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Detection of Pneumonia using Chest X-ray Images by utilizing Deep Learning Techniques

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Abstract

According to the World Health Organization (WHO), Pneumonia is one of the leading causes of mortality in India. Chest X-rays are generally utilized to make the diagnosis, however, while X-ray technology is prevalent, properly reading X-rays is an exercise that requires expertise by radiologists. To overcome this issue, we have proposed a pneumonia detection system that involves deep learning which may help to diagnose the illness more quickly, even in the case of early diagnosis, and in the case of rural areas. In this proposed study, we will use a convolutional neural network (CNN) for pneumonia detection from chest X-ray images. The dataset is obtained from Kaggle and features X-ray images separated by Normal and Pneumonia images. This research is intended to help with pneumonia detection as it may lead to quicker, more reliable decision making; decrease the dependence on expert evaluation; and improve the process of healthcare.

Introduction

Diagnosis of pneumonia is important for successful treatment. The symptoms, depending on the kind of pneumonia, age, and general health, can be chest pain, cough, fever, nausea or vomiting, and shortness of breath. These symptoms, however, can also occur in other respiratory illnesses, and therefore, diagnosis of pneumonia solely based on the symptoms is not easy. Each year, numerous children and adults are killed by pneumonia because it is not diagnosed in time. In some areas, it is difficult to get an accurate diagnosis since there are few doctors or equipment. Computers can come to the rescue here. With the aid of special computer programs and X-ray images, we can program computers to recognize pneumonia. This can assist doctors in diagnosing pneumonia quicker and more accurately, saving lives. Early and

correct diagnosis of pneumonia is crucial for successful treatment and management.

A variety of techniques for pneumonia detection are employed, including chest X-rays, CT scans, laboratory exams, and lately, artificial intelligence (AI) and machine learning (ML) methods, which have proved useful in enhancing the accuracy and speed of pneumonia detection. This has created growing interest in AI-based pneumonia detection tools due to the capabilities of these methods to diagnose pneumonia faster, more precisely, and with greater efficiency. The most prevalent means of diagnosis is a chest X-ray that takes the reading of an expert radiologist, which in turn can be time-consuming and challenging particularly where there are no health centers. Infections of the lungs are a major public health concern worldwide, with pneumonia being one of the

most serious and fatal presentations. Regardless of its influence, the conventional technique for detection often involves laborious manual interpretation of chest X-rays, particularly for areas with resource constraints. The potential of revolutionary change in detection of pneumonia comes through deep learning algorithms like Convolutional Neural Networks, enabling fast, precise, and computer-aided diagnosis. A series of experiments are performed for this study in creating a model of convolutional neural network in which the algorithm classifies a chest X-ray image as pneumonia or normal. This work is centered on the application of a CNN model based on the VGG19 architecture for automatic pneumonia detection in chest X-ray images.

Literature Review

Nigus Asnake et al. implement a model combines Convolutional Neural Networks for feature extraction and Support Vector Machines (SVMs) for classification, achieving 99% in F1-score, recall, precision, and accuracy. This indicates its remarkable performance and efficiency in data classification tasks [1]. Dejun Zhang et al. discuss a study using a CNN-based model and DHE for pneumonia diagnosis with 96.07% accuracy and 94.41% precision. The future work aims to classify viral and bacterial pneumonia [2]. Alhassan Mabrouk et al. suggest a method for classifying normal and pneumonia patients from chest X-rays using CNN Ensemble Learning (EL). Three different architectures are used: DenseNet169, MobileNetV2, and Vision Transformer. The proposed approach utilizes a global average pooling layer and fully connected layers for classification, outperforming others and demonstrating high accuracy [3]. C'esar Ortiz-Toto et al. studied methods for textural image characterization for pneumonia detection in chest x-ray images. The models showed notable improvements in performance, with increases in accuracy and F-Score of up to 8% compared to standard radiomics-based methods[4]. Vikash Chouhan et al. developed a method to classify pneumonia in chest X-ray images based on transfer learning with deep learning models. By leveraging pretrained models (AlexNet, DenseNet121, Inception V3, GoogLeNet, and ResNet18), the ensemble model outperformed individual architectures. Future improvements could be made by increasing the dataset size, applying data augmentation, and incorporating hand-crafted features[5]. In an automated CAD system for pneumonia detection, Rohit Kundul et al. accomplished deep transfer learning-based classification of X-ray images. The ensemble framework combines decision scores from three CNN models

(GoogLeNet, ResNet-18, and DenseNet-121), achieving high accuracy (98.81%) on the Kermany dataset and 86.86% on the RSNA dataset. The approach outperforms existing methods and is domain-independent, making it applicable to various computer vision tasks[6]. M. F. Hashmi et al. present a deep residual network for pneumonia detection, achieving 98.14% accuracy, 99.71% AUC, and 98.3% F1 score. The model uses compound scaling, data augmentation, and transfer learning to overcome dataset limitations, with future work focusing on localizing affected lung areas in X-rays[7]. M. F. Hashmi et al. propose an automatic pneumonia detection model using deep transfer learning techniques, achieving high accuracy (98.86%) and an impressive F1 score (99.00%). The model combines transfer learning, data augmentation, and a weighted classifier to address overfitting and outperforms existing methods, with future work focusing on more efficient weight estimation and incorporating patient history for improved predictions[8]. Ola M. El Zein et al. introduce a hybrid SVM-based model for pneumonia classification from X-ray images, achieving 97% accuracy and outperforming state-of-the-art models. The model combines transfer learning with hinge loss in SVM, and future work will focus on multi-class classification, pneumonia grading, and hyperparameter optimization[9]. K. Islam et al. explore the use of pretrained deep neural networks as feature extractors for pneumonia classification from X-ray images, improving traditional classification methods[10]. S. Parveen and K. B. Khan et al. present a CAD model for classifying normal and pneumonia cases in chest X-ray images, showing comparable performance to radiologists. The model can enhance healthcare access in areas with limited radiologist availability, with proper preprocessing ensuring optimal results[11].

Methodology

Dataset Description:

The dataset that was utilized in the study consists of 5856 images of chest X-ray classified into (4273 pneumonia and 1583 normal). This dataset was made freely available for download from Kaggle. The dataset consists of three folders: training, validation and test. The share of data assigned to training, validation and testing is so imbalanced. For this reason, the datasets were merged and split into training, validation and test datasets shown in Table 1. In conclusion, there were 5216 images included in the training dataset, 16 in the validation set and 624 in the test set. Fig 1. Shows the workflow of the dataset.

Dataset	Normal	Pneumonia	Total Images
Train	1341	3875	5216
Test	234	390	624
Validation	8	8	16
Total	1583	4273	5856

Table1.DatasetDistribution

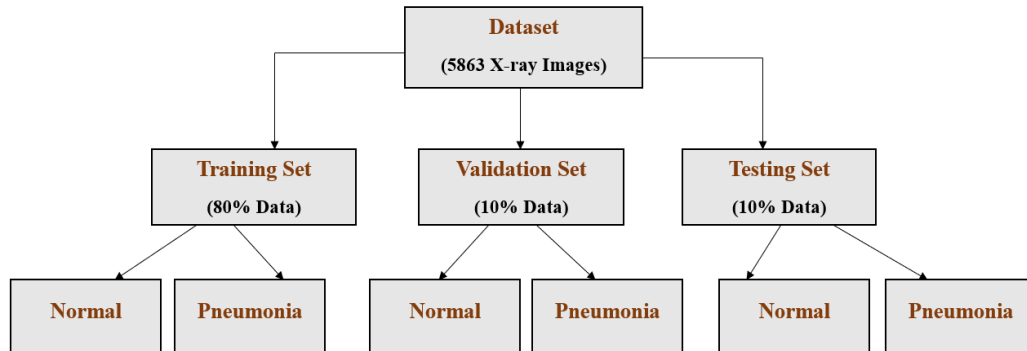


Figure 1.Dataset Workflow

During this implementation, we have implemented the VGG19 model, based on the CNN algorithm.

Convolutional Neural Networks:

Introduction to Convolutional Neural Networks: The main purpose for which the Convolutional Neural Network is used in most of the image classification activities is to reduce the computational complexity of the model. This computational complexity is likely to increase when the input are images. A Convolutional Neural Network or CNN is a deep learning model specially designed for visual data analysis. In this study, we are building a CNN that classifies the chest X-ray images into pneumonia or normal images. In contrast to previous machine learning approaches where features were manually generated, a CNN has the ability to automatically extract features from the images.

VGG19 is a convolutional neural network comprised of 19 layers that include 16 convolutional layers and 3 fully connected layers, with the activation functions ReLU and Softmax. It is prominently known for capturing detailed characteristics in images, which makes it optimal for detecting pneumonia.

1. VGG19 Use: For part of this study, VGG19 is used as a feature extractor; examine its pre-trained convolutional network by measuring an X-ray image and extracting the related characteristics. The extracted features are then passed to the fully connected layers ago classification occurs.

2. Benefits of VGG19 Use:

- Deep feature extractor: Due to multiple convolutional layers, VGG19 can capture complex patterns in medical images.
- Transfer learning: By implementing a pre-trained model of VGG19 its accuracy sharply improves with considerably less processing time while being trained.

VGG19 Architecture:

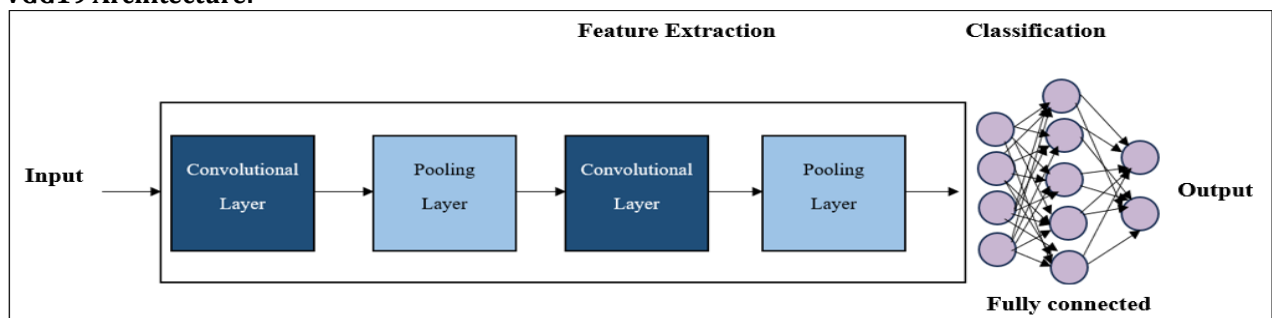
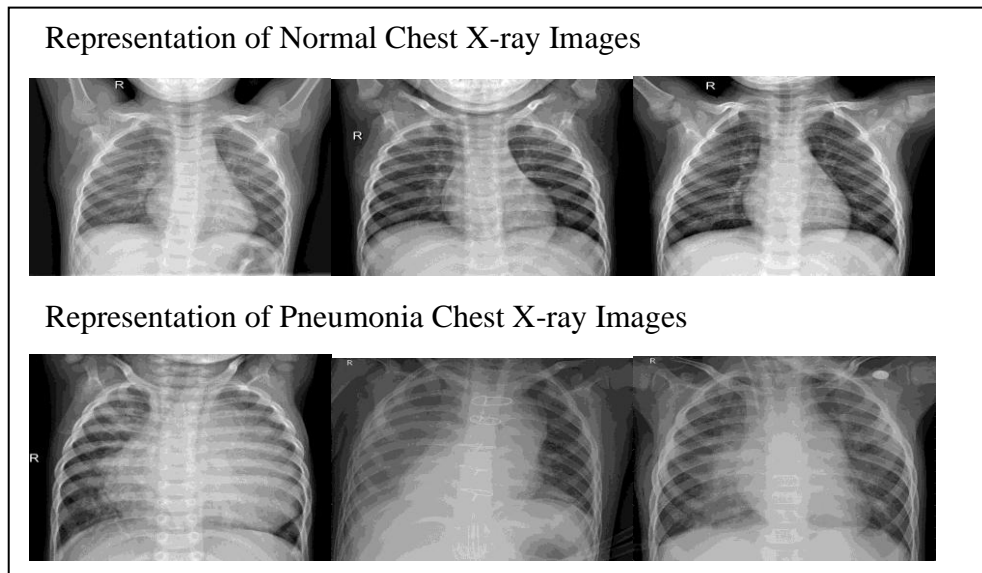


Figure 2. VGG19 Architecture



Pneumonia detection in deep learning models showed that VGG19 achieved the most accuracy (97.08%) followed by AlexNet (95.98%), while

MobileNetV2 (82.14%) achieved lower accuracy due to the lightweight model architecture, which show that VGG19 is the most effective model.

Model Name	Accuracy (%)	Description
VGG19	97.08	A deep CNN with 19 layers that effectively extracts important features from chest X-ray images, making it highly suitable for pneumonia detection.
MobileNetV2	82.14	A lightweight CNN optimized for mobile and real-time applications.
AlexNet	95.98	A simple CNN with 8 layers, performs well but not as powerful as VGG19.

Table 2. Comparison table of deep learning models for pneumonia detection

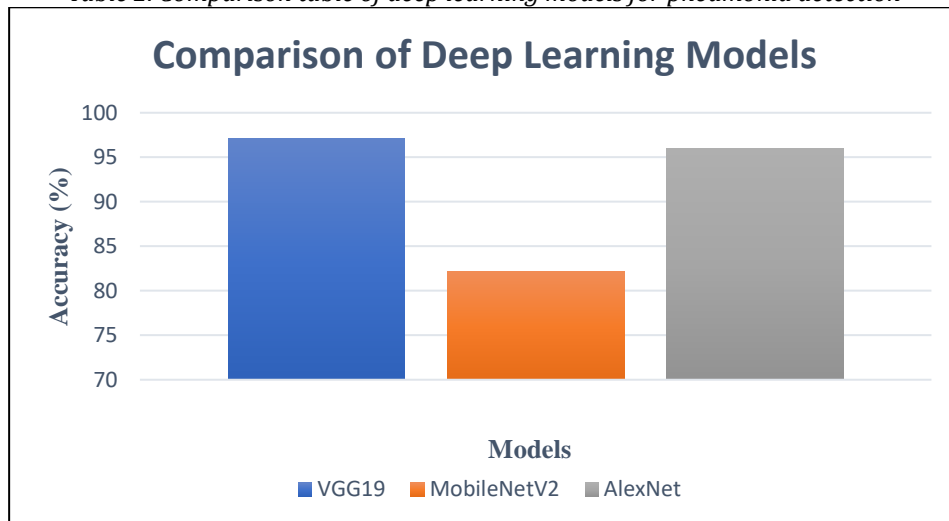


Figure 4. Comparison graph of deep learning models for pneumonia detection

This plot shows the accuracy of three deep learning models-VGG19, MobileNetV2, and AlexNet on pneumonia detection from chest X-ray images. VGG19 produced the best accuracy (97.08%), followed by AlexNet (95.98%), and MobileNetV2 had the poorest performance

(82.14%), making it useful for lightweight cases.

Output:

The output of our project demonstrates that it effectively detects and predicts whether a chest X-ray image is normal or pneumonia.

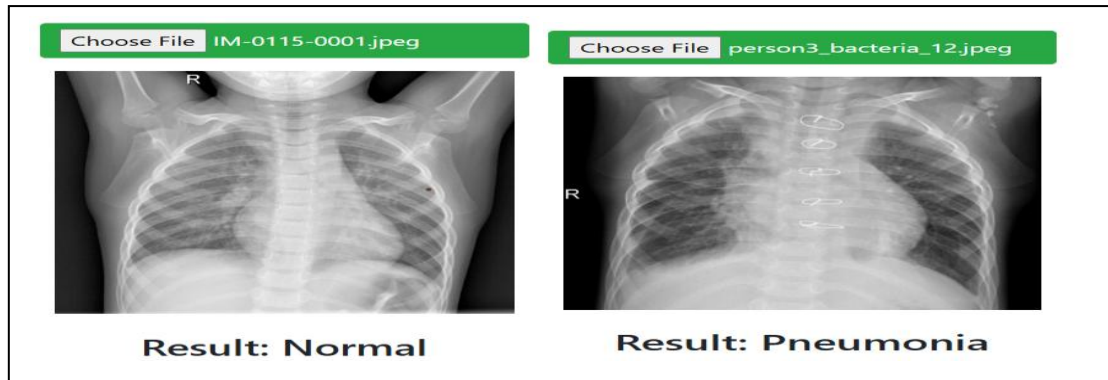


Figure 5. Output of Chest X-ray Image

Conclusion

We have got a neat study where we put together a deep learning-based model to detect pneumonia using VGG19, using chest X-ray images. The model did a great job extracting features and classifying the images as pneumonia or normal with high accuracy. The method used transfer learning, which reduced the training time but still produced strong results. In addition to VGG19, we compared the model performance to MobileNetV2 and AlexNet to assess the VGG19 model performance. Results indicated VGG19 performed the best with an accuracy of 97.08%. Overall, this study provides evidence that deep learning can be a reliable method of automated diagnosis for pneumonia, particularly using a CNN model (e.g. VGG19), and provide a faster and more accurate medical assessment.

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