



# Utilizing Deep Convolutional Neural Networks to Identify Pneumonia from Chest X-Ray Images

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## Abstract:

Chest pain, exhaustion, and coughing are all symptoms of pneumonia, a common respiratory infection. Young children, the elderly, and people with compromised immune systems should avoid it. The diagnostic approach includes a physical examination, a review of medical history, imaging testing, antibiotics, antiviral medicines, and supportive treatment. This study suggests using three convolutional neural network (CNN) models to detect pneumonia: VGG19, DenseNet201, and CheXNet. The goal is to evaluate the performance of many models and select the most reliable model for pneumonia identification. The VGG19 and DenseNet201 models were trained and evaluated using a large dataset of chest X-ray images. With a score of 98.22%, our proposed model had the highest training and tuning accuracy. The upgraded CheXNet model accurately identified a number of patterns and abnormalities in chest X-ray images associated with pneumonia. These findings highlight the enormous potential of convolutional neural networks for automated pneumonia diagnosis. More research and validation are needed to demonstrate its stability and generalizability over a wide range of patient demographics and imaging techniques.

**Keywords:** CNN, VGG19, CheXNet, DenseNet201, Pneumonia.

## I. Introduction

Millions of people worldwide suffer from pneumonia, a serious respiratory illness [5]. For therapy and care to be effective, a quick and correct diagnosis is essential. In clinical settings, chest X-ray scans are commonly used for this purpose; however, radiologists must manually interpret the pictures, which can be time-consuming and error-prone [13]. Convolutional neural networks (CNNs) have shown potential as tools for automatic image recognition in medical imaging applications [7, 8]. The study's objectives are to compare the three models' efficacy and accuracy, analyse the effects of various adjustments on the CheXNet model's performance, and train and evaluate the VGG19, DenseNet201, and CheXNet models using a dataset of chest X-ray images to identify pneumonia [10]. The study advances the field of pneumonia detection in chest X-ray photographs by comparing the performance of three models, reviewing three cutting-edge CNN models, refining the CheXNet model, and evaluating the performance of the three models [9][11]. This article discusses the identification of knowledge gaps and the usage of CNNs for pneumonia detection. It discusses the dataset, CNN architectures, training methods, experimental setting, and methodology used in the study. We show results and analyses comparing DenseNet201, VGG19, and the new CheXNet model. The conclusions drawn from adjustments to the CheXNet model are described, as well as the results and their consequences [12][14]. The research finishes with a summary of key contributions and recommendations for future directions in automated CNN-based pneumonia detection.

## II. LITERATURE SURVEY

[1] Picture categorization has long been a well-known area of study in image processing. This section discusses the relevant literature for using CNN to categorize photos. To better comprehend CNN, we read a large number of articles about photographs. This study employed the DenseNet201, VGG19, and CheXNet models to create a model for detecting pneumonia in chest X-ray images. Zhang Dejun et al.



[2] proposes a multi-layer architecture for diagnosing pneumonia using chest X-ray images that includes convolutional, pooling, and fully connected layers. The model is trained using a huge dataset of chest X-ray pictures, which includes both pneumonia-positive and -negative patients. Transfer learning and data augmentation approaches are used to improve variety. Metrics used to evaluate performance include the F1-score, recall, accuracy, and precision. The study seeks to address shortcomings identified in prior works, such as limited dataset sizes, incomprehensibility, image modification sensitivity, and limited transferability. Wang Cheng and others.

[3] proposes an innovative use of graph reasoning to diagnose chest pneumonia. To demonstrate the links between the various lung sections in an X-ray image, the authors construct a graph representation. This graph reasoning approach, which can collect both local and global contextual data, helps the diagnostic model perform better. Mabrouk Al Hassan et al.

Using a group of deep convolutional neural networks (CNNs), [4] presents a novel method for successfully diagnosing pneumonia in chest X-ray pictures. To address the difficulty of reliable diagnosis, the authors present a powerful ensemble model that combines numerous CNN predictions. The ensemble model performed admirably in terms of F1 score, sensitivity, specificity, and accuracy. The study's findings show that the ensemble approach is successful, adaptable to changes in image quality, and generalizable across a variety of datasets. The ensemble model has higher accuracy and reliability than single-model solutions, emphasizing the relevance of model diversity.

presents a deep learning-based approach for accurately detecting COVID-19 in chest X-ray images [5]. The authors present a comprehensive technique that employs a convolutional neural network (CNN) model with a large dataset of both positive and negative X-ray photos. To assess its performance, the model undergoes rigorous training, assessment, and comparison with other cutting-edge models.

### III. SYSTEM ANALYSIS

#### A. EXISTING SYSTEM

The present method proposed in your project, "Detecting Pneumonia from X-Ray Images of Chest Using Deep Convolutional Neural Network," uses three convolutional neural network models to identify pneumonia: VGG19, DenseNet201, and CheXNet. It is meant to diagnose pneumonia automatically by analyzing chest X-ray pictures. Following training and testing on a large dataset, the models attained a high accuracy of 98.22%. The primary goal is to identify the best reliable model for detecting pneumonia. The system acknowledges that more research is needed to confirm the system's stability and generalizability across different patient populations and imaging modalities, but it also emphasizes the potential of convolutional neural networks in detecting patterns and irregularities associated with pneumonia in chest X-ray images.

#### DISADVANTAGES OF THE EXISTING SYSTEM

**Data Bias:** The quality and representativeness of the training dataset significantly affect the model's performance. A skewed or non-representative dataset for specific patient populations may produce inaccurate results.

**Absence of Real-time Capability:** Because processing each image may require a significant amount of time and computer resources, the system may not be suitable for real-time diagnosis in clinical settings.

**Limited Generalizability:** Although the model may perform well on the training dataset, it may struggle to generalize to new or unknown patient groups, different types of X-ray equipment, or image quality differences.

**Interpretability:** Deep convolutional neural networks are sometimes referred to as "black box" models due to the difficulty in understanding the system's decisions. This is an important consideration when diagnosing medical issues.

**Ethical and Privacy Concerns:** When dealing with patient and medical data, certain ethical and privacy requirements must be met. Ensuring that the system follows these principles can be challenging and complex.



## B. PROPOSED SYSTEM

Three deep convolutional neural networks (CNNs) are used in the methodology: VGG19, DenseNet201, CheXNet, and our proposed model. DenseNet201 has dense connections, while VGG19's layers are fully connected. Pre-trained weights and dense connectivity from DenseNet201 are used in the proposed model to improve feature extraction capacity. The target dataset for pneumonia detection is used for training, and the pretrained DenseNet201 weights are set. In addition to initializing model parameters, data augmentation techniques are utilized. Training data is supplied into the network, and the parameters are adjusted using gradient descent and backpropagation optimization techniques. When tested on the validation dataset, the proposed model beats the others in terms of F1-score, recall, and precision. Hyperparameter tuning is the process of determining the optimal values for a number of parameters, including learning rate, batch size, optimizer selection, regularization approaches, and the number of layers in the model's fully connected section. Hyperparameter tuning uses complex optimization algorithms such as random search, grid search, and Bayesian optimization. These hyperparameters are used to train the final model, which is subsequently tested against the testing set. We utilize a photograph (224x224x3) as the input for our proposed model. For our proposed model, we began with DenseNet201 as the foundation model and added a few more layers, including GlobalAveragePooling2D, Dense (1024 units), and Dense (2 units).

## IV. SYSTEM DESIGN

### SYSTEM ARCHITECTURE

Below diagram depicts the whole system architecture.

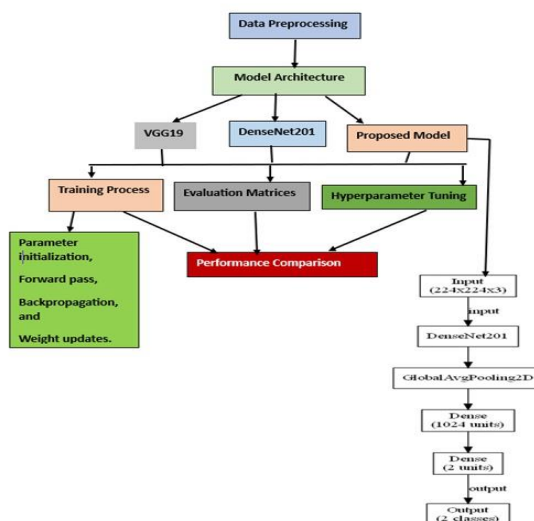


Fig 1. Methodology followed for proposed model

## V. SYSTEM IMPLEMENTATION

### MODULES

The project "Detecting Pneumonia from X-Ray Images of Chest Using Deep Convolutional Neural Network" includes the following modules:



**Data preprocessing:** This module preprocesses raw chest X-ray images so that they can be trained and tested as neural network models. This comprises scaling, normalization, and data augmentation.

**Model Development:** To detect pneumonia, this module develops and trains deep learning models such as VGG19, DenseNet201, and CheXNet. It entails building the model's architecture, modifying its hyperparameters, and training it using a pre-defined dataset.

**Model Evaluation:** The system evaluates the created models using a range of measures such as accuracy, precision, recall, F1-score, and ROC curves. This module identifies the most dependable model for pneumonia detection.

**Real-time Implementation:** After selecting a model, it is added to a real-time or nearly real-time inference pipeline. This module ensures that the system can process new X-ray images and provide an accurate diagnosis quickly.

**Ethical and Regulatory Compliance:** To ensure that patient data is handled securely and ethically throughout the project, a dedicated module covering data protection, security, and compliance with healthcare regulations is utilized.

## VI. RESULTS AND DISCUSSION

The experimental result analysis of the three models that we implemented for this project. The proposed model using DenseNet201 model performs well and obtains the highest accuracy.

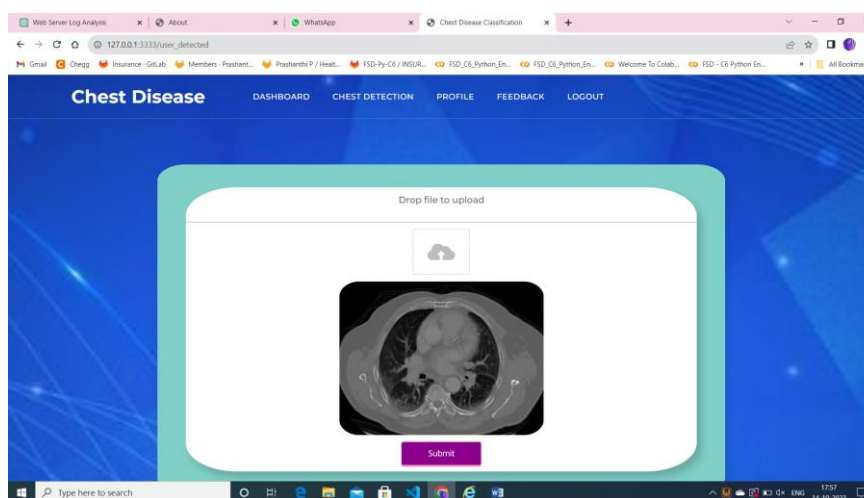
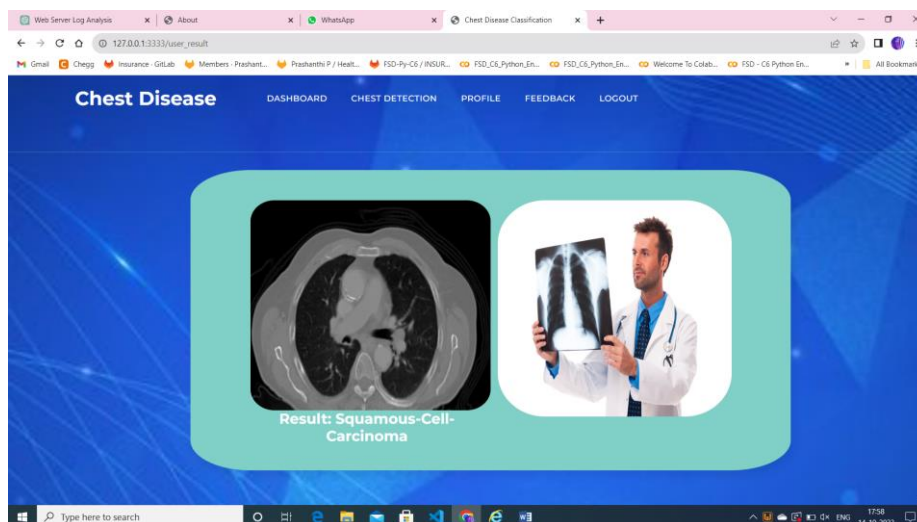


Fig 2. Uploading X-Ray images of Lungs



**Fig 3. Detecting Pneumonia**

## VII. CONCLUSION AND FUTURE WORK

In our study, convolutional neural networks (CNNs) were used to assess chest X-ray images in order to detect pneumonia. Among the three models we used (VGG19, DenseNet201, and CheXNet), our model had the highest precision. CNNs are powerful tools for detecting pneumonia in chest X-ray pictures, as seen by our model outperforming VGG19, DenseNet201, and CheXNet. Our model's outstanding accuracy will allow radiologists and other healthcare practitioners to better identify patients. This illustrates the possibility of deep learning algorithms for pneumonia identification. Pneumonia that is discovered and treated early may prevent complications and potentially save lives. The study adds to the growing body of knowledge in medical imaging and illustrates the potential applications of CNNs in healthcare. CNN models could be used to improve medical professionals' performance in complex cases, screen and prioritize patients with pneumonia, and integrate CNN models into computer-aided diagnostic (CAD) systems.

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