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Pneumonia Recognition in Chest X-rays through Convolutional Neural Networks (CNN)

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Abstract: Pneumonia is a major threat to respiratory health and can be caused by bacterial or viral illnesses. Untreated pneumonia can be fatal, underscoring the significance of early diagnosis. The goal of this work is to automate the process of discriminating between pneumonia caused by bacteria and viruses utilizing digital X-ray pictures. The text commences with a comprehensive summary of the progress made in enhancing the precision of pneumonia diagnosis. It then proceeds to elucidate the approach employed by the writers. The four distinct deep convolutional neural networks (CNNs) employed for transfer learning are SqueezeNet, AlexNet, ResNet18, and DenseNet201. A set of 5247 pictures, including chest X-rays displaying bacterial, viral, and normal states, were preprocessed and used transfer learning to train the classification task. The authors of the study have delineated three methods for classifying pneumonia: distinguishing between normal and viral, differentiating between bacterial and viral, or identifying a combination of all three. 98% of the photos correctly classified as both viral and bacterial pneumonia, 95% for both normal and pneumonia instances, and 93.3% as all three forms of pneumonia. Its performance substantially outperforms the previously known accuracies. Therefore, the suggested study may aid radiologists in diagnosing pneumonia more quickly and expedite airport screenings for individuals with the illness.

Keywords: pneumonia; transfer learning; deep learning; chest X-ray Images; image processing.

1. Introduction

Around the world, Pneumonia stands as the primary cause of mortality among children. Approximately 25% of children aged five and below succumb to pneumonia annually, impacting approximately 1.4 million young individuals. [1]. Annually, pneumonia affects a staggering two billion individuals worldwide. Both viruses and bacteria have the capacity to induce pneumonia, a respiratory illness. Antiviral and antibiotic drugs have been shown to be successful in treating illnesses brought on by viruses and bacteria.

It is critical to diagnose bacterial or viral pneumonia as soon as possible and to start therapy as soon as possible ,can greatly diminish the probability of a patient's condition worsening and resulting in mortality. [2]. Currently, the most reliable way to identify pneumonia is thought to be a chest X-ray[3]. Pneumonia is not always evident on X-rays, and it is sometimes mistaken for other benign abnormalities or other diseases. Furthermore, specialists may misclassify images of bacterial or viral pneumonia, which could result in patients receiving the incorrect medicine and a deterioration of their condition [4-6]. Significant subjective discrepancies have been observed in the diagnoses of pneumonia made by radiologists. There is a chronic lack of qualified radiologists in low-resource countries (LRC), particularly in rural regions. Computer-aided detection (CAD) solutions are desperately needed to help radiologists meet this issue,identify different types of pneumonia, as they rely on chest X-ray pictures for this purpose.

Artificial Intelligence (AI)-based solutions are currently being used for several biomedical issues (e.g., brain tumour identification, detecting breast cancer. [7-10]. One class of deep learning methods is Convolutional Neural Networks (CNNs),that have gained a lot of traction in the scientific community due to their impressive image classification capabilities [11]. Deep Learning: Deep learning methods for machine learning from chest X-rays are becoming more and more popular since they are simple to apply with inexpensive imaging techniques and have a wealth of data to train various models. Among the various research organizations that have utilized deep learning algorithms for pneumonia diagnosis, only one has specifically documented the ability to differentiate between bacterial and viral pneumonia [12], while whereas a number of research teams [1] [12-25] describe how deep learning algorithms can be used to diagnose pneumonia.

In numerous studies, writers have experimented with adjusting the deep layered CNN's settings in order to identify pneumonia. Radiographs of the lungs obtained for the purpose of diagnosing pneumonia may show interstitial or alveolar patterns of widespread opacity. In a laboratory context, the presence of alveolar infiltration—particularly lobar infiltrates—on a chest radiograph is indicative of bacterial infection.[26]. In our research on Pneumonia Recognition in Chest X-rays through Convolutional Neural Networks (CNN), we draw inspiration from a novel deep learning technique proposed in a paper focusing on highly accurate image retrieval, incorporating auto-correlation, gradient computation, and feature fusion. Once more, viral pneumonia may be associated with interstitial infiltrations on radiographs. This work proposes a unique system using blockchain-based federated learning to quickly detect and isolate COVID-19 situations, gathering information from many sources while protecting privacy concerns. The suggested model, which included IELMs and CapsNet, showed better accuracy (98.99%) when it came to COVID-19 patient classification using chest CT images. This paper presents CDC Net, a convolutional neural network model, in the context of detecting numerous chest infections. It achieves an AUC of 0.9953, accuracy of 99.39%, recall of 98.13%, and precision of 99.42%. Its higher performance is validated by comparative comparisons with other CNN-based pre-trained models.These may be the distinguishing characteristics of the machine learning algorithms utilised to differentiate between viral and bacterial pneumonia. Promising outcomes have been reported by certain researchers, Numerous scholars have investigated this subject, including Xianghong et al., Liang et al., as well as Krishnan et al, and Vikash et al.Multiple teams utilized CNN models incorporating Teams used lung field segmentation and rib suppression approaches to meet different categorization issues. In contrast, other teams prioritized the utilization of CNN visualization techniques to Determine the child-specific Region of Interest (ROI) in chest X-rays, enabling the detection of pneumonia and differentiation between viral and bacterial types. Vikash et al. employed ensembles of pre-trained ImageNet models [27] to identify pneumonia utilising the deep learning framework's idea of transfer learning. In Xianghong et al. a modified version of the VGG16 model was employed. The deep convolutional neural network is employed for the classification of pneumonia, while the fully convolutional network (FCN) is used to find and identify the lung sections.Wang et al. [13] utilised a deep learning approach on an X-ray dataset of 32,717 patients, with encouraging results. The authors of [14] continued to use CNN in conjunction with data augmentation to improve performance through training on a limited number of images. Using an ensemble of several networks, Rajpurkar et al. identified pneumonia as one of fourteen illnesses using 121 layer CNN developed using chest X-ray data. To solve the gradient vanishing problem, The 3D Deep Convolutional Neural Network was utilised by Jung et al. with dense connections and shortcuts. Furthermore, The Region-based CNN is a deep neural network that was employed by Jaiswal et al. [17]and Siraz et al. to categorise lung images. By utilizing the RetinaNet ensemble and implementing picture enhancing techniques, the precise location of the pneumonia may be accurately identified. In, fourteen thoracic illnesses were accurately identified by the application of feature extraction techniques and a pretrained DenseNet-121. Using AlexNet and GoogLeNet, Sundaram et al. used data augmentation strategies to get an AUC value between 0.94 and 0.95. The authors achieved superior performance compared to their competitors by making modifications to a two-network ensemble architecture, as demonstrated by the remarkable 0.99 area under the curve (AUC) value.

When employing deep learning algorithms to classify distinguishing between bacterial and cases of viral pneumonia as well as normal instances. utilizing X-rays to diagnose pneumonia pictures, the maximum accuracy recorded in the aforementioned literatures was 93.6% and 96.84%, respectively. As a result, there is a lot of opportunity to improve the outcome, especially in identifying bacterial and viral pneumonia, by combining multiple outperforming algorithms into an ensemble model, using new deep learning algorithms or tweaking the existing ones that are producing better results. The proposed paper presents a transfer learning approach and evaluates the capabilities of SqueezeNet, AlexNet, ResNet18, and DenseNet201, four distinct pre-trained network designs. This study's most significant contribution is a transfer-learning strategy based on convolutional neural networks (CNNs), which uses multiple pre-trained algorithms can more precisely detect and categorise viral and bacterial pneumonia than earlier studies. Furthermore, the details of the methodology used in the paper are provided in the publication, which any research group can use to benefit from this work. Furthermore, radiographic results are still not very good at pointing to the source of pneumonia. The reason for conducting this research was to better distinguish between bacterial and viral pneumonia by using machine learning to diagnose pneumonia using radiograph analysis in the first place. The rest of the paper is divided into the following sections: Section 3 outlines the study's methodology and includes information on the dataset's specifics as well as the pre-processing procedures that were taken to get the data ready for testing and training. Section 2 lists the several pre-trained networks that were used for the investigation. The findings of the classification algorithms are given in Section 4, where they are also compared with those of a few other recent studies and discussed. Lastly, Section 5 presents the conclusion.

2. Overview of the History of Algorithms for Deep & Machine Learning

2.1. CNNs (Convolutional Neural Networks)

The enhanced image categorization capabilities of Convolutional Neural Networks (CNNs) are a significant factor contributing to their rapid surge in popularity. The network's convolutional layers and filters aid in the more accurate extraction of spatial and temporal aspects of images. Implementing a method to evenly distribute the weight between the layers aids in minimizing computing demands.

With two limitations on their architecture, CNNs are essentially feedforward artificial neural networks (ANNs): first, to preserve spatial structure, Furthermore, to reduce the overall count of model parameters, the neurons' weights inside the same filter are shared. Furthermore, neurons within the same filter exhibit connections exclusively with adjacent patches of the image. The network's ability to classify is enabled by a fully connected layer, dimensionality reduction is achieved through a max-pooling (subsampling) layer, and feature learning is performed by a convolutional layer are the three basic components of a CNN. An overview of the architecture of CNN is shown in Figure 1.

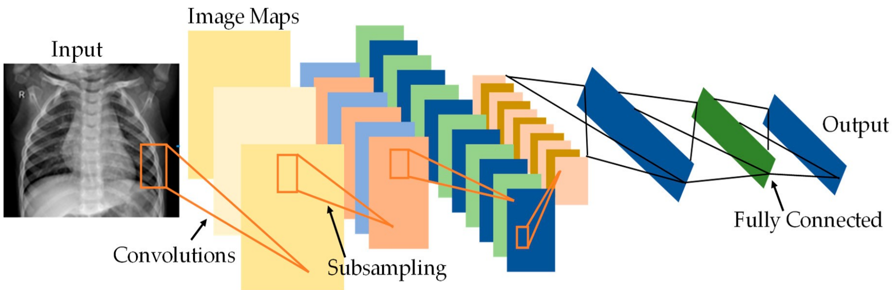


Figure 1. CNN Architecture.

2.2. Transfer Learning in Deep CNN

In general, Larger datasets yield superior performance for CNNs than smaller ones. When using CNN in applications , transfer learning can be useful when dealing with tiny datasets.

Figure illustrates the conceptualizing knowledge of transfer learning by demonstrating how a trained model from a larger dataset—like ImageNet— It is possible to utilize with a limited dataset. Recently, transfer learning—applying knowledge from one job to another—has demonstrated promise in real-world industries including manufacturing, healthcare, and baggage screening.This eliminates the need for a big dataset and shortens the training period, both of which are necessary for the deep learning algorithm during its construction from the ground up.

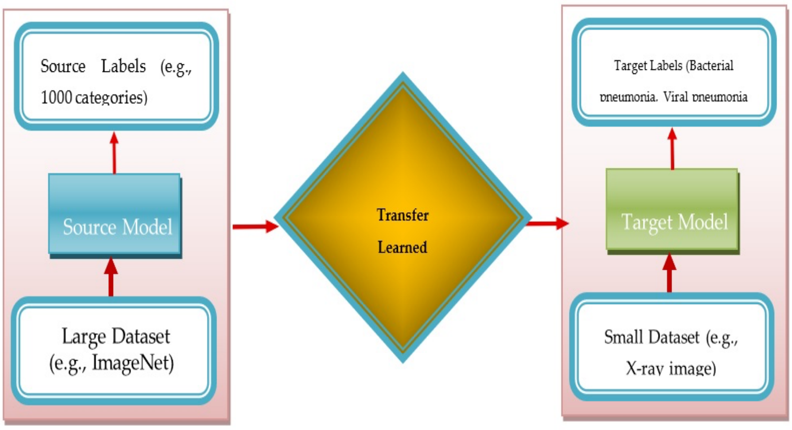


Figure 2. TL(transfer learning) concepts.

2.3. Pre-Trained CNNS

Four well-known convolutional neural networks AlexNet[11], DenseNet[28], ResNet[29], and SqueezeNet[30] were employed in this study to do deep learning. The following was a a succinct synopsis of these trained networks

2.3.1. AlexNet

To classify over a thousand distinct types, AlexNet employs deep layers with sixty million parameters and six hundred thousand neurons. There are a total of six levels in the network: two FLCs, Five CLs, One Softmax layer and three pooling layers make up the architecture [11]. The dimensions of the supplied picture should be 227 × 227 × 3. in order for AlexNet to function. The first CL uses 96 kernels with an 11 × 11 × 3 size and a four pixel stride to alter the input image. The data is sent into the second layer, and Figure 3 summarises the remaining information.

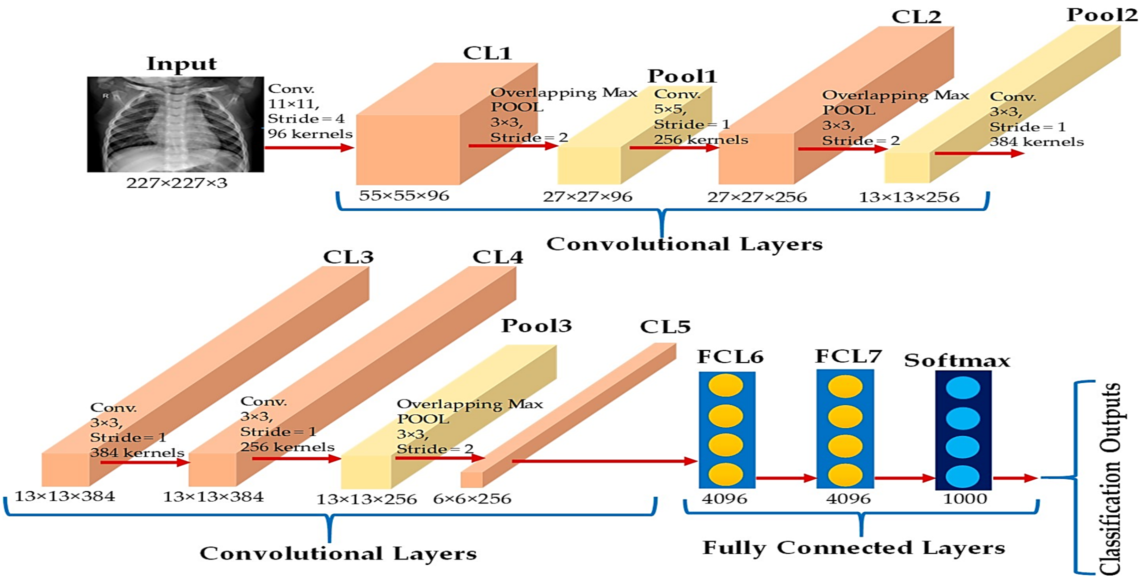


Figure 3. Structure of AlexNet

2.3.2. ResNet18

The initial architecture of ResNet, an abbreviation for Residual Network, which was created to tackle two problems, deterioration and the vanishing gradient, is shown in Figure 4 [29]. Relative learning aims to tackle both of these issues. There are three versions of ResNet available: ResNet18, ResNet50, and ResNet101. Each version differs from the other based on the number of layers. ResNet has demonstrated efficacy in utilizing transfer learning for classifying biological images[30]. This research employed ResNet18 to detect instances of pneumonia. During training, ResNet prioritizes residuals over features, which sets it apart from deep neural networks' layers that usually learn either basic or intricate features.

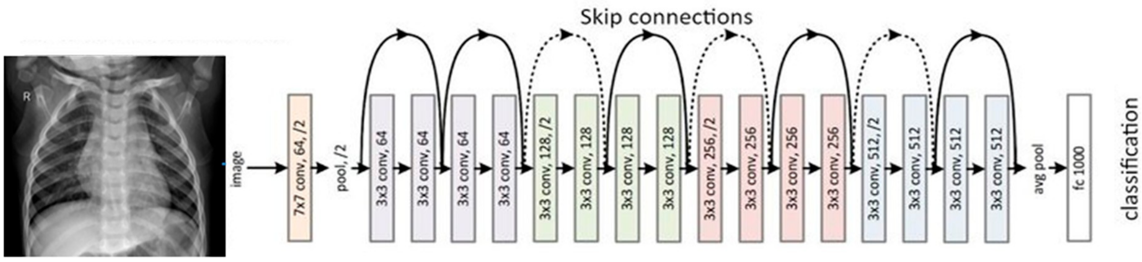


Figure 4. Structure of ResNet18.

2.3.3. DenseNet201

Because it doesn't train redundant feature maps, DenseNet, using fewer parameters than a standard CNN, a condensed version of the Dense Convolutional Network [31]. With just 12 filters, DenseNet produces a negligible amount of new feature maps. DenseNet121, DenseNet169, DenseNet201, and DenseNet264 are the four distinct variations of DenseNet. DenseNet201 was utilised in this paper to diagnose pneumonia [28]. DenseNet (shown in Figure 5) offers easy and quick access to the original input picture for each layer in addition to gradients obtained using the loss function. DenseNet is a superior option for picture classification as a result of the considerable reduction in computing cost.

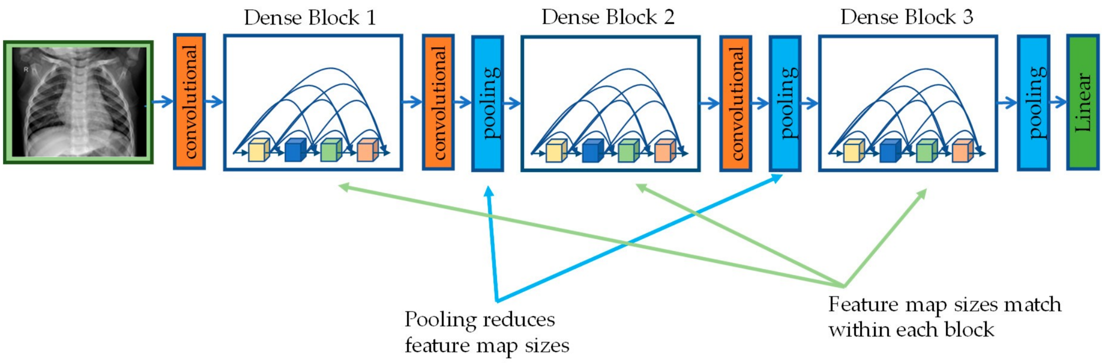


Figure 5. DenseNet201 architecture

2.3.4. SqueezeNet

In addition to SqueezeNet, another convolutional neural network (CNN) was trained utilizing the ImageNet database[28]. SqueezeNet, having undergone training with over a million images, possesses a parameter count that is fifty times smaller than that of AlexNet. The expand layer and squeeze layer together form the module of fire, which is the network's core element. The extend layer receives data from the squeeze layer and applies a combination of 1 × 1 and 3 × 3 convolutional filters. Here, only 1 × 1 convolutional filters are employed[32]. This is illustrated in Figure 6. Here, In order to distinguish between presentations of bacterial and viral illnesses and to diagnose pneumonia, we employ the pre-trained SqueezeNet model.

3. Methodology

3.1. Dataset

5247 chest X-ray pictures in all, ranging in resolution from 400p to 2000p, were extracted from the database of Kaggle Chest X-ray Pneumonia for this study[33]. Table 1 illustrates that of the 5247 chest X-ray images, 1341 are of healthy individuals and 3906 are of those suffering from pneumonia, comprising 2561 images of pneumonia bacteria and 1345 images of pneumonia viruses. Some episodes of pneumonia may involve a combination of viral and bacterial infections. No instances of co-infection between bacteria and viruses were found in the dataset utilized for this study. This dataset was utilized to segregate a training set from a test set.

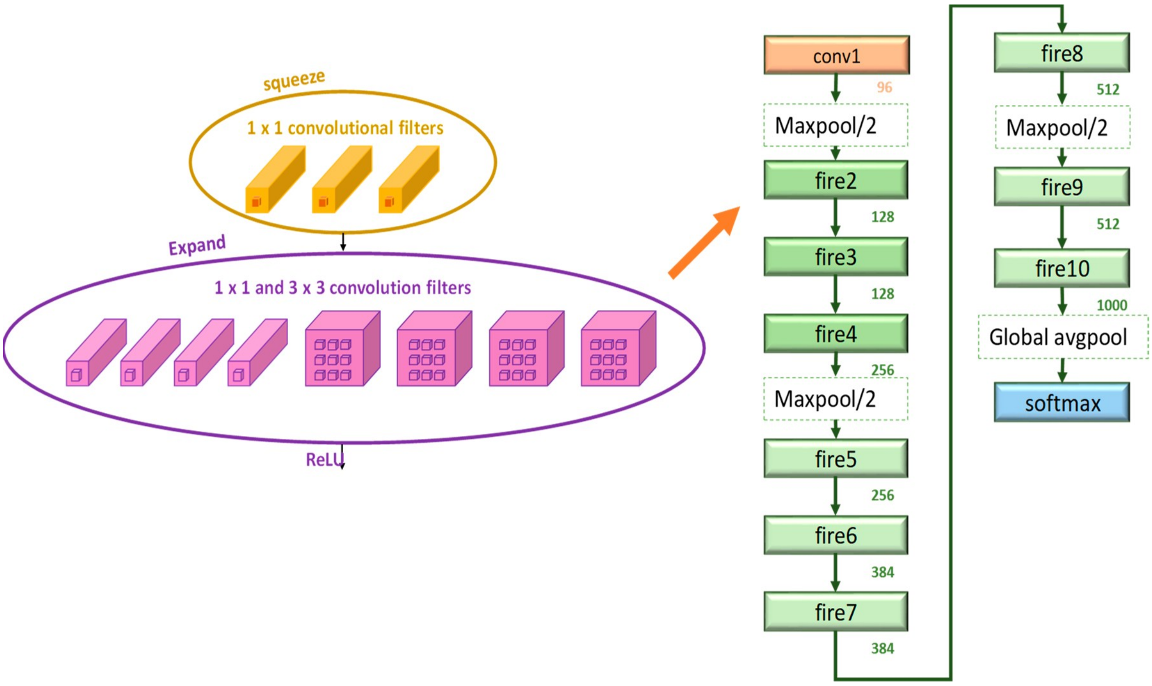


Figure 6. Architecture of SqueezeNet

Table 1. Complete dataset details.

Cases	**Type of Images**	**No of X-ray Images**
Case A	Normal Cases	1341
Case B	Bacterial Pneumonia Cases	2561
Case C	Viral Pneumonia Cases	1345
Total Cases	Total	5247

A variety of test and train images (using augmentation) for various evaluation trials are displayed in table 2 Using the training dataset, four distinct algorithms were trained and subsequently assessed using the test dataset. Two samples of chest X-rays for viral, bacterial, and normal pneumonia are shown in figure 7.

Table 2. Information about the test and training sets.

Train Images	**Test Images**	**Cases**	**Types**
4500	205	Normal	Normal and Pneumonia
4500	214	Pneumonia	
4500	199	Normal	Normal, Bacterial, and Viral Pneumonia
4500	197	Bacterial Pneumonia	
4500	201	Viral Pneumonia	
4500	197	Bacterial Pneumonia	Bacterial and Viral Pneumonia
4500	201	Viral Pneumonia	

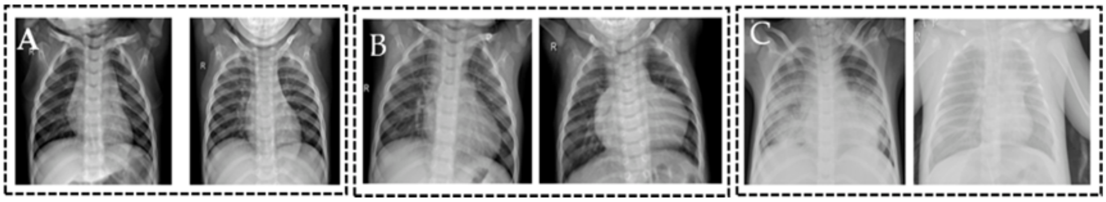


Figure 7. Chest X-rays

Using MATLAB, the researchers in this work taught, assessed, and tested a variety of algorithms (2019a). In Figure 8, we can see the overall methodology of the investigation. After preprocessing the image sets, data is added to them. Then, the training process begins with pre-trained algorithms such as ResNet18, SqueezeNet, DenseNet201, and AlexNet, as well as any methods that the test dataset has been used to evaluate. Every model was trained on a 64-bit version of Windows 10 machine with an Intel© i7-core @3.6GHz CPU, 16GB of RAM, and a 2GB graphics card with a GPU. Table displayed the various parameters utilised to train the CNN models. Although ResNet and DenseNet have numerous variations, this study chose ResNet18 and DenseNet201 since they were easily accessible for Matlab 2019a. Furthermore, in terms of radiographic classification, ResNet18 performs better than previous ResNet models.

Table 3. Various pre-trained CNN models' training settings

Tool	Pre-Trained Models	Dimention	Optimizer	Momentum	Batch size	LR(learning rate)
Matlab (2019a)	AlexNet	227 ×227	Gradient Descent	0.9	16	0.0003
	ResNet18	224 ×224				
	DenseNet201	224 ×224				
	SqueezeNet	227 ×227				

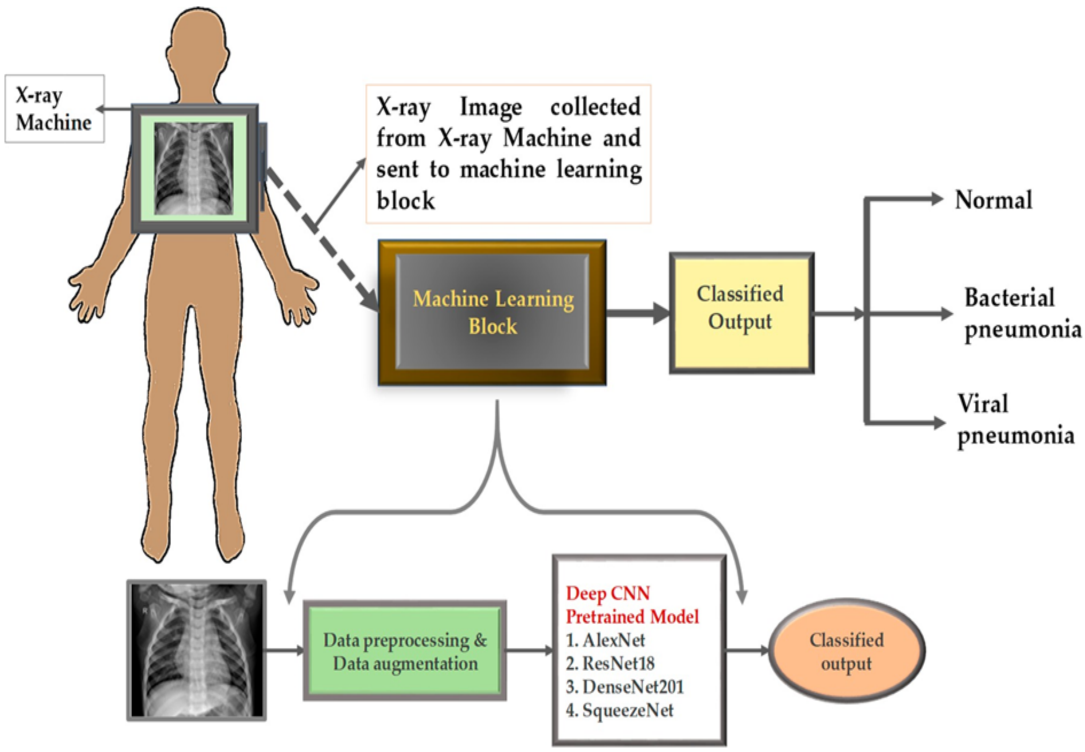


Figure 8. Architecture of SqueezeNe

3.1.1. Preliminary processing

X-ray image resizingAs a crucial step during the preparation of the data procedure, scaling the X-ray pictures was necessary because different algorithms had varying specifications regarding their size. The resized photographs for ResNet18 and DenseNet201 were 224 × 224 pixels, whereas the resized shots for

AlexNet and SqueezeNet were 227 × 227 pixels. Furthermore,Every image was normalised using the pre-trained model's specifications.

3.2. Data Augmentation

CNNs demonstrate their full potential when used to large datasets, as previously said. On the contrary, the functioning database is quite little in size. Utilizing data augmentation techniques to enlarge a restricted dataset is a widely employed tactic during the training of deep learning systems. According to reports, deep learning systems have the ability to improve their classification accuracy by employing data augmentation approaches. Just adding more information to the current dataset will improve the performance of deep learning models without requiring additional data collection. The authors of this work produced additional training sets by developing three innovative augmentation procedures: translation, scaling, and rotation in addition to the existing data augmentation approaches used by numerous deep learning frameworks, as shown in Figure 9.

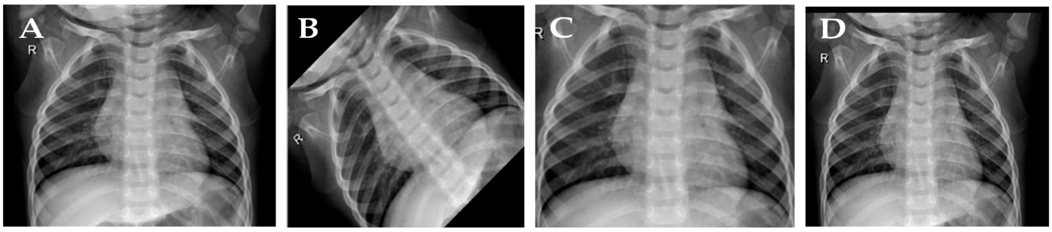


Figure 9. X-ray Chest images: (A) original, (B) rotated, (C) scaled, and (D) translated.

To enhance an image, it is common practice to rotate it clockwise by an angle between zero and three hundred degrees. Each pixel in the image frame is rotated as part of this procedure, which also fills up areas where pixels are absent.. A rotation of 315 degrees (45 degrees anticlockwise) was employed in this work. Another technique for image augmentation is scaling, which is the process of increasing or decreasing the image's frame size. Ten percent of the image magnification was applied overall, as seen in Figure 9C. One can perform image translation by shifting the image in one of two directions: horizontally (width shift), laterally (change in height), or in both directions simultaneously. We translated 10% of the original image horizontally and vertically.

Activation Layer Visualization

By comparing the regions in a picture that exhibited activation in the convolutional layers matching the relevant areas of the original pictures, we were able to examine the image's connecting the convolutional layers to their respective areas in the original images features. Many 2D arrays known as channels make up each layer of a CNN. Several networks were trained on the input image, and the first convolution layer's output activations were analyzed.

Figure 10 displays the activations for several network models. The activation map was normalised to fall between 0 and 1 because it can have a wide range of values. We analysed and contrasted the most significant activation channels with the original image.

Figure displays the activations for several network models. The activation map was normalised to fall between 0 and 1 because it can have a wide range of values. We analysed and contrasted the most significant activation channels with the original image. The study found that these channels respond to edges, with negative effects on dark-left/light-right edges and favourable effects on light-left/dark-right.

Most convolutional neural networks are trained with the primary goal of identifying basic visual components like edges and colours within the initial layer of convolution. Convolutional layers that are deeper are incorporated into the neural network to improve its recognition of increasingly complex objects. Following layers combine characteristics from earlier levels to increase the intricacy of its characteristics. For each model, The activation map in the initial convolutional layers is displayed in Figure 10, the activation channel with the highest power, and the convolutional layer with the greatest depth.

3.3. Different Experiments

In this study, patients with viral pneumonia and those with bacterial pneumonia were divided into two groups. For performance assessments and comparisons, three categories: viral, bacterial, and normal pneumonia were utilised. Through transfer learning, the study also employed four distinct deep learning algorithms.

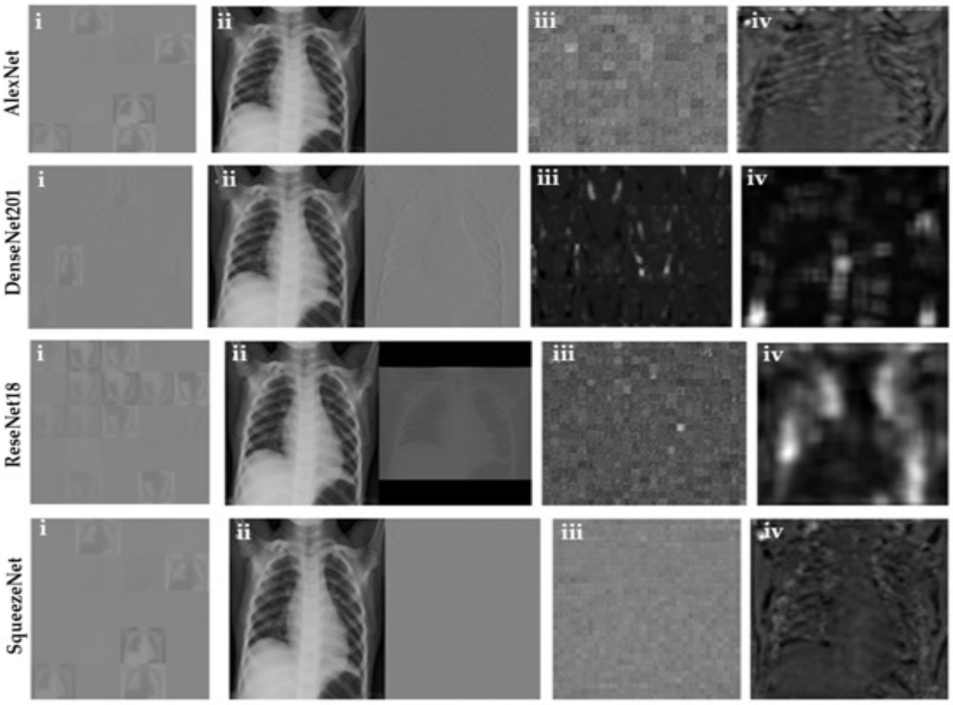


Figure 10. The activation map shows the outcomes of several network models, such as: (i) the 1st-layer of convolution, (ii) the specific channel with the highest activation, (iii) a collection of pictures from the deeper layer, (iv) the consolidated in the deep convolution layer in a unified pictures margins.

Three phases made up the experiment that was conducted for this study. The dataset was first split into two groups: pneumonia and normal. The dataset was split into three categories in the second step: viral, bacterial, and normal pneumonia. The last stage involved dividing the dataset into two groups: pneumonia caused by viruses and bacteria. Images of common, viral, and bacterial pneumonia were categorised using an end-to-end training technique.

3.4. Performance Matrix for Classification

In this investigation, five-fold cross-validation was employed to train and evaluate four CNNs. After training is finished, The six performance measures—accuracy, sensitivity or recall, specificity, precision (PPV), area under the curve (AUC), and F1 score—are employed to assess and contrast the functionality of various networks for the testing dataset. Six performance indicators for several deep CNNs are displayed below:

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

$$Sensitivity = \frac{(TP)}{(TP + FN))}$$

$$Specificity = \frac{(TN)}{(FP + TN)}$$

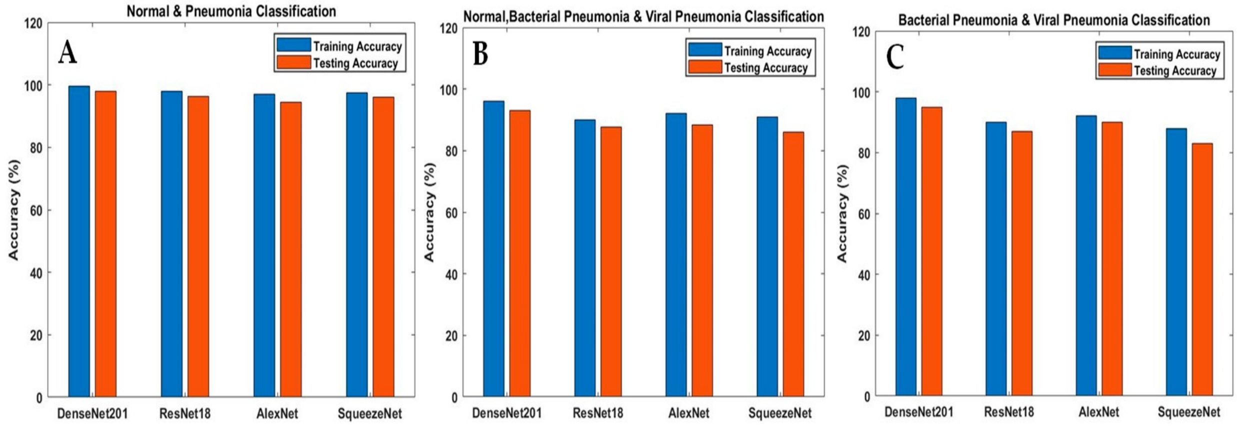
$$Precision = \frac{(TP)}{(TN + FP)}$$

$$F1\ Score = \frac{(2 *\ TP)}{(2 * TP + FN + FP)}$$

When classifying patients into normal or pneumonia categories to indicate the number of pneumonia images that were correctly identified as such, normal images that were correctly identified as normal, normal images that were mistakenly labelled as pneumonia, and pneumonia images that were mistakenly labelled as normal, the terms True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) were used, in that order.. In contrast, during the classification of viral and bacterial pneumonia. The numbers of pictures of viral pneumonia that were correctly classified as such, pictures of bacterial pneumonia that were identified as such, and viral pneumonia images that were mistakenly identified as such were indicated, respectively, by the metrics TP, TN, FP, and FN.

4. Results and Discussions

Figure 11 compares the training and testing accuracy of various convolutional neural networks (CNNs) used for categorization schemes. Among the three classification methods, DenseNet201 is yielding superior outcomes in terms of quality for both testing and training. The researchers reported classification accuracy of the percentages were 98% for both pneumonia and normal cases, 93.3% for instances of bacterial and viral pneumonia, and 95% for cases of both types of pneumonia.. AUC sis a critical metric for assessing a classification model's efficacy across many categorization schemes, as shown in **Error! Reference source not found.**. **Error! Reference source not found.** makes it even clearer that DenseNet201



performs better in comparison to the other algorithms.

Figure 11. Accuracy in training and testing comparison utilising different models for the classification of CaseA, Case B, and Case C.

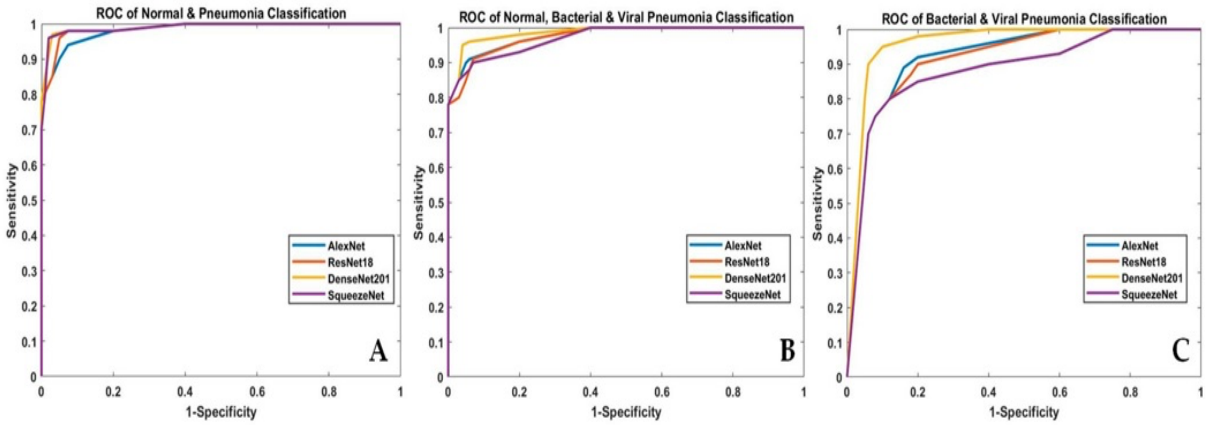
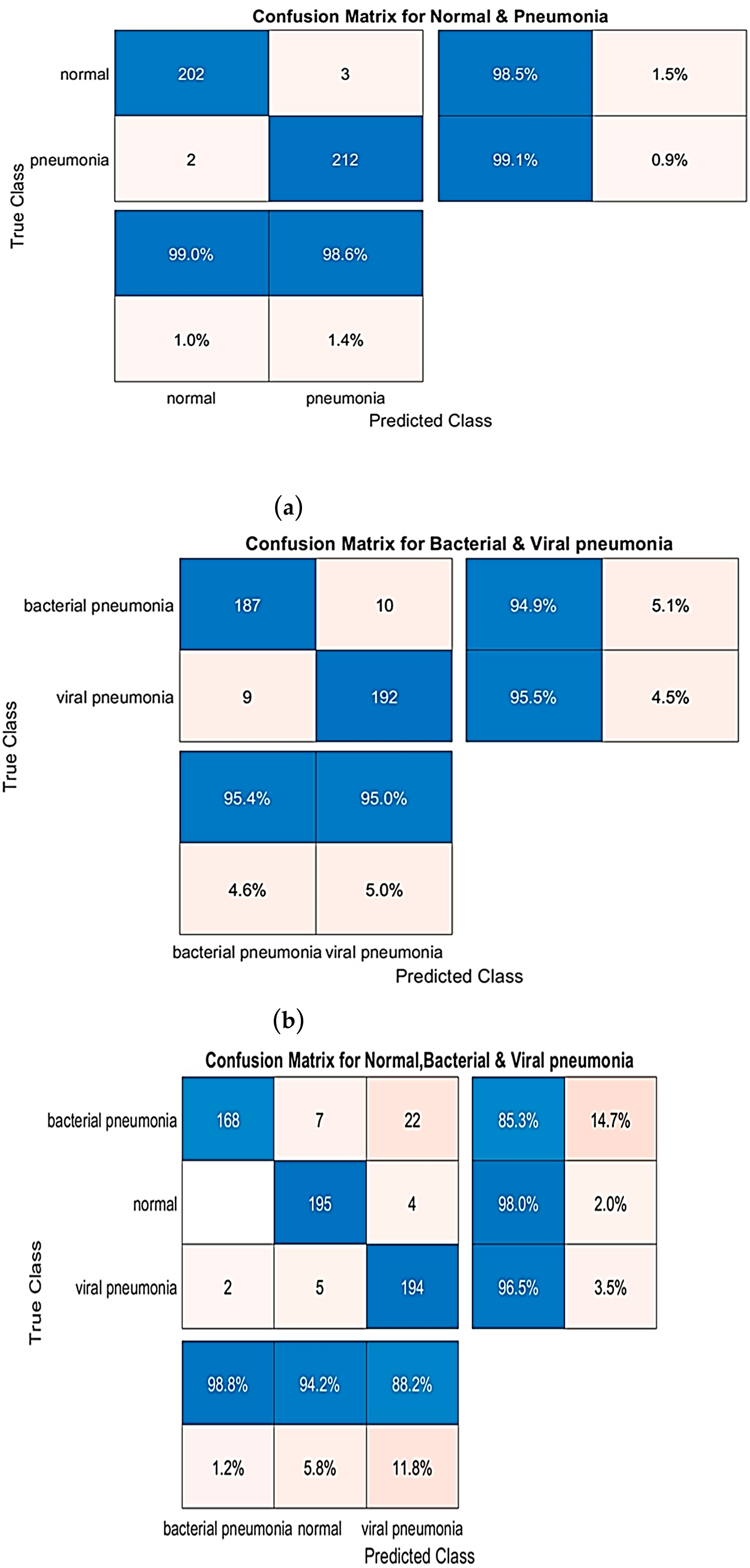


Figure 12. The effectiveness of CNN-based models in differentiating between Case A, normal, Case B , and Case C is assessed through a (ROC) curve comparison.

The confusion matrix for the pre-trained Densenet201 model, which performs better, is shown in Figure 13 for three different classes.

Table no 4 presents a concise overview of the performance measures of various convolutional neural network (CNN) algorithms that were assessed for the three distinct classification techniques. DenseNet201 demonstrates superior performance compared to other models across three distinct categorization methods, as seen by several performance indicators.

Furthermore, the authors have conducted a comparative analysis of the findings presented in the research with those of other published studies on the identical subject matter. The diagnosis of pneumonia by the use of CXNet-m1, a deep learning system, was documented by Vikash and colleagues[21]. The method demonstrated 99.6% sensitivity, 93.28% precision, and 96.39% accuracy. The efficacy of VGG16 CNNs to differentiate between bacterial, viral, and benign pneumonias was evaluated by Krishnan et al.[34]. Pneumonia diagnosis has a sensitivity of 99.5%, precision of 97.7%, and accuracy of 96.2%. In contrast, the scores for identifying between pneumonia caused by bacteria and viruses were 98.4%, 92%, and 93.6%, respectively. Table 4 presents a comprehensive analysis of research that compares different kinds of pneumonia, as detected using chest X-rays, with previous studies conducted on this topic.



(a)

(b)

(c)

Figure 13. The classification outcomes for using the DenseNet201 model, normal pneumonia, bacterial and viral pneumonia, and normal, bacterial, and viral pneumonia are shown in the confusion matrix.

Table 4. Various deep learning networks use different performance criteria.

Assignment	Pretrained model	Accuracy	Sensitivity (Recall)	Precision	Precision (PPV)	Area under Curve (AUC)	F1 Scores
Normal and Pneumonia	SqueezeNet	0.961	0.94	0.98	0.985	0.96	0.961
	AlexNet	0.945	0.953	0.926	0.931	0.942	0.943
	ResNet18	0.964	0.97	0.95	0.954	0.963	0.965
	DenseNet201	**0.98**	0.99	0.97	0.97	0.98	0.981
Normal, Bacterial, and Viral Pneumonia	AlexNet	0.884	0.883	0.941	0.886	0.911	0.885
	ResNet18	0.877	0.88	0.94	0.875	0.91	0.909
	DenseNet201	**0.933**	0.932	0.967	0.937	0.95	0.935
	Squeeze-Net	0.860	0.858	0.929	0.870	0.893	0.862
Viral and Bacterial Pneumonia	AlexNet	0.90	0.94	0.845	0.86	0.89	0.921
	ResNet18	0.87	0.92	0.82	0.83	0.87	0.873
	DenseNet201	**0.95**	0.96	0.94	0.95	0.952	0.952
	SqueezeNet	0.83	0.905	0.75	0.79	0.83	0.84

Table 5. Contrast with recent comparable studies.

Author	Data	Research Method	Accuracy %

Ozturk et al.[35]	1000 CXR	Yolo - DarkNet	87
Das et al. [36]	1006 CXR	CNN + transfer learning	91.6
Nikolaou et al. [37]	15,153 CXR	EfficientNetB0, TL	95
Alhudjaif et al.[36]	1218 CXR	DenseNet-201	94.9
Srivastav et al.[38]	5856 CXR	DCGAN, CNN, TL	94.5
Singh and Tripathi[39]	5856 CXR	Quaternion CNN	93.7
* Our work	5247 Kaggle Chest X-ray	Pretrained Model CNN	96.9

* The literature's top-performing algorithms are indicated by **, which displays this study's performance..

DesneNet201 is the most accurate prototype currently under development for automatically classifying pneumonia data into three categories: bacterial, viral, and normal. By using an ensemble of pre-trained CNN techniques and a larger dataset for network training, future research may concentrate on improving detection accuracy.esneNet201 exhibits the highest accuracy among current research in creating a model that has automated classification pneumonia data into three categories: viral, bacterial, and normal. Future research could focus on enhancing detection accuracy by using an ensemble of previously learned models and training the network on a bigger dataset on convolutional neural network methods.

5. Conclusions

This paper suggests a transfer learning approach for autonomously detecting pneumonia and its subtypes using deep convolutional neural networks (CNNs).. We conducted training and testing on four widely-used CNN-based deep learning algorithms to differentiate individuals with and without pneumonia based on chest x-ray pictures. Among the four deep CNN networks that were evaluated, DenseNet201 performed to the best possible level. 98% of the photos depicting the right classifications for normal and pneumonia, bacterial and viral pneumonia, and normal, bacterial, and viral pneumonia were made. The precision for the same categories was 97%. Regarding bacterial, viral, and normal pneumonia, as well as bacterial and viral pneumonia, the recall rate was 96%. For both bacterial and viral pneumonia, the specific accuracy was 93.3% and 93.7%, respectively. For viral, bacterial, and normal pneumonia, the accuracy was 93.2%. For viral, bacterial, and typical pneumonia, the recall rate was 99%. Annually, this disease has the potential to cause fatalities in millions of youngsters. An accurate diagnosis of the illness, along with a prompt intervention and appropriate treatment regimen, has the potential to prevent numerous fatalities. During periods of global or developing country medical crises, when healthcare professionals are inundated, Computer-aided diagnosis, or CAD, is a life-saving technique. Furthermore, the input pictures that came from the X-ray equipment exhibit significant inconsistency as a result of the wide range of expertise levels among radiologists. When trained on a small dataset including complex data, like photos, the DenseNet201 model performs remarkably well in diagnosing pneumonia cases, displaying decreased bias and improved generalisation. We are sure that the radiologist will be able to obtain more medically useful images and quickly identify cases of pneumonia with our computer-aided diagnostic tool. This CAD technique can be applied in various settings, such as screening pneumonia patients at airports, due to its quick classification.

Author Contributions: The conceptual framework presented in this study originated from the collaborative efforts of Memoona Shakeel and Dr Ahmad Naeem, with Memoona Shakeel leading the formulation of the theory and execution of calculations. The validation of analytical procedures fell under the purview of Memoona shakeel and Muhammad Qasim Shafiq. Significantly, Dr Ahmad Naeem played a vital role by encouraging Memoona Shakeel to delve into a specific area, and overseeing the study's outcomes. Each author, including Dr Naeem Aslam, actively contributed to the final manuscript, having extensive conversations on the results during the whole investigation process.

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