N.W (2024). Additionally, the shortage of radiology experts in these areas and long waiting times for diagnoses exacerbate the severity of the disease and contribute to increased mortality rates. Diagnostic radiography, although cost-effective and rapid, may lead to misinterpretations due to visualized opacities.

To address these challenges, recent studies have explored machine learning techniques, particularly deep learning models like convolutional neural networks (CNNs), to aid in pneumonia diagnosis using high-resolution imaging modalities such as computed tomography (CT) scans. One such study developed a deep learning architecture tailored for diagnosing severe pneumonia cases from chest X-rays. Leveraging a dataset from the Radiological Society of North America, this study focused on specialized zones within the chest X-rays for improved diagnostic accuracy.

In recent years, the healthcare landscape has witnessed the emergence of various technologies such as genomics and imaging, which have brought forth vast and intricate datasets in Asnake, N.W., Salau (2024). While chest X-ray images remain a primary diagnostic tool for pneumonia, they can pose challenges due to their nuanced nature, sometimes leading to misclassifications by expert radiologists and subsequent incorrect treatments (Lamia A, Fawaz A (2022)). This underscores the need for an automatic and intelligent model to aid radiologists in accurately diagnosing different types of pneumonia from chest X-ray images Goyal, S., Singh, R (2023).

Deep learning, a subset of machine learning inspired by the brain's structure and function, has emerged as a powerful tool in medical image analysis Kareem, A., Liu, H (2022). These algorithms excel at

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quantifying, identifying, and classifying patterns within medical images by learning features directly from data, eliminating the need for manual feature design based on domain-specific knowledge. Convolutional neural networks (CNNs) are a prominent example of deep learning models utilized in this context. These layers specialize in processing images and extracting low-level features, such as edges, while efficiently capturing temporal and spatial dependencies with the aid of filters. Unlike traditional feed-forward layers, CNNs significantly reduce computational complexity by sharing weights and utilizing fewer parameters. As a result, CNNs offer an effective approach for medical practitioners to diagnose and classify specific medical conditions with accuracy (Z. Li et al 2019 ; M. K. Gourisaria 2023). The structure of the paper is as follows: Section 2 provides a detailed review of related works, summarizing relevant research on the topic. Section 3 describes the dataset utilized in this study. Section 4 outlines the proposed methodology implemented in the research. Section 5 examines the results and compares them with findings from recent studies. Finally, Section 6 concludes the paper by summarizing key insights and proposing directions for future research.

2 RELATED WORKS

In the field of disease detection, numerous researchers have been actively engaged in developing automated detection models. Deep learning techniques have emerged as valuable tools for enhancing productivity, especially in computer-assisted diagnosis technologies, notably within medical imaging, image classification, and image restoration Venkateswara Reddy. (2022). Author in Shagun Sharma. (2023) proposed deep learning (DL) model comprises several stages: data collection, preprocessing, feature extraction, training, testing, classification, and pneumonia prediction. During data preprocessing, the data is balanced and normalized, ensuring it falls within a normalized range of [0-255]. Subsequently, the normalized data is inputted into the VGG16 model for feature extraction Liu, Y (2023). This step involves extracting pertinent features from the images, facilitating the classification and prediction process. With its 16 layers encompassing input, convolution, pooling, dense, and output layers, VGG16 enables comprehensive feature extraction. The significant challenges faced in pneumonia detection include the large number of patients and the shortage of medical experts and supporting staff. The development of deep learning-based methods for early detection of pneumonia has garnered significant attention in recent years due to their potential to improve diagnostic accuracy and efficiency. By leveraging advanced computational techniques and large datasets of annotated medical images, researchers have made significant strides in developing deep learning models capable of detecting pneumonia infections at an early stage Shadi A. (2022).

In the study discussed in Lamia A. (2022), pneumonia emerges as a rapidly spreading disease, posing significant risks to individuals' health and well-being. Biomedical diagnosis of pneumonia typically involves a range of diagnostic tools and the assessment of various clinical features. However, limitations in expert availability and tool accessibility hinder these efforts. To address this challenge, the researchers are developing a mobile application employing deep learning techniques to classify pneumonia cases. The aim is to create a prototype mobile app capable of detecting pneumonia using neural networks. Utilizing high-level tools like Create ML simplifies the process by eliminating complexities such as determining neural network layers, initializing model parameters, or selecting algorithms. This approach enables broader accessibility to the model, allowing users to access it via a mobile application. With a dataset comprising over 5,000 real images, an image classification model is trained using Create ML, a tool that offers a user-friendly graphical interface, requiring no specialized knowledge for operation.

In their study Khalaf Alshamrani. (2022), the authors optimized a model using data augmentation techniques, resulting in slightly better precision compared to the original model. They utilized this improved model to develop a web application capable of processing images and providing predictions to users. The classification model they developed achieved a prediction accuracy of 78%. The authors noted that precision could be further enhanced by adjusting parameters such as the number of epochs. Their research aimed to showcase the potential of artificial intelligence in creating deep-learning models to aid healthcare professionals in early pneumonia detection, emphasizing the importance of such technology in public health initiatives.

In Dalya S. (2022), a deep learning model is introduced for the detection of pneumonia disease from chest X-ray images. It is noted that the number of layers does not consistently lead to improved accuracy, and increasing the number of layers in neural networks may sometimes result in decreased performance. During the construction of the CNN model, an optimal number of layers was determined, which resulted in the highest accuracy achieved.

In Rajasenbagam, T., (2023), researchers introduced a Deep Convolutional Neural Network (CNN) aimed at detecting pneumonia infection in lung tissues using chest X-ray imagery. The Deep CNN models were trained on a Pneumonia Chest X-ray Dataset consisting of 12,000 images depicting both infected and uninfected chest X-rays. This dataset underwent preprocessing and was curated from the Chest X-ray8 dataset. Through the application of a Content-based image retrieval technique, images within the dataset were annotated with metadata and additional content information. Data augmentation techniques were then employed to expand the image count in each class Farhan, A.M.Q (2023), utilizing basic manipulation methods and the Deep Convolutional Generative Adversarial Network (DCGAN). The VGG19 network was employed in the development of the proposed Deep CNN model. Notably, this model achieved a classification accuracy of 99.34% when tested on unseen chest X-ray images D. S. V. Kancherla (2023).

Many studies have introduced methodologies aimed at addressing the challenge of class imbalance. One such approach involves leveraging Generative Adversarial Networks (GANs), specifically a fusion of Deep Convolutional Generative Adversarial Network (DCGAN) and Wasserstein GAN with gradient penalty (WGAN-GP), to augment the minority class "Pneumonia." Concurrently, Random Under-Sampling (RUS) techniques are employed on the majority class "No Findings" to mitigate the effects of class imbalance (Shorten, C.2019 and Schaudt, D 2023). Various researchers have utilized AI and CNN-based techniques for pneumonia detection, as outlined in Table 1.

This study aims to introduce an efficient deep learning framework tailored for pneumonia detection using chest X-ray images, achieving a harmonious balance between accuracy and complexity while offering a cost-effective solution for medical and radiology professionals. The outlined objectives are as follows:

- Utilizing a CNN model to detect pneumonia from chest X-ray images, serving as a feature extraction and classification scheme.
- Exploring and evaluating the performance of CNN and other deep learning models in accurately classifying pneumonia cases.
- Developing a versatile model capable of discerning between normal and abnormal (pneumonia) chest X-ray images.

Table 1: Comparison of the results with some state of the art methods.

Study	Dataset	Method	Accuracy Rate
Lamia A. 2022	The dataset of more than 5,000 real images	Multilayer Perceptron (MLP), Random forest, Sequential Minimal Optimization (SMO)	84%
Shagun Sharma. 2023	https://www.kaggle.com/datasets/prashant268/chest-xray-covid19-pneumonia	Vgg16	92.15%
Jain DK. 2022	"Curated Dataset for COVID-19 Posterior-Anterior Chest Radiography Images (X-Rays)	Vgg16	94%
		Vgg19	95%
		Xception	96%
Goyal, S. 2023	Covid-19 Radiography Database (C19RD) collected from Kaggle (https://www.kaggle.com/tawsifurrahman/covid19-radiography-database)	F-RNN-LSTM	95.04%
Fatma Taher. 2022	CXR images were produced at the Rashid Hospital Radiology Department in Dubai in the United Arab Emirates	CNN	94%
Proposed model	**lung disease dataset collected from Kaggle (https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia)**	**CNN+Adam optimizer**	**96%**

3 DATASET DESCRIPTION

The dataset, sourced from Kaggle, is organized into two main directories: "train" and "test." Each directory contains subdirectories, one containing X-ray radiographs of pneumonia cases and the other containing radiographs of normal lungs.

Specifically, 5,856 anteroposterior CXR images from pediatric patients aged 1 to 5 years were selected for analysis. Two labels, "pneumonia" and "normal," were assigned to categorize the images accordingly. Following an adjustment and consolidation of initial data classifications, the entire image dataset was split into 70% for training and 30% for testing purposes.

This allocation was made to ensure a comprehensive evaluation of the system's performance. Consequently, 5,216 X-ray images were allocated for training, while 640 radiographs were reserved for testing the system's efficacy. These images are chest X-rays (anterior-posterior) obtained from retrospective cohorts of pediatric patients aged one to five years old at Guangzhou Women and

Children's Medical Center. The chest X-ray imaging was conducted as part of the routine clinical care of the patients.

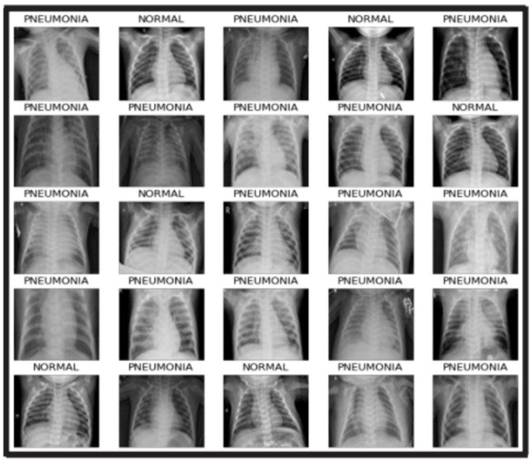

Figure 1: Samples of the dataset.

Before inclusion in the dataset, all chest radiographs underwent quality control screening to eliminate any low-quality or unreadable scans. Subsequently, the diagnoses for the images were assessed by two expert physicians to ensure accuracy before being used for training the AI system. Additionally, a third expert verified the evaluation set to address any potential grading errors, further enhancing the reliability of the dataset.

4 PROPOSED METHODOLOGY

The proposed deep learning framework has undergone multiple constructions and training sessions, exploring various parameters to select optimal hyperparameters and achieve a balanced performance architecture. Broadly, it comprises two primary stages. The initial stage involves several images preprocessing steps, including image resizing to obtain a standardized size and rescaling pixel values to fall within the [0,1] interval. Subsequently, the second stage focuses on feature extraction and image classification using the proposed Convolutional Neural Network (CNN) models (figure2).

A CNN consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers, that work together to automatically learn spatial hierarchies of features from input images. The convolutional layers apply filters (or kernels) to the images to detect local patterns such as edges, textures, and shapes. Pooling layers reduce the spatial dimensions of the data, retaining important features while improving computational efficiency. Finally, the fully connected layers at the end of the network make predictions based on the features learned by the convolutional and pooling layers.

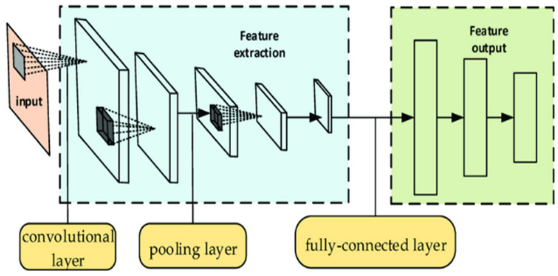

Figure 2: CNN structure (Sun, Shuo & Sun. 2022).

The feature extraction stage constitutes the second component of the CNN architecture, comprising three blocks, each containing a convolution layer, maximum pooling layer, and dropout layer. Within the convolutional layer, input images are transformed into matrix representations. The convolution operation is applied between the input matrix and a feature kernel of a specified dimension, resulting in a feature map. This operation effectively reduces the dimensions of the image, facilitating further processing. Data augmentation methods [23-24] prove beneficial in addressing the imbalance and scarcity of data in certain classes when dealing with limited and uneven datasets (Figure 3). This approach proves particularly useful for achieving a balance in the number of images across different MRI classes related to brain tumors and for expanding the overall dataset. Various augmentation techniques, including rotation, cropping, height and width adjustments, filling operations, zooming, and horizontal rotation brightening, are employed to augment images and rectify class imbalances. Given the unbalanced nature of our dataset, this augmentation technique is applied to artificially increase the number of images for each class, particularly those with fewer instances.

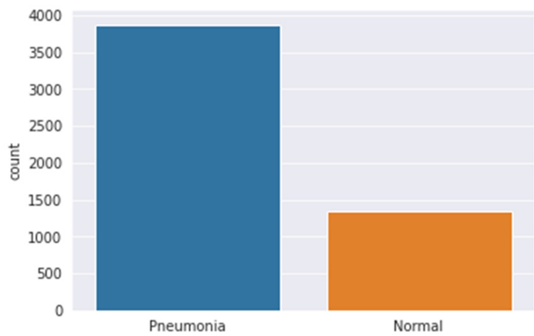

Figure 3: Imbalanced Data.

Given the apparent class imbalance in the dataset, with potentially fewer instances of the "Pneumonia" class compared to the "Normal" class, a strategy to counter this issue involves leveraging data augmentation techniques. By employing data augmentation, we aim to augment the training dataset by generating synthetic examples, thereby increasing the number of instances available for training.

This approach not only addresses class imbalance but also enhances the robustness and generalization ability of the machine learning model. To mitigate the risk of overfitting, expanding our dataset through artificial means is crucial. This involves introducing variations to the existing data via minor transformations, thereby increasing its size. Techniques that manipulate training data while preserving their labels are known as data augmentation methods. Common augmentations include grayscale conversions, horizontal and vertical flips, random cropping, colour adjustments, translations, rotations, and more. By applying a subset of these transformations to our training data, we can substantially augment the number of examples, leading to the creation of a highly robust model.

For data augmentation, I implemented several transformations to enhance the training dataset, including randomly rotating some images by up to 30 degrees, zooming in or out by up to 20%, shifting images horizontally by 10% of their width and vertically by 10% of their height, and randomly flipping images horizontally. These techniques were applied to increase the diversity of the training data and improve the model's ability to generalize. Once our model is prepared, we proceed to fit the augmented training dataset. The imbalance in clinical datasets, with a majority of abnormal cases and fewer normal cases, could indeed lead to overfitting, as the model might disproportionately favour the majority class. To mitigate this, our study implemented data augmentation techniques to increase the diversity and representation of normal cases through transformations like rotation, flipping, and scaling. Additionally, we employed class balancing strategies, such as adjusting class weights during training, to penalize misclassification of the minority class more heavily.

We validated the model using stratified cross-validation to ensure an even class distribution across folds and monitored evaluation metrics such as recall, precision, and F1-score, which are sensitive to imbalanced data. These approaches ensured the development of a balanced and reliable model for pneumonia detection. The proposed approach consists of two main steps. Firstly, we introduce a normalization method specifically designed for chest X-rays, with the goal of removing unnecessary components while retaining crucial information. Following this, Deep Convolutional Neural Networks (CNNs) are utilized, with a preference for using the ADAM optimization function to build predictive models using the normalized dataset. ADAM combines the benefits of the Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation (RMSProp), computing adaptive learning rates for each parameter to enhance training efficiency and convergence Figure 4 provides an overview of the proposed approach. The model, consisting of 6,026,324 parameters, employs a multi-branch convolutional architecture with three distinct branches, each featuring different lengths and kernel sizes to optimize feature extraction. Smaller kernels specialize in detecting localized features such as edges and textures, while larger kernels capture more global patterns like shapes and contours.

By varying the branch depths, the model combines shallow layers for basic feature recognition with deeper layers that learn complex, high-level abstractions. This design enables the model to process input data at multiple scales, enriching its feature representation and enhancing its ability to analyse fine-grained details alongside broader patterns.

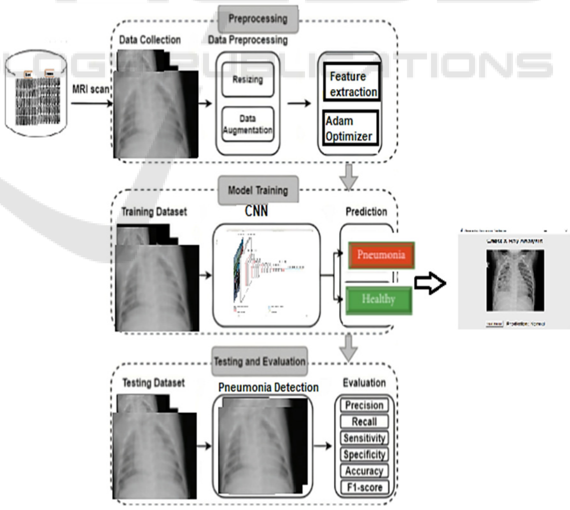

Figure 4: Proposed Architecture.

5 RESULTS AND DISCUSSION

For assessing the performance of the model, several evaluation metrics are employed to gauge the classification outcomes, particularly for pneumonia classification from lung X-rays. The primary evaluation metrics utilized include accuracy, recall (sensitivity), and F1-score. These metrics are calculated using the following equations:

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Precision}=\frac{TP}{TP+FP} \quad .. \quad (2)$$

$$\text{Sensitivity(Recall)}=\frac{TP}{TP+FN} \quad (3)$$

$$\text{F1-score}= 2/((1/Precision) + (1/\text{Recall})) \quad (4)$$

Here, TP denotes true positives, TN denotes true negatives, FP denotes false positives, and FN denotes false negatives. These metrics collectively provide a comprehensive evaluation of the model's performance in detection pneumonia cases from chest X-ray images. Figure 5 illustrate view of the pneumonia detection application. The initial step involves obtaining the patient's information, including their name, gender, age, phone number, history of hypertension, and the neurologist's name. Once the user correctly fills out this information, they are prompted to upload the lung X-ray images. Upon submitting the chest X-Ray Images, the application initiates the analysis using learning models to determine the presence of a pneumonia infection.

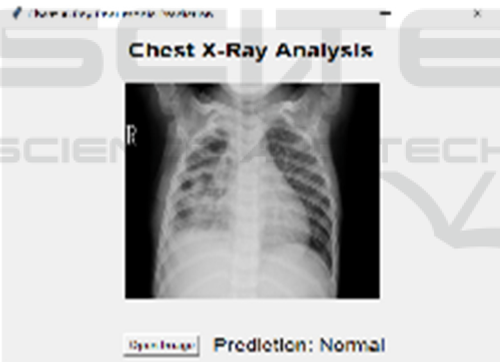

Figure 5: Pneumonia Detection Application.

Final output of the proposed method using 12 numbers of epoch has been shown in Figure 6. shows the model accuracy and the corresponding loss with respect to the number of epochs.

Our proposed model outperforms the previously developed approaches demonstrating accuracy of 96% and the loss is 1%. Our experimental results illustrate that the proposed CNN model exhibits superior convergence compared to the ANN approach, Random Forest classifier, Transfer learning algorithms, and other CNN models. As indicated in Table 2, our model attained the highest accuracy rate of 96% and the best F1-Score of 94%, along with a precision of 93%. The values attained by our proposed CNN model stand out for their

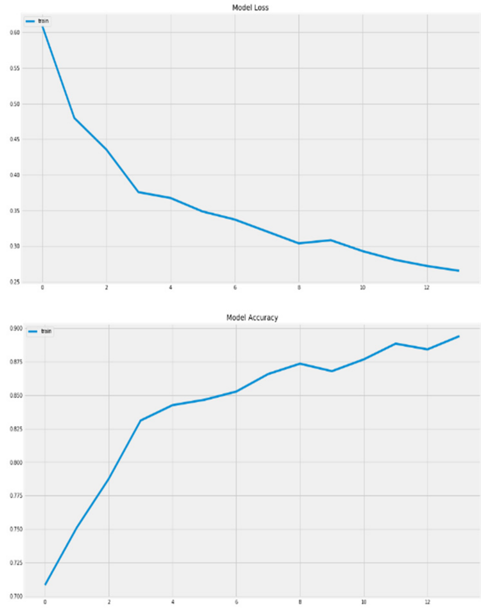

Figure 6: The model accuracy and loss over the epochs

exceptional performance, surpassing those achieved by the previously mentioned models. Table 2 presents a comparison of pneumonia detection accuracy between our proposed novel framework and state-of-the-art models. While our proposed model achieved accuracy that surpasses the state-of-the-art, it's important to note that directly comparing accuracy may not be entirely objective.

Table 2: Comparative study.

Study	Method	Accuracy Rate
Lamia A. 2022	Multilayer Perceptron (MLP), Random forest, Sequential Minimal Optimization (SMO)	84%
Shagun Sharma. 2023	Vgg16	92.15%
Jain DK. 2022	Vgg16	94%
	Vgg19	95%
	Xception	96%
Goyal, S. 2023	F-RNN-LSTM	95.04%
Fatma Taher. 2022	CNN	94%
Proposed model	**CNN+Adam optimizer**	**96%**

6 CONCLUSIONS AND FUTURE WORK

This study presents an automated method for pneumonia detection using X ray scans, leveraging a deep learning model for automated feature extraction from the images. The main goal of this research was to achieve improved classification performance with faster learning rates compared to traditional deep learning (DL) models. Despite the limited training data available, experimental results demonstrate the effectiveness of the proposed model. Its success can be attributed to minimal preprocessing requirements and the absence of handcrafted features, making it suitable for diverse x ray classifications. Future research aims to expand the classification to include additional labels while enhancing accuracy. Future work should aim to validate the proposed system beyond Chest X-ray (CXR) images. It is imperative to extend the validation to include other imaging modalities such as computerized tomography (CT) scans and Magnetic Resonance Imaging (MRI). This expansion of validation will enhance the applicability and robustness of the system across various medical imaging techniques. Future work in pneumonia detection using X-ray chest images could focus on the exploration of more advanced architectures, such as deeper or hybrid convolutional neural network (CNN) models, which could improve detection accuracy by capturing more complex features and patterns. Additionally, the integration of transfer learning from pre-trained models on large, diverse datasets could significantly enhance performance, particularly when labelled training data is scarce.

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