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# Convolutional Neural Networks for Automatic Detection of Pneumonia

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**Abstract:** *Pneumonia is a fatal disease found to cause infection in one or both the lungs. It can be caused by various types of microorganisms that are bacteria, viruses, fungi. This infection causes inflammation in the alveoli that allows fluid or pus to subsume in alveoli making it difficult to breathe. Moreover, the contagiousness of this infection makes it more harmful. Approximately 33% of the deaths in India are caused due to pneumonia reported by the World Health Organization (WHO). Pneumonia currently diagnosed using a Chest X-Ray evaluated by an expert radiotherapist. This process is exerting and travail and often leads to a difference in opinion among the experts. Thus developing a solitary automatic system would be beneficial for identification, preventing further transmission and treatment in remote areas. Due to the triumph of Convolutional Neural Networks (CNNs) in analyzing medical reports, attention to such medical problems is unambiguously incumbent. Also, due to the rise of pre-trained CNN models that trained on millions of images has made the work much easier one considered as inevitable. We analytically determine the optimal CNN model for the purpose.*

***Keywords***: **Deep Convolutional Neural Networks, SVM, Transfer Learning, Naive Bayes, Pneumonia detection, Computer-aided diagnostics, Medical Imaging.**

## 1. INTRODUCTION

Pneumonia is an illness that disturbs the alveoli of the lungs and is a mortal account for about 16% of the world deaths [1], being the world's leading cause for deaths among the children. Pneumonia is responsible for almost 127,000 deaths in India[2] the numbers are rising due to the spread of novel coronavirus. Pneumonia has killed over 1 million children in worldwide in 2018 and remains one of the most life-threatening diseases if not detected at early stages, especially after the novel Covid-19 pandemic, which has shaken medical institutions around the globe due to increased spike in daily pneumonia cases far-flung the controlled limits that can be treated by medical professionals.

Pneumonia detection is usually performed through a professional examination of chest X-ray (CXR). The diagnosis is further confirmed through clinical history, laboratory exams, and vital signs. Additional confirmation is done because it is difficult to diagnose pneumonia on CXR due to the presence of other conditions in the lungs such as bleeding, volume loss, lung cancer, fluid overloading, post-surgery changes. Due to the involvement of a high number of factors, there is an unambiguous need for an automatic system to detect pneumonia automatically with a low percentage of error.

Over recent years, one of the major research domains in machine learning is Computer Aided Designs (CAD). Various Deep Learning models prove to be prime in the extraction of useful features in image classification tasks. The role of pre-trained CNN models is cardinal in the case of transfer learning as these pre-trained models are trained and tested on datasets that include millions of images that are almost impossible to replicate for a small group of people. Availability of pre-trained CNN models like ResNet[3], AlexNet[4], VGGNet[5], DenseNet[6].

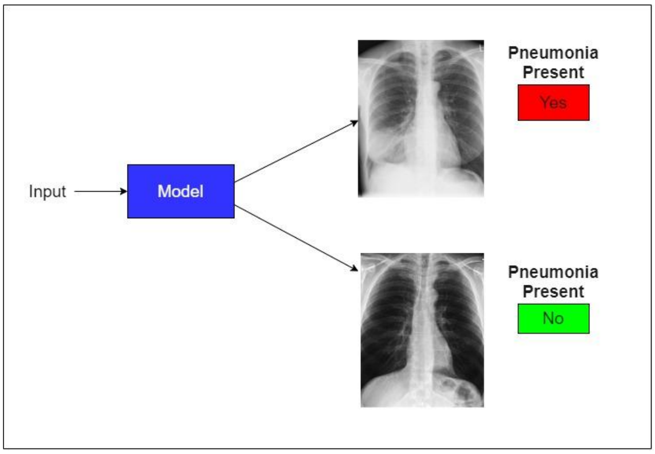


**Fig 1:** An example of normal CXR VS Pneumonia CXR

## 2. RELATED WORKS

The latest improvements in the field of Machine Learning and AI mainly due to large scale usage of Convolutional Neural Networks (CNNs) and the availability of free datasets. That was once considered to be rare and has assisted various algorithms to perform much better that was not considered to be commonplace a few years ago. The automated diagnosis of varied diseases has received growing interest. The low performance of several CNN models on diverse abnormalities proved that a single model cannot be used for all purposes. So for the better exploration of machine learning in chest screening, Wang et al. (2017) [9] released a larger dataset of frontal chest X-Rays.

Recently, Pranav Rajpurkar, Jeremy Irvin, et al. (2017)[10] explored this dataset for detecting pneumonia they referred their model as ChexNet that uses DenseNet-121 layer architecture for detecting all the diseases from the dataset.

### 3. DATASET DESCRIPTION

The Dataset used is ChestX-ray publicly available on Kaggle[7] that contains about 112,120 images of frontal chest X-rays collected from 30,805 patients. Each X-ray image is labeled with one or more out of 14 different pectoral diseases and is expected to have accuracy greater than 90%. For this work, following the past trend, we consider the labels to be 100% true for pneumonia detection.

All images in the dataset are 1024 in height and 1024 in width. Images with labels as pneumonia count up to 1431. To have a balance in the dataset and avoid underfitting or overfitting, We have taken 1439 radiographic images of negative examples (images labeled with 'No Findings'). The final dataset size includes 1431 positive examples (images labeled with pneumonia) and 1439 negative examples (images labeled with 'No Findings') making it a total of 2870 samples. Further, the dataset was divided into two parts called training and testing and following the conventional method and dividing the dataset in an 80%:20% ratio for the training set and test set. The images were downscaled from 1024 by 1024 to 224 by 224 resolution before providing input to the given network.

### 4. METHODOLOGY OF PROPOSED MODEL

The proposed pneumonia detection system uses the 'VGG-19 Model'. The architecture of the above model has been divided into three orthodox stages called the preprocessing and augmentation, the feature-extraction stage, and the classification stage.

#### 4.1. The preprocessing and augmentation stage

Considering the fact the available dataset is not large enough following images augmentations were employed to reduce reduction:

- Horizontal flip
- Mild rotations (random up to 10 degrees)
- For some images level of blur, noise, and gamma changes.

Initially, our dataset included 2870 images (1431 positive samples and 1439 negative samples), after augmentation, the dataset consisted of a total of 8600 images (4300 positive samples and 4300 negative samples).

The complexity remains very high if the inputs are images of high resolution, so to reduce computational complexity, we downscale the 3-channel 1024 by 1024 images to 224 by 224 images consisting of 3-channels using Convolutional Neural Networks.

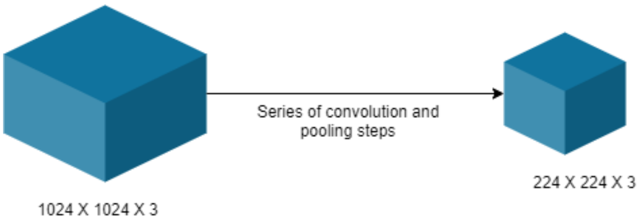


**Fig 2**: Demonstrating Complexity reduction using CNN

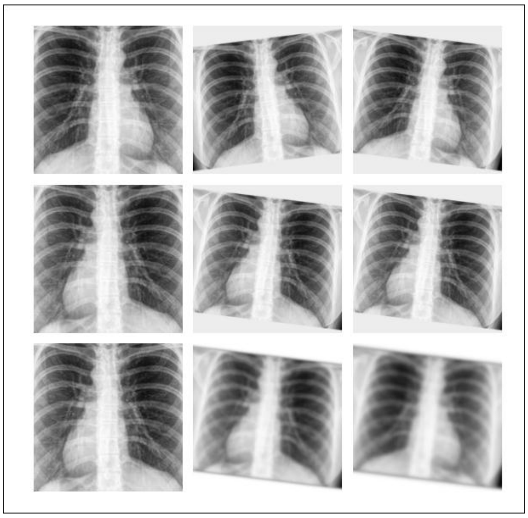

**Fig 3**: Example of chest X-ray with mild rotations, horizontal flips, and random noise

#### 4.2. The Feature-extraction Stage

Although the feature extraction task was done using varied pre-trained models, the best results were obtained using the VGG-19 model. Therefore, this stage deals with the description of the VGG-19 model architecture

#### 4.2.1. Architecture of VGG-19 model

The previously successful model AlexNet which came out in the year 2012, improved on the traditional Convolutional Neural Networks. VGG-19 is a successor of AlexNet[4]. VGG-19 carries and uses ideas from previously existing models and improves them and uses Deep Convolutional Neural Network to improve its accuracy[5]. VGG-19 is a variant of the VGG model and contains 19 layers.

An input of 224 by 224 by 3 is provided as input to the VGG-19 model. The mean RGB pixel value is computed over the whole training set and is subtracted from the RGB value of each pixel as a preprocessing step. Kernel of size 3 by 3 with a stride size of 1 pixel is used

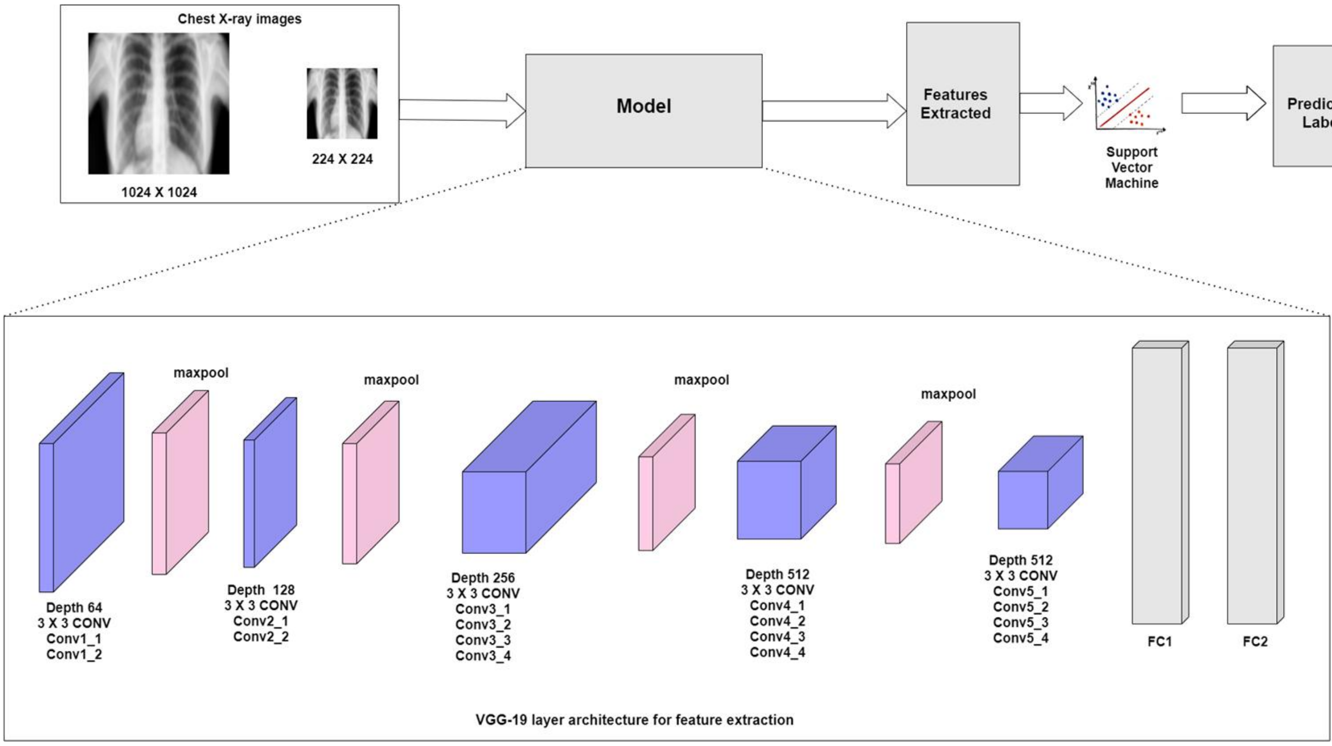


**Fig 4:** Represents a flow diagram of our methodology applied

that enables them to cover the whole notion of the image.

Spatial padding was used to preserve the spatial resolution of the image. Pooling layers consist of max-pooling layers of window size 2 by 2 and stride 2. ReLU (Rectified Linear Unit) is used to introduce non-linearity to make the model classify with better accuracy and improve computational time as compared to previous models using tanh or sigmoid activation functions. Finally, there are two fully connected layers of size 4096 and 1000 respectively. At last, we connected the 1000 node fully connected layer to any binary classifiers such as Naive Bayes, SVM (Support Vector Machine), Random Forest, k-nearest neighbors to obtain the model with optimal accuracy and least training time.

### 4.2.2. Extraction of features

The process of feature extraction from the model applies to all the layers except for the final classification layer in the network. For simplicity and ease of working, we used the last fully connected layer with 1000 nodes. Hence 1000 features were finally extracted and represented as 1000 X 1 input vectors to different binary classifiers.

### 4.3. The classification stage

After the process of feature extraction, various classifiers such as SVM, Random Forest, etc were used for classification. But optimal results were found to be attained when using Support Vector Machine (SVM). So basically our proposed methodology uses features extracted from the VGG-19 model which were fed on the Support Vector Machine (SVM) for classification purposes for best results. Let us suppose a set of training data as (x1,y1),(x2,y2).......(xn,yn) and the data needs to be separated into two sets of classes where $x^i \in F^d$ is the feature vector and $y^i \in (0,1)$ represents the label class. The task of the Support Vector Machine in binary classification is to find out the best hyperplane for the mentioned training data such that the margin between the classes is maximum and is capable of separating the data points of the two classes.

## 5. EXPERIMENTAL SETUP

For pre-trained CNN model's we used ResNet[3], AlexNet[4], VGGNet[5], DenseNet[6]. We evaluated the performance of the above mentioned CNN models using classifiers such as Naive Bayes, Support Vector Machine, k-nearest neighbor, etc. The results found supported VGG-19 as best suited model for our purpose with Support Vector Machine (SVM) proving to be the best functioning classifier.

Accuracy = (Correct Predictions)/(Total Predictions)

**Table 1: Results obtained by various classifiers on VGG-19 Model**

| Feature extractor | Classifier | ACCURACY |
|---|---|---|
| VGG-19 | Naive Bayes | 0.7195 |
| VGG-19 | SVM | **0.8640** |
| VGG-19 | Random Forest | 0.7588 |
| VGG-19 | K-nearest neighbors | 0.7982 |

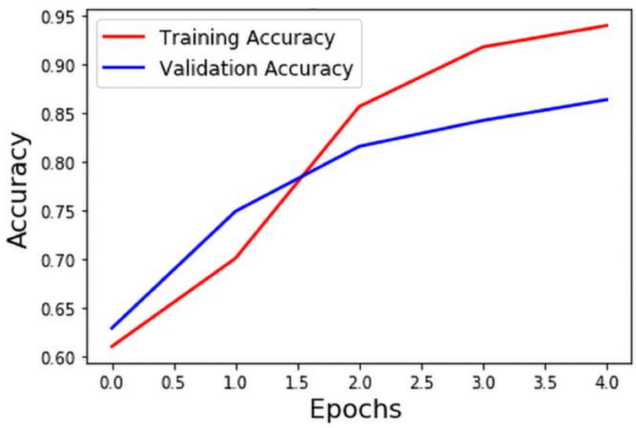


**Fig 5:** Model Accuracy

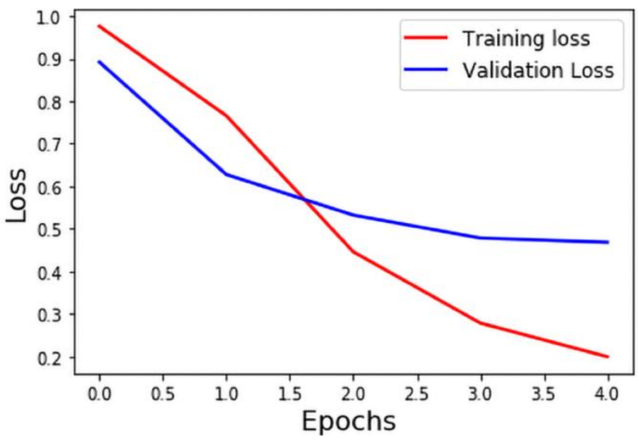


**Fig 6:** Model Loss

The above figures(Fig 5, Fig 6) and Table (Table 1) indicate that the VGG-19 model works best with Support Vector Machine (SVM) to detect pneumonia from X-ray images.

## 6. RESULTS AND DISCUSSION

Our customized model (a combination of VGG-19 model and Support Vector Machine for classification) resulted in high accuracy in classifying abnormal ('Pneumonia' labeled) and normal ('No Findings' labeled) chest X-ray radiographic images. Initially, we trained with different pre-trained CNN models like ResNet[3], AlexNet[4], VGGNet[5], DenseNet[6] with eclectic classifiers and found that the best results are obtained from using the VGG-19 model with Support Vector Machine (SVM) as the classifier.

## 7. LIMITATIONS

Although the results obtained were satisfactorily acceptable, there are still some limitations in our customized model. First, we posit that none of the patients have a pre-medical history, meaning there is a lack of medical history associated with the patient. We made predictions based on X-ray images only. Also, in our diagnosis, only frontal X-ray images were used but it has been successfully proved that lateral X-ray images also help in the diagnosis of pneumonia[8]. Though we tried to reduce the complexity as far as possible, the model involves a lot of layers and complex calculations that make its working time mishap.

## 8. CONCLUSION

Machines can imitate humans to a certain extent. Hence in some cases, even the most powerful of the machines and technologies cannot overplay the role of professionals in a particular field. The presence of expert radiologists is inescapable through the development of AI technologies is pretty accurate. Our study mainly aims for remote areas, where the presence of itinerant medical experts is exiguous. Early detection of Pneumonia can save many lives and reduce the burden on our medical infrastructure. We observed the performance of various pre-trained CNN models along with different classifiers based on obtained results selected the VGG-19 model and Support Vector Machine (SVM) classifier. With this progression of experiments conducted, we aim to provide a strong base for pre-trained models and classifiers to be used in further medical analysis research. Our study will likely lead to the development of better algorithms for the detection of Pneumonia.

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