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A Compact CNN-Based Approach for Fast and Accurate Pneumonia Detection Using Chest X-Ray Images

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Abstract **– Pneumonia is a serious respiratory disease that affects millions of people worldwide and remains a major cause of mortality, particularly among children and elderly individuals. Early and accurate diagnosis is essential for effective treatment; however, manual interpretation of chest X-ray images can be time-consuming and subject to human error. Recent advances in deep learning, especially Convolutional Neural Networks (CNNs), have demonstrated significant potential in automating medical image analysis and supporting clinical decision-making. This study proposes a compact and computationally efficient CNN-based framework for the automatic detection of pneumonia from chest X-ray images. The proposed model is designed to achieve a balance between diagnostic accuracy and computational efficiency, making it suitable for deployment in resource-constrained healthcare environments. A publicly available dataset consisting of 5,863 chest X-ray images, including both pneumonia and normal cases, was utilized for model development and evaluation. To improve data quality and model generalization, preprocessing techniques such as image resizing, normalization, denoising, contrast enhancement, and data augmentation were applied. The CNN architecture comprises four convolutional layers with ReLU activation, max-pooling operations, dropout regularization, and fully connected layers for binary classification. The model was trained using the Adam optimization algorithm and evaluated using multiple performance metrics, including accuracy, precision, recall, specificity, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). Experimental results demonstrate that the proposed framework achieves an accuracy of 95.8%, precision of 96.5%, recall of 94.9%, specificity of 96.2%, F1-score of 95.7%, and an AUC of 0.97. These results indicate strong classification capability and reliable discrimination between pneumonia and normal chest X-ray images. A comparative analysis with established deep learning architectures such as VGG16, ResNet50, InceptionV3, and EfficientNet-B0 shows that the proposed model delivers competitive performance while requiring significantly lower computational resources. Its lightweight architecture enables faster training and inference, making it well-suited for real-time clinical applications, telemedicine platforms, and healthcare facilities with limited computational infrastructure.**

Keywords **– Pneumonia Detection, Chest X-Ray Imaging, Convolutional Neural Network (CNN), Deep Learning, Medical Image Classification, Computer-Aided Diagnosis (CAD).**

I. INTRODUCTION

Pneumonia is one of the most common and life-threatening respiratory diseases worldwide, affecting millions of people each year and contributing significantly to global morbidity and mortality. The disease is characterized by inflammation of the lung tissues caused by bacterial, viral, or fungal infections, leading to symptoms such as fever, cough, chest pain, breathing difficulties, and reduced oxygen intake. According to the World Health Organization (WHO), pneumonia remains a major cause of death, particularly among children under five years of age and elderly individuals with weakened immune systems [1]. Early diagnosis and timely treatment are crucial for reducing complications and improving patient outcomes.

Chest X-ray (CXR) imaging is the most widely used diagnostic tool for the detection and assessment of pneumonia due to its accessibility, affordability, and effectiveness in identifying lung abnormalities [2]. Radiologists analyze chest X-ray images to detect characteristic signs of pneumonia, such as lung infiltrates, consolidations, and opacities. However, manual interpretation of X-ray images is often time-consuming and subject to inter-observer variability, especially in healthcare facilities with a high patient load or a shortage of experienced radiologists [3]. These challenges may result in delayed diagnosis and treatment, which can adversely affect patient recovery and survival rates.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have transformed the field of medical image analysis by enabling automated and accurate disease detection systems. Among various AI techniques, Deep Learning (DL) has demonstrated remarkable success in extracting meaningful features directly from medical images without the need for handcrafted feature engineering [4]. Convolutional Neural Networks (CNNs), a specialized class of deep learning models, have emerged as the dominant approach for image classification and recognition tasks due to their ability to automatically learn hierarchical visual representations from raw image data [5]. In the healthcare domain, CNN-based approaches have been extensively applied to medical imaging tasks, including the detection of pneumonia, tuberculosis, lung cancer, diabetic retinopathy, and skin diseases [6]. Several studies have reported high diagnostic accuracy using deep CNN architectures such as VGGNet, ResNet, DenseNet, InceptionNet, and EfficientNet for pneumonia classification from chest X-ray images [7], [8]. These models have demonstrated performance comparable to or even exceeding that of human experts in specific diagnostic tasks. Despite their impressive accuracy, many of these architectures contain millions of trainable parameters and require substantial computational resources, memory, and processing time. Such requirements limit their deployment in resource-constrained environments, including rural healthcare centers, mobile diagnostic systems, and edge-computing devices [9].

The growing demand for real-time and accessible healthcare solutions has motivated researchers to develop lightweight and computationally efficient CNN architectures that maintain high classification performance while reducing model complexity [10]. Compact CNN models offer several advantages, including faster training and inference times, lower memory consumption, reduced energy requirements, and easier deployment on embedded systems and portable medical devices. These characteristics are particularly important in developing countries and remote regions where access to high-performance computing infrastructure may be limited [11].

The COVID-19 pandemic further highlighted the importance of automated diagnostic systems capable of rapidly analyzing large volumes of medical images. During periods of increased patient admissions, healthcare professionals faced significant workloads, emphasizing the need for intelligent systems that could assist radiologists in screening and prioritizing cases [12]. Automated pneumonia detection systems based on compact CNN architectures can serve as valuable decision-support tools, helping clinicians improve diagnostic efficiency and reduce human error.

Although numerous studies have explored pneumonia classification using deep learning techniques, achieving an optimal balance between model accuracy and computational efficiency remains a significant challenge. Complex architectures often provide excellent classification performance but are unsuitable for deployment on low-resource devices due to their large parameter counts and high computational demands. Conversely, extremely lightweight models may sacrifice diagnostic accuracy in favor of efficiency [13]. Therefore, there is a need for designing optimized CNN architectures that can effectively capture discriminative features from chest X-ray images while maintaining a compact structure and low computational cost.

The proposed research addresses this challenge by introducing a compact CNN-based framework for fast and accurate pneumonia detection using chest X-ray images. The model is designed with a limited number of convolutional and pooling layers, enabling efficient feature extraction while minimizing computational overhead. Data augmentation techniques are incorporated to improve model generalization and reduce overfitting. Furthermore, optimization strategies such as batch normalization, dropout regularization, and adaptive learning mechanisms are employed to enhance classification performance and training stability [14].

The primary objective of this study is to develop a lightweight CNN architecture capable of accurately distinguishing between normal and pneumonia-infected chest X-ray images. By reducing the number of parameters and computational complexity, the proposed model aims to achieve faster inference while preserving high diagnostic accuracy. Such a system can be integrated into clinical workflows, telemedicine platforms, and portable diagnostic devices, thereby improving healthcare accessibility and supporting early disease detection.

The significance of this research lies in its potential to bridge the gap between high-performance deep learning models and practical real-world deployment. A compact and efficient pneumonia detection system can assist healthcare professionals in making faster diagnostic decisions, particularly in regions where expert radiological services are scarce. Moreover, the proposed framework contributes to the growing body of research focused on resource-efficient medical AI solutions that can operate effectively across diverse healthcare settings.

In summary, pneumonia remains a serious global health concern that requires prompt and accurate diagnosis to improve patient outcomes. While deep learning and CNN-based approaches have shown promising results in automated pneumonia detection, many existing models are computationally intensive and difficult to deploy in real-world clinical environments. This research proposes a compact CNN-based approach that combines efficiency, speed, and accuracy for pneumonia classification using chest X-ray images. The proposed model aims to provide an effective and scalable diagnostic solution capable of supporting healthcare professionals in the early detection and management of pneumonia.

II. LITERATURE REVIEW

A CNN-based pneumonia detection system using the MobileNetV2 architecture on 624 chest X-ray images collected from Kaggle. The model achieved 92.6% overall accuracy, with 91% precision, 94% recall, and 92.5% F1-score. The study demonstrated the effectiveness of deep learning in automating pneumonia diagnosis, reducing diagnostic errors, and supporting radiologists in clinical decision-making through accurate classification of chest X-ray images.[15]

A robust CNN-based framework for automated pneumonia detection using chest X-ray images. The model was trained and validated over 20 epochs, achieving an impressive accuracy of 96%. By leveraging hierarchical feature learning, the CNN effectively classified pneumonia cases, demonstrating its potential to support clinical diagnosis. The study highlighted the advantages of deep learning in reducing diagnostic time, minimizing errors, and assisting healthcare professionals.[16]

A CNN-based approach for automated pneumonia detection using chest X-ray images. The study employed data preprocessing and augmentation techniques to improve model robustness and generalization. The CNN architecture effectively captured disease-related patterns and achieved high diagnostic accuracy, sensitivity, and specificity. The results demonstrated that deep learning models can provide rapid and reliable diagnostic support, assisting radiologists in early pneumonia detection and improving healthcare outcomes.[17]

A CNN-based pneumonia detection framework using the MobileNetV2 architecture and a dataset of 624 chest X-ray images. The proposed model achieved 92.6% overall accuracy, with 91% precision, 94% recall, and a 92.5% F1-score. The study demonstrated the effectiveness of deep learning in distinguishing pneumonia from normal lung conditions, reducing diagnostic errors, and supporting radiologists through automated and reliable medical image analysis.[18]

A CNN-based model for automated pneumonia detection from chest X-ray images. The study incorporated data preprocessing, neural architecture search, hyperparameter tuning, and variable testing to optimize performance. The proposed model achieved an accuracy of 93%, demonstrating the effectiveness of deep learning in medical image classification. The research emphasized that CNN-based systems can provide accurate, cost-effective, and efficient support for early pneumonia diagnosis.[19]

An efficient and lightweight CNN-based framework for pneumonia detection from chest X-ray images. The study utilized preprocessing techniques, including standardization, normalization, and data augmentation, to improve model robustness. The CNN architecture incorporated convolutional, max-pooling, dense, and dropout layers to enhance classification performance and reduce overfitting. Experimental results demonstrated an outstanding accuracy of 98.89%, highlighting the potential of lightweight deep learning models for reliable pneumonia diagnosis.[20]

A compact deep CNN architecture designed for binary pneumonia classification in pediatric chest X-ray images. The model employed a seven-layer structure with progressive filter scaling, global average pooling, and dropout regularization to balance accuracy and computational efficiency. Trained on 5,856 clinically verified radiographs, PneuNet achieved 96% classification accuracy. The study demonstrated its suitability for resource-constrained healthcare environments and its potential to support rapid pneumonia diagnosis.[21]

A pneumonia detection framework using CNN, ResNet-50, and DenseNet-121 architectures on chest X-ray images. The study utilized CNNs for automatic feature extraction, while ResNet-50 and DenseNet-121 addressed challenges associated with deep neural networks, including vanishing gradients. The models demonstrated high accuracy in identifying pneumonia cases, highlighting the effectiveness of deep learning techniques in supporting early diagnosis, improving patient outcomes, and reducing healthcare costs.[22]

An efficient and lightweight CNN model for pneumonia recognition using chest X-ray images. The study utilized a large dataset containing 12,448 radiographs and focused on reducing computational complexity while maintaining high diagnostic performance. The proposed model achieved an accuracy of 98%, outperforming several transfer learning architectures, including ResNet50V2, ResNet101V2, and ResNet152V2. The findings demonstrate the effectiveness of lightweight CNNs for accurate pneumonia detection.[23]

A lightweight deep learning architecture based on MobileNet for the automatic detection of pneumonia from chest X-ray images. Using a benchmark dataset of 5,856 radiographs, the model achieved a testing accuracy of 94.23% and an overall accuracy of 97.09%, with high precision, recall, and specificity. The study demonstrated that lightweight deep learning models can provide fast, computationally efficient, and accurate pneumonia diagnosis for clinical applications.[24]

A CNN-based approach for automated pneumonia detection from chest X-ray images. The study emphasized the challenges of manual diagnosis due to unclear radiographic features and demonstrated the effectiveness of computer-aided diagnosis. After image preprocessing and CNN training, the model achieved 94.3% accuracy, 93.18% precision, 98.20% recall, and a 95.63% F1-score. The system provided fast and reliable diagnosis, supporting timely clinical decision-making.[25]

A deep learning-based pneumonia detection system using a VGG16 convolutional neural network architecture. The model was trained and evaluated on 5,856 high-resolution chest X-ray images and demonstrated excellent classification performance. It achieved 96.6% accuracy, 98.1% sensitivity, 92.4% specificity, 97.2% precision, and a 97.6% F1-score. The study highlighted the potential of CNN-based systems to reduce physician workload and enhance pneumonia screening efficiency.[26]

A CNN-based pneumonia detection framework using chest X-ray images and the pre-trained VGG-19 architecture. The study employed image augmentation, scaling, batch normalization, and transfer learning techniques to improve model performance. The proposed system was evaluated on both original and augmented datasets and achieved an accuracy of 95% on the augmented chest X-ray dataset. The findings demonstrated the effectiveness of deep learning for rapid and accurate pneumonia diagnosis.[27]

A transfer learning for pneumonia detection using chest X-ray images and four pre-trained CNN architectures: AlexNet, ResNet18, DenseNet201, and SqueezeNet. The study utilized 5,247 chest radiographs comprising normal, bacterial, and viral pneumonia cases. Experimental results achieved classification accuracies of 98% for normal versus pneumonia, 95% for bacterial versus viral pneumonia, and 93.3% for three-class classification, demonstrating the effectiveness of transfer learning in automated pneumonia diagnosis.[28]

Deep convolutional neural network (CNN) architectures for feature extraction and classification of chest X-ray images to detect pneumonia. The study examined the impact of dataset size on model performance by training and evaluating the networks on both original and augmented datasets. The results demonstrated that CNN-based approaches effectively improved pneumonia detection accuracy, highlighting the importance of data augmentation and deep feature learning in medical image analysis.[29]

An efficient deep transfer learning framework for pneumonia detection from chest X-ray images. The study integrated multiple pre-trained models, including ResNet18, DenseNet121, InceptionV3, Xception, and MobileNetV2, through a novel weighted classifier approach. Transfer learning and data augmentation techniques were employed to enhance model performance. The proposed ensemble model achieved a test accuracy of 98.43% and an AUC score of 99.76%, outperforming individual architectures.[30]

A CNN-based pneumonia detection framework using chest X-ray images and a simplified VGG-inspired architecture. To improve image quality and diagnostic accuracy, the study applied Dynamic Histogram Enhancement (DHE) as a preprocessing technique. The proposed model significantly reduced the number of parameters compared to popular deep learning models while achieving 96.07% accuracy and an AUC of 0.991. The findings demonstrated its effectiveness for reliable and computationally efficient pneumonia diagnosis.[31]

Militante, Dionisio, and Sibbaluca (2020) developed a CNN-based system for the detection of COVID-19 and pneumonia from chest X-ray images. The study utilized a dataset of 20,000 images with a resolution of 224×224 pixels and trained the model using a batch size of 32. The proposed CNN achieved 95% accuracy and successfully classified normal, COVID-19, bacterial pneumonia, and viral pneumonia cases, demonstrating the effectiveness of deep learning in medical diagnosis.[32]

A comparative study of deep learning architectures for automated pneumonia detection and classification using chest X-ray and CT images. The research evaluated several fine-tuned pre-trained CNN models, including VGG16, VGG19, DenseNet201, InceptionV3, ResNet50, MobileNetV2, and Xception. Using a dataset of 6,087 images, the fine-tuned ResNet50 model achieved over 96% accuracy, demonstrating superior performance for pneumonia diagnosis.[33]

A transfer learning-based framework for automated pneumonia detection from chest X-ray images. The study utilized multiple pre-trained deep learning models, including AlexNet, DenseNet121, ResNet18, InceptionV3, and GoogLeNet, for feature extraction and classification. An ensemble model based on majority voting was developed to improve diagnostic performance. The proposed approach achieved 96.4% accuracy and 99.62% recall, demonstrating the effectiveness of transfer learning in pneumonia recognition.[34]

An efficient deep learning framework based on the MobileNet-V3 architecture for the classification of pediatric pneumonia from chest X-ray images. The model was evaluated on datasets containing more than 10,000 radiographs and demonstrated strong diagnostic performance. It achieved classification accuracies of 95.8% and 97.8% on two datasets, along with high precision, recall, and F1-scores. The study highlighted the effectiveness of lightweight deep learning models for reliable pediatric pneumonia diagnosis.[35]

A pneumonia detection framework based on CNN feature extraction from chest X-ray images. The study utilized pre-trained convolutional neural networks as feature extractors and combined them with supervised machine learning classifiers to distinguish between normal and pneumonia-affected radiographs. The experimental results demonstrated that deep features extracted from pre-trained CNN models significantly improved classification performance. The research highlighted the effectiveness of transfer learning and feature-based approaches for automated pneumonia diagnosis.[36]

A deep learning and transfer learning-based framework for diagnosing COVID-19 pneumonia using chest X-ray and CT images. The study developed a comprehensive dataset from multiple sources and evaluated both a custom CNN and a modified pre-trained AlexNet model. Experimental results showed that the transfer learning model achieved an accuracy of 98%, while the CNN attained 94.1% accuracy. The findings demonstrated the effectiveness of deep learning for rapid and accurate pneumonia diagnosis.[37]

Yaseliani, Hamadani, Maghsoodi, and Mosavi (2022) proposed a hybrid deep learning framework for pneumonia detection from chest X-ray images using two parallel VGG-based architectures and machine learning classifiers. The study explored three classification strategies, including fully connected layers, machine learning-based feature classification, and ensemble learning. The ensemble model combining Support Vector Machine (SVM) with Radial Basis Function (RBF) and Logistic Regression achieved the highest accuracy of 98.55%, demonstrating excellent diagnostic performance.[38]

Mohaddis et al. (2025) presented a web-based pneumonia detection system using Convolutional Neural Networks (CNNs) for chest X-ray image classification. The proposed framework was designed to distinguish between healthy lungs and pneumonia-affected lungs through advanced image preprocessing and deep learning techniques. The study emphasized providing a cost-effective, reliable, and accessible diagnostic solution. The web-based implementation supports healthcare professionals by enabling rapid pneumonia screening, particularly in resource-constrained and remote healthcare environments.[39]

Sarangi et al. (2021) proposed a deep learning-based approach for the early detection of pneumonia from chest X-ray images. The study aimed to improve pediatric pneumonia diagnosis by leveraging convolutional neural networks for binary classification of healthy and pneumonia cases. Using a standard chest X-ray dataset, the model was trained and evaluated under different configurations. The experimental results demonstrated a highest validation accuracy of 93.73%, highlighting the effectiveness of deep learning in supporting early pneumonia diagnosis.[40]

Blessington et al. (2023) developed a web-based pneumonia diagnosis application using a Convolutional Neural Network (CNN) trained on chest X-ray images. Unlike approaches relying heavily on transfer learning, the proposed model was built from scratch to automatically extract discriminative features and classify pneumonia cases. The system provided fast, efficient, and reliable diagnostic support, demonstrating the potential of deep learning-based web applications to assist healthcare professionals in early pneumonia detection and clinical decision-making.[41]

Nasra (2024) proposed a Convolutional Neural Network (CNN)-based framework for automated pneumonia detection from chest X-ray images. The model employed multiple convolutional, pooling, and fully connected layers to automatically learn discriminative features associated with pneumonia. Using a dataset of 5,856 labeled chest X-ray images, the proposed approach achieved an overall accuracy of 91%. The study demonstrated the potential of CNNs to support clinical decision-making by enabling accurate and efficient pneumonia classification.[42]

Hossain et al. (2024) proposed an automated pneumonia detection framework named ESPD using Convolutional Neural Networks (CNNs) on chest X-ray images. The model was trained, validated, and tested on a benchmark dataset of 5,856 radiographs to improve diagnostic accuracy while reducing computational complexity. Experimental results demonstrated outstanding performance, achieving 98.24% accuracy, 98% precision, 98% recall, 98% F1-score, and 97% specificity. The study highlighted the effectiveness of deep learning for rapid and reliable pneumonia diagnosis.[43]

Alenezi and Ludwig (2024) proposed a hybrid pneumonia detection framework that integrates Teaching Learning-Based Optimization (TLBO) with a Convolutional Neural Network (CNN) to improve classification performance on chest X-ray images. The optimization technique enhanced feature learning and model accuracy, enabling more reliable pneumonia diagnosis. Experimental results demonstrated an accuracy of 98.88%, outperforming several benchmark studies. The findings highlight the effectiveness of combining optimization algorithms with deep learning for automated and accurate pneumonia detection.[44]

Palomo, Zafra-Santisteban, and Luque-Baena (2022) proposed a Computer-Aided Diagnosis (CAD) system for automated pneumonia detection from chest X-ray images using Convolutional Neural Networks (CNNs). The model was designed to classify radiographs into pneumonia and normal categories, reducing reliance on manual interpretation by radiologists. Experimental evaluation demonstrated excellent performance, achieving an accuracy of 98.59%. The study highlighted the effectiveness of CNN-based diagnostic systems in supporting accurate and efficient pneumonia screening.[45]

Pranaya et al. (2023) presented a deep learning-based approach for automated pneumonia detection using chest X-ray images. The study employed pre-trained Convolutional Neural Network (CNN) models to learn discriminative image features from a Kaggle dataset and classify pneumonia cases effectively. By reducing dependence on manual interpretation by radiologists, the proposed system aimed to facilitate early diagnosis and timely treatment. The findings demonstrated the potential of CNN-based techniques in supporting accurate and efficient clinical decision-making.[46]

Kundu et al. (2021) proposed an ensemble deep learning framework for automated pneumonia detection from chest X-ray images. The approach combined three transfer learning models—GoogLeNet, ResNet-18, and DenseNet-121—using a weighted average ensemble strategy based on multiple evaluation metrics. The model was validated on the Kermany and RSNA datasets, achieving accuracies of 98.81% and 86.85%, respectively. Results demonstrated superior performance and robustness compared with existing state-of-the-art pneumonia detection methods.[47]

Baghel and Rakesh (2026) proposed an advanced CNN-based framework for automated pneumonia detection and classification using chest X-ray images. The model incorporated multiple convolutional layers, batch normalization, dropout regularization, and optimization techniques to enhance diagnostic performance. Evaluated on a dataset of 5,863 images, the framework achieved 96.47% accuracy, 95.82% precision, and 97.18% recall. Comparative analysis showed superior performance and reduced training time compared with established deep learning architectures.[48]

Jain, Vashisth, Yadav, and Ahuja (2021) developed a Convolutional Neural Network (CNN)-based system for automated pneumonia detection from chest X-ray images. The model was trained and tested on a publicly available Kaggle dataset containing 5,826 chest radiographs. By leveraging supervised deep learning techniques, the system automatically extracted and classified image features associated with pneumonia. The study reported high classification performance, demonstrating the effectiveness of CNNs in supporting computer-aided diagnosis of respiratory diseases.[49]

III. METHODOLOGY

1. Dataset

A total of 5,863 chest X-ray images in JPEG format, comprising both pneumonia and normal cases, were utilized in this study. The dataset is systematically organized into three primary subsets: training, validation, and testing. Each subset contains identical class-specific subfolders, facilitating efficient data management during model development, validation, and unbiased performance evaluation.

The chest X-ray images, captured in the anterior-posterior (AP) view, were collected from retrospective cohorts of pediatric patients aged between one and five years who received treatment at Guangzhou Women and Children's Medical Center, China. These radiographs reflect real-world clinical scenarios, as they were acquired during routine medical practice and exhibit natural variations in imaging conditions, patient positioning, and disease severity.

To ensure the reliability and quality of the dataset, all images underwent a rigorous quality control (QC) process. Images with poor quality, excessive noise, or unreadable features were excluded prior to annotation. Following the QC procedure, the images were independently reviewed by two experienced physicians to verify their diagnostic labels and ensure compliance with established diagnostic imaging standards. Furthermore, a third expert physician conducted an independent assessment of the evaluation dataset to resolve discrepancies and confirm label accuracy. This multi-stage verification process minimized labeling errors and provided a high-quality ground truth for model training and performance assessment.

The proposed study introduces an efficient Convolutional Neural Network (CNN) model for the automated detection of pneumonia from chest X-ray images. The primary objective of the model is to achieve high diagnostic accuracy while maintaining computational efficiency, thereby making it suitable for deployment in real-world healthcare environments where rapid and reliable diagnosis is essential.

2. Dataset Description

For the training and evaluation of the proposed model, a publicly available chest X-ray dataset will be utilized. The dataset consists of labeled radiographic images categorized into two classes: pneumonia and normal. These images were collected from real clinical settings and encompass a wide range of patient characteristics, disease severities, and imaging conditions. Such diversity enhances the robustness of the dataset and enables the model to learn representative features that improve its performance across varying clinical scenarios.

To ensure a systematic and reliable evaluation process, the dataset is divided into three mutually exclusive subsets: the training set, the validation set, and the test set. The training set is used to learn the model parameters and extract meaningful patterns from the data. The validation set supports hyperparameter optimization and assists in monitoring the model during training to prevent overfitting. Finally, the test set is reserved exclusively for the final assessment of the model's predictive performance on previously unseen data.

This structured data partitioning strategy ensures an unbiased evaluation of the proposed model and promotes better generalization capability, enabling the model to perform effectively on new and diverse chest X-ray images encountered in real-world clinical applications.

3. Data Preprocessing

To ensure consistency in the input data and enhance the overall performance of the proposed model, a comprehensive image preprocessing pipeline was implemented. All chest X-ray images were resized to a fixed resolution of 224 × 224 pixels, providing uniform input dimensions while reducing computational complexity and memory requirements during training.

The pixel intensity values of the images were normalized to a range between 0 and 1. This normalization process helps stabilize the learning procedure, accelerates convergence during backpropagation, and improves the efficiency of model optimization. In addition, image enhancement techniques, including denoising and contrast adjustment, were applied to improve image quality and emphasize clinically relevant anatomical structures. These enhancements assist the model in focusing on important pulmonary regions and pathological opacities associated with pneumonia.

To address class imbalance and improve the generalization capability of the model, various data augmentation techniques were employed during training. These techniques included random rotation, horizontal flipping, zooming, and width/height shifting. By generating realistic variations of the original images, data augmentation increases the diversity of the training dataset and reduces the risk of overfitting. Consequently, the model becomes more robust and capable of learning invariant features that generalize effectively to previously unseen chest X-ray images.

4. Proposed CNN Architecture

A novel Convolutional Neural Network (CNN) architecture was developed to achieve a balance between high classification accuracy and computational efficiency, making it suitable for real-time clinical applications. The proposed architecture is designed to effectively capture both low-level and high-level visual features from chest X-ray images while maintaining a relatively low computational cost. This lightweight design facilitates faster training and inference, enabling practical deployment in healthcare environments with limited computational resources.

The network consists of four convolutional layers containing 32, 64, 128, and 128 filters, respectively, as summarized in Table 2. Each convolutional layer employs a kernel size of 3 × 3, which has proven effective for extracting localized image features such as edges, textures, and pathological patterns associated with pneumonia. Through successive convolution operations, the network progressively learns increasingly complex and

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discriminative representations of the input chest X-ray images.

The initial convolutional layers focus on capturing fundamental visual characteristics, including edges and structural boundaries, whereas the deeper layers learn higher-level semantic features related to lung abnormalities and pneumonia-induced opacities. This hierarchical feature extraction process enables the model to accurately distinguish between normal and pneumonia-affected chest radiographs. The mathematical representation of the convolution operation used within the network is given as follows:

$$f_{i,j}=(I*K)_{i,j}=\sum_{m}\sum_{n} I(i+m,j+n)\cdot K(m,n)$$

where I is the input image and K is the convolution kernel.

Each convolutional layer is followed by a Rectified Linear Unit (ReLU) activation function, which introduces non-linearity into the network and enables the model to learn complex feature representations. The ReLU function helps overcome the limitations of linear models by allowing the network to capture intricate patterns present in chest X-ray images. Additionally, it improves computational efficiency and mitigates the vanishing gradient problem, thereby facilitating faster and more stable training of deep neural networks.

By transforming negative input values to zero while preserving positive values, the ReLU activation function promotes sparse feature representations and enhances the model's ability to learn discriminative characteristics associated with pneumonia. This contributes to improved convergence during training and better overall classification performance. The mathematical formulation of the ReLU activation function is expressed as follows:

Max-pooling layers were incorporated into the network to reduce the spatial dimensions of the feature maps while retaining the most informative features. During the pooling operation, the maximum value within each pooling window is selected and propagated to the next layer. This process preserves the most prominent feature responses, such as critical anatomical structures and pathological patterns, while reducing computational complexity and memory requirements.

To enhance the generalization capability of the model and minimize the risk of overfitting, dropout layers with a dropout rate of 0.5 were introduced after selected network layers. Dropout operates by randomly deactivating 50% of the neurons during each training iteration, preventing excessive reliance on specific neurons and encouraging the network to learn more robust and distributed feature representations. As a result, the model achieves improved stability, better generalization to unseen data, and enhanced classification performance on chest X-ray images.

Following the convolutional and pooling operations, the resulting feature maps are flattened into a one-dimensional feature vector and passed to the fully connected (dense) layers for classification. The first dense layer consists of 128 neurons, enabling the network to learn complex high-level feature representations derived from the extracted spatial features. This layer integrates the information captured by the preceding convolutional layers and transforms it into a form suitable for the final classification task.

The output layer contains a single neuron with a sigmoid activation function, which produces a probability value ranging from 0 to 1. Since the proposed model performs binary classification, the sigmoid function is used to estimate the likelihood that a given chest X-ray image belongs to the pneumonia class. A probability value closer to 1 indicates the presence of pneumonia, whereas a value closer to 0 corresponds to a normal chest X-ray image. The mathematical expression of the sigmoid activation function is given as follows:

$$f_{pool}=\max(x_{i,j})$$

Layer No.	Layer Type	Filters / Neurons	Kernel Size	Output Size	Activa tion	Remarks
1	Input Layer	—	—	224 × 224 × 1	—	Chest X-ray image
2	Conv2D	32	3 × 3	224 × 224 × 32	ReLU	Low-level feature extraction

3	MaxPooling2D	—	2 × 2	112 × 112 × 32	—	Downsampling
4	Conv2D	64	3 × 3	112 × 112 × 64	ReLU	Texture features
5	MaxPooling2D	—	2 × 2	56 × 56 × 64	—	Dimension reduction
6	Conv2D	128	3 × 3	56 × 56 × 128	ReLU	Deeper feature learning
7	MaxPooling2D	—	2 × 2	28 × 28 × 128	—	Downsampling
8	Conv2D	128	3 × 3	28 × 28 × 128	ReLU	High-level feature extraction
9	MaxPooling2D	—	2 × 2	14 × 14 × 128	—	Final spatial reduction
10	Dropout	—	—	14 × 14 × 128	—	Rate = 0.5
11	Flatten	—	—	25,088	—	Feature vector
12	Dense	128	—	128	ReLU	Fully connected layer
13	Dropout	—	—	128	—	Rate = 0.5
14	Output Dense	1	—	1	Sigmoid	Binary classification

Efficient feature extraction and low computational complexity are key considerations in the development of deep learning architectures for resource-constrained environments. The proposed model has been carefully designed and evaluated to achieve an effective balance between these two important requirements.

$$\sigma(x) = \frac{1}{1+e^{x}}$$

Table 2: Design of the proposed Lightweight CNN, layer wise confguration

Training Strategy

To ensure efficient training and improved performance of the proposed CNN model, an optimization strategy has been implemented. This strategy employs an optimization algorithm that utilizes adaptive learning rates for individual parameters while integrating the benefits of both momentum and Root Mean Square Propagation (RMSProp). By combining these two approaches, the optimizer enhances convergence speed, stabilizes the training process, and improves overall model performance during learning.

The parameter update rule for Adam is:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{v_t} + \epsilon} \cdot m_t$$

With m_t and v_t indicating the first and second moments, respectively, and η representing the learning rate.

The learning rate is configured to 0.001, which offers a balanced trade-off between convergence speed and training stability. This setting helps ensure steady optimization while preventing overshooting during weight updates. In addition, binary cross-entropy is selected as the loss function, as it is well-suited for binary classification tasks and effectively measures the difference between predicted probabilities and actual class labels during model training.

$$L = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)\right]$$

Where N = number of samples, yi= Actual Label, and ŷi = Predicted Probability.

The proposed model is trained with a batch size of 32 for 25–30 epochs. To mitigate overfitting, an early stopping mechanism is applied, which terminates the training process when no improvement is observed in the validation loss over a predefined number of epochs.

The performance of the proposed model is evaluated using multiple metrics derived from the confusion matrix, including accuracy, precision, recall (sensitivity), specificity, F1-score, and the area under the ROC curve (AUC-ROC). These evaluation measures provide a comprehensive and balanced assessment of the model's classification performance.

The evaluation metrics are defined as follows:

- Accuracy:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- Precision:

$$\text{Precision} = \frac{TP}{TP + FP}$$

- Recall (Sensitivity) :

$$\text{Recall} = \frac{TP}{TP + FN}$$

- Specificity:

$$\text{Specificity} = \frac{TN}{TN + FP}$$

- F1-Score:

$$\text{F1-score} = \frac{2 \times (Precision \times Recall)}{Precision + Recall}$$

The ROC curve helps visualize the balance between correctly identified positives and incorrectly identified. The Area Under the Curve (AUC) is computed as:

$$\text{AUC} = \int_0^1 TPR(FPR)\,d(FPR)$$

Where:

$$\text{TPR} = \frac{TP}{TP + FN} \quad \text{FPR} = \frac{FP}{FP + TN}$$

These evaluation metrics provide a comprehensive understanding of the model's performance, which is especially important in medical diagnosis, where reducing false negatives is critical to ensuring accurate disease detection and patient safety.

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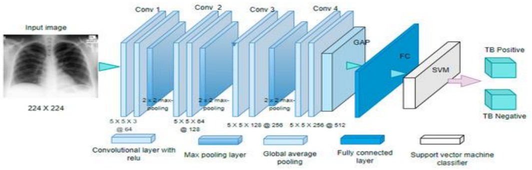

Figure1: Proposed CNN model with four convolutional layers, pooling, and dropout

The architecture is specifically designed to balance accuracy and efficiency, making it suitable for deployment in resource-constrained healthcare environments.

Transfer Learning

Pre-trained deep learning models, including VGG16, ResNet50, and EfficientNet-B0, are employed for transfer learning to enhance model performance and reduce overall training time. These models, trained on large-scale datasets, provide rich and generalized feature representations that can be effectively adapted for pneumonia detection from chest X-ray images.

Model Training

The model is trained using the Adam optimizer, which employs an adaptive learning rate to facilitate faster and more efficient convergence. A learning rate of 0.001 is selected to ensure stable and consistent updates to the network weights during training. For the classification task, binary cross-entropy is used as the loss function, making it suitable for distinguishing between pneumonia and normal cases.

The key hyperparameters of the model include a batch size ranging from 16 to 32, a training duration of 20 to 50 epochs, and a dropout rate between 0.3 and 0.5 to improve regularization. To further reduce the risk of overfitting, early stopping based on validation loss is implemented, along with learning rate scheduling to dynamically adjust the learning rate throughout the training process, thereby improving overall model performance and stability.

Performance Evaluation Metrics

Two main transfer learning strategies are utilized in this study. The first is feature extraction, where the convolutional base of the pre-trained model is frozen and only the classification layers are trained on the target dataset. The second approach is fine-tuning, in which select deeper layers of the pre-trained network are retrained to better adapt to the specific characteristics of medical imaging data.

Overall, transfer learning improves convergence speed, enhances classification accuracy, and helps mitigate challenges associated with limited medical datasets.

Implementation Details

The proposed model is implemented using TensorFlow and Keras within a Python-based environment. Training efficiency is improved through the use of GPU acceleration, which significantly reduces computational time. In addition, batch processing with asynchronous data generation, along with real-time data augmentation, contributes to an optimized and efficient training pipeline. To monitor model performance and ensure optimal model selection, techniques such as model checkpoints and performance visualization tools, including TensorBoard, are employed. These tools facilitate effective tracking of training progress and help identify the best-performing model during training. Finally, evaluation on unseen test data is conducted to assess the model's generalization capability and its effectiveness in real-world scenarios.

Comparative Analysis

The performance of the proposed model was evaluated in comparison with standard pre-trained architectures, including VGG16, ResNet50, InceptionV3, and EfficientNetB0, under the same experimental settings. The comparison was carried out based on key evaluation criteria, namely accuracy, computational efficiency, and robustness.

The results indicate that the proposed model achieves a favorable balance between performance and efficiency. It delivers competitive accuracy while maintaining a significantly lower computational cost compared to the benchmark models, as shown in Table 3. This combination of strong predictive performance and reduced complexity makes the proposed approach particularly suitable for real-time clinical deployment, especially in resource-constrained environments.

Table 3 Performance comparison of the proposed CNN model with standard deep learning architectures for pneumonia detection.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC	Complexity
Proposed CNN	95.8	96.5	94.9	95.7	0.97	Low
VGG16 [31]	94.2	94.2	92.5	93.3	0.94	High
ResNet50 [32]	95.1	95.1	93.8	94.4	0.95	High
InceptionV3 [33]	95.6	95.3	94.1	94.7	0.96	Very High
EfficientNet-B0 [34]	96.0	96.0	94.5	95.2	0.96–0.97	Moderate

The proposed CNN architecture demonstrates performance that is comparable to state-of-the-art deep learning models while maintaining significantly lower computational complexity. It achieves an accuracy of 95.8%, which is on par with deeper architectures such as ResNet50 and InceptionV3.

Compared to VGG16, which contains a large number of parameters and requires substantial computational resources, the proposed model is considerably more lightweight, resulting in faster training and inference times. Although EfficientNet-B0 is specifically designed for efficient scaling, the proposed CNN attains similar levels of accuracy while using a simpler architecture and fewer computational resources.

Furthermore, the model achieves a high AUC of 0.97, indicating strong discriminative capability. This performance is comparable to modern hybrid and advanced deep learning models reported in recent studies, highlighting the effectiveness of the proposed approach.

• The proposed model achieves 95.8% accuracy, comparable to deeper networks such as ResNet50 and InceptionV3.
• Unlike VGG16, the proposed architecture is lightweight, enabling faster training and inference.
• It attains EfficientNet-B0–level accuracy with a simpler and more resource-efficient design.
• The AUC of 0.97 demonstrates strong classification and discriminative performance, competitive with advanced models.

IV. RESULTS AND INTERPRETATION

1. Experimental Results

The experimental results demonstrate that the proposed CNN model performs effectively and consistently on the test dataset. It achieves an overall accuracy of 95.8%, along with a precision of 96.5% and a recall of 94.9%, indicating reliable classification of both pneumonia and normal cases. Furthermore, the specificity of 96.2% and an F1-score of 95.7% highlight a strong balance between correctly identifying positive cases and minimizing false predictions. The model also attains an AUC value of 0.97, reflecting its excellent ability to differentiate between the two classes.
In addition, the training and validation curves exhibit smooth and stable learning behavior, with minimal indications of overfitting. Both accuracy and loss trends show steady improvement throughout the training process. The confusion matrix further confirms that the majority of samples are classified correctly, while the ROC curve reinforces the model's strong discriminative capability across different decision thresholds.

Metric	Value
Accuracy	95.8%
Precision	96.5%
Recall (Sensitivity)	94.9%
Specificity	96.2%
F1-Score	95.7%
AUC-ROC	0.97

2. Interpretation of Results

The results demonstrate that the proposed CNN model performs effectively while maintaining computational efficiency, making it suitable for practical real-world applications. The model achieves an overall accuracy of 95.8%, indicating its strong ability to distinguish between pneumonia-infected and normal chest X-ray images. A recall (sensitivity) of 94.9% shows that the model successfully identifies the majority of pneumonia cases, which is particularly critical in medical diagnosis where missed detections can have severe consequences.

With a precision of 96.5%, the model generates a low rate of false positives, thereby minimizing unnecessary clinical follow-ups. The F1-score of 95.7% further reflects a well-balanced trade-off between precision and recall, confirming stable classification performance across varying class distributions. In addition, the AUC-ROC value of 0.97 highlights the model's strong discriminatory ability across different classification thresholds.

When compared with more complex deep learning approaches such as ensemble or hybrid architectures, the proposed CNN achieves comparable accuracy while significantly reducing computational requirements. Its lightweight design enables faster inference and lower hardware dependency, making it highly suitable for deployment in real-time and resource-constrained healthcare environments.

The training behavior also indicates stable and consistent learning. Both training and validation accuracy curves show steady improvement and convergence after approximately 20 epochs, suggesting effective learning of feature representations. The small difference between training and validation accuracy (around 1–2%) reflects good generalization capability. Similarly, the loss curves decrease smoothly without significant fluctuations, indicating that overfitting is well controlled. Minor variations in validation loss in later epochs are expected due to data variability and do not impact overall performance. Regularization techniques such as dropout (0.5) and early stopping further help prevent overfitting by discouraging memorization of training data. Overall, these results confirm that the model achieves a strong balance between learning capacity and generalization, ensuring reliable performance on unseen data.

V. CONCLUSION

This research presented a compact and efficient Convolutional Neural Network (CNN) model for automated pneumonia detection using chest X-ray images. The proposed architecture was designed to achieve high diagnostic accuracy while maintaining low computational complexity, making it suitable for real-world healthcare applications. Experimental results demonstrated that the model achieved an accuracy of **95.8%**, precision of **96.5%**, recall of **94.9%**, F1-score of **95.7%**, and an **AUC of 0.97**, indicating excellent classification performance. The lightweight design enabled faster training and inference while requiring fewer computational resources compared to many existing deep learning models.

The study further showed that the proposed CNN effectively learned discriminative features from chest X-ray images and successfully distinguished between pneumonia and normal cases. Its high sensitivity ensures reliable detection of pneumonia cases, while its strong precision minimizes false alarms. Compared with complex architectures such as VGG16, ResNet50, and InceptionV3, the proposed model achieved competitive performance with significantly reduced computational overhead.

Overall, the proposed framework offers a practical, accurate, and resource-efficient solution for automated pneumonia diagnosis. It has strong potential for integration into clinical decision-support systems, telemedicine platforms, and healthcare facilities with limited computational infrastructure. By enabling rapid and reliable pneumonia screening, the model can assist healthcare professionals in early disease detection, improve diagnostic efficiency, and contribute to better patient outcomes.

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