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EFFECTIVE DETECTION OF LUNG DISEASE FROM X-RAY IMAGES USING CONVOLUTIONAL NEURAL NETWORKS (CNNS) AND VARIOUS ARCHITECTURES

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Abstract
A quick and correct diagnosis is essential for providing patients with quality care since lung illnesses continue to be a major worldwide health problem. The use of Convolutional Neural Networks (CNNs) in the diagnosis of lung illnesses from X-ray images is thoroughly examined in this research using a variety of architectural configurations. The goal is to improve illness classification and identification accuracy and reliability while giving radiologists and other healthcare workers a useful tool. In this study, we used InceptionResNetV2, DenseNet121, VGG16, and Xception, Convolutional neural networks (CNNs) in four distinct configurations. To make a model work better, we need a large dataset. Hence, we gathered the datasets from Kaggle; The First dataset contains 5863 X-ray images, and the second dataset we gathered has 2237 X-ray images from the COVID-19 Radiography Database, both of which are freely accessible on Kaggle. After the dataset collection, we got good accuracy, precision, recall, and f1-score. For the proposed models, 8100 chest X-rays total, including the chest X-rays were preprocessed and trained to detect bacteria, viruses, and normal chest conditions. The Experimental results confirmed that InceptionResNetV2 provides the best classification accuracy as compared to other methods. InceptionResNetV2 achieved the highest accuracy, precision, recall, and F1-Socre of 98.33%, 98.39, 98.21, and 98.30%, respectively. Therefore, this study may be useful in the faster diagnosis of pneumonia by chest X-rays.

Keywords: Pneumonia, Deep Learning, Convolutional Neural Network CNN, Image Classification.

Introduction
Lung damage occurs as a result of pneumonia, an acute respiratory infection. Pus and other fluids are contained in the air sacs., which is a fatal disease [1]. Pneumonia primarily includes two types:

bacterial and viral. The symptoms of bacterial pneumonia are typically more severe. The primary contrast between viral and bacterial pneumonia is the way of treatment. While bacterial pneumonia requires antibiotic therapy, viral pneumonia often heals on its own better [2]. The disease is pervasive everywhere in the world. Its main cause is a high degree of pollution.
In Pakistan, pneumonia claims the lives of 90,000 kids each year. The Pneumonia affects families and kids all throughout the world, despite being more prevalent in South Asia and sub-Saharan Africa. Pneumonia is the second-leading cause of death for children under five in Pakistan, where it is particularly common in nations with high mortality rates. Prior to the interventions, In Abbottabad City, there were 14 pneumonia-related there are 1 death for every 1000 children under the age of five., Pakistan. According to official autopsy procedures, 44% young children under the age of five are killed by pneumonia in a community in Pakistan’s north between 1988 and 1991. An autopsy conducted verbally by "Aga Khan Health Services" in Pakistan [3-5], In northern regions, pneumonia continues to be the leading cause of death for infants and kids between the ages of 1 and 4 years.

An inflammation of the lung parenchyma known as pneumonia can be brought on by a variety of physical and chemical causes, immune system impairment, pathogenic bacteria, and improper medications [6]. Depending on the pathogenesis, pneumonia further can be classified as non-infectious or infectious. Non-infectious pneumonia can be further subdivided into immune-related pneumonia and aspiration pneumonia, while infectious pneumonia can be further subdivided into viral, bacterial, chlamydial, mycoplasma, etc. [7]. Early diagnosis of Treatment of pneumonia with the appropriate medication can significantly improve the outcome reduce the risk of the patient's condition deteriorating and finally dying [8]. Several new technologies, like genomics and imaging, have arisen in recent years that provide complex and enormous amounts of healthcare data [9]. The best technology for diagnosing pneumonia is a chest radiograph, however because these pictures are not always clear and can occasionally be misdiagnosed by professional radiologists as benign abnormalities or other diseases, patients may receive the wrong medication, aggravating their condition. To assist When examining chest X-rays to determine which types of pneumonia are present, radiologists are able to identify an autonomous and intelligent model is required. As a subfield of machine learning, deep learning uses algorithms that mimic the structure and function of the human brain [10]. Deep learning algorithms, which have recently been developed, aid in quantifying, identifying, and categorizing patterns with the help of this layer model, images may be processed and their basic features, like edges, extracted. Using filters, CNN layers may effectively capture the temporal and spatial connections in images. CNN layers use a weight-sharing method with much fewer parameters than conventional feedforward layers, which lowers the computational complexity. As a result, our established approach helps physicians in accurately diagnosing and categorizing particular medical disorders [11]. A key benefit of this is to provide efficient deep learning of the framework chest X-ray image-based pneumonia identification that balances accuracy and complexity performance while also offering a less expensive tool for medical and radiological experts. These are the locations that are taking part:
(i) The first approach includes using a CNN version as a characteristic extraction and classification technique to perceive pneumonia from chest X-ray pictures.
(ii) Next stage will be to look into how effectively CNN and other DL models classify pneumonia.
(iii) The development of a model that can distinguish between typical and abnormal images.

• PNEUMONIA

The air sacs in one or both lungs might become inflamed with pneumonia. The air sacs may fill with fluid or pus (purulent material), which can result in fever, chills, coughing up mucus or pus, and breathing difficulties. Pneumonia can be caused by a variety of species, including viruses, fungi, and bacteria. The severity of pneumonia can vary from mild to potentially lethal. The most

susceptible include young children, elderly people, people with impaired immune systems, and people with medical conditions.as seen in Figure 1.1.
The following are the primary forms of pneumonia based on the cause of the infection, where the infection was transmitted, and how the infection was acquired:

• BACTERIAL
Streptococcus pneumonia is the most frequent cause of Bacterial pneumonia. Bacterial pneumonia can also be brought on by Legionella pneumophila and Chlamydophila pneumonia.

• VIRAL
Respiratory viruses are frequently the cause of pneumonia in sensitive populations, such as young children and the elderly. Compared to bacterial pneumonia, the symptoms of viral pneumonia usually go away fast and lightly. A physical examination or a chest X-ray can be used to diagnose pneumonia. However, because an X-ray offers a more thorough image of the heart, blood vessels, and lungs, it may aid in the diagnosis depending on the severity of symptoms and the possibility of consequences. During the X-ray analysis process, the radiologist will assess if there are any infiltrates, which are opacities in the lung fields that suggest pulmonary infection. This test can identify pneumonia complications such as abscesses and pleural effusions, which are accumulations of fluid around the lungs.

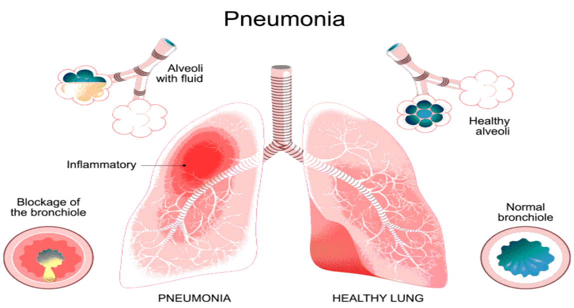
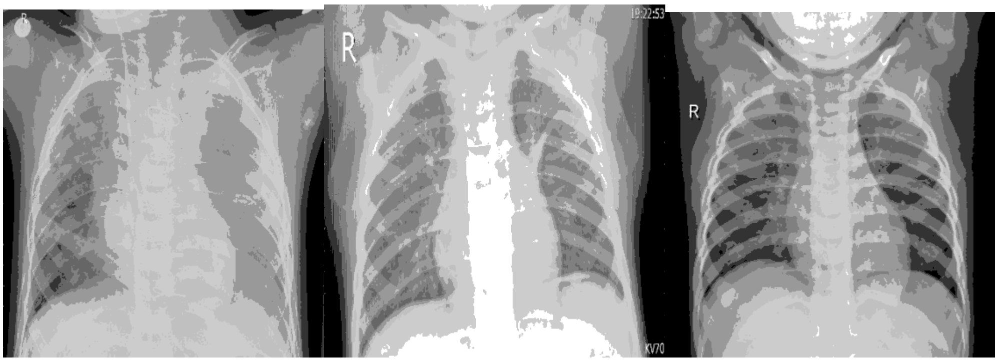


Figure 1.1: Pneumonia and Healthy Lung

• OBJECTIVES
The main goal of this initiative is to establish whether or not a person has pneumonia. With the advancement of technology, deep learning approaches are now capable of detecting pneumonia from chest X-ray images. The technique uses X-ray pictures to automatically identify viral and bacterial pneumonia.
Thesis objectives are:

• MAIN OBJECTIVE:
Implementing a model to find and categorize the following types of pneumonia in chest X-ray images, as shown in Figure 2:
- Bacterial.
- Viral.
- Normal.



Bacterial **Viral** **Normal**

Figure 1.2: Pneumonia and normal radiographs.

1.2.2. SPECIFIC OBJECTIVES:

• Review pneumonia diagnosis and detection.
• Lower the price of diagnostic procedures and frequent imaging.
• Improve your ability to detect with deep learning.

• SCOPE OF THE PROPOSED WORK

For an extensive variety of applications, which include the field of medical imaging, deep learning models have assured superior results with strong generalization capabilities compared to previous methods. Deep convolutional neural networks (CNNs) are frequently employed in the research community because they have had great success with image classification, object recognition, and picture segmentation challenges. In this study, an existing convolutional neural network architecture (DenseNet), which was created for a classification task in a natural image dataset (ImageNet), is modified along with the network's pretrained weights and then calibrated for an X-ray dataset for the diagnosis of pneumonia. As a result, the system makes advantage of deep TL to extract elements from the X-ray image that help determine whether a patient has pneumonia. Further research was done to determine the ideal number of dense blocks that should be adjusted for transfer learning without compromising performance.

TRANSFER LEARNING TL

DL algorithms needs lot of data to work well, however the models struggle because of a shortage of training data. TL approach, which is effective in addressing the issue of insufficient training data, is currently used to handle this challenge.[12]. The relationship between the pre-trained model and the novel DL algorithm can be compared to that of a teacher and student in TL. The instructor acquires in-depth knowledge of a subject before imparting it to the learner. Deep learning algorithms can be trained fast and successfully with a limited amount of labelled data because to the useful and effective learning technique known as transfer learning [13]. The main idea behind this learning strategy is to use earlier tasks of a model as a starting point for training it for new, related tasks. TL is used by medical imaging researchers since it is rapid and easy to apply and does not require a large annotated dataset for training[15]. Pre-trained models can assist a model trained on a smaller dataset in becoming more accurate and adapting to a certain domain [15]

2.1 BACKGROUND OF DEEP LEARNING METHODS

In this chapter, we first go through the InceptionResNetV2, DenseNet121, VGG16, and Xception architecture of convolutional neural networks (CNNs). Lastly, a brief explanation of the performance criteria used to rank the models in the experimental experiments is provided.

2.2. DEEP LEARNING FUNDAMENTALS

As a subfield of machine learning (ML), "deep learning" (DL) describes the use of methods that mimic the way the human brain or neural networks work. It is called an ANN because of its simulation of the brain's neural circuits and related functions. The deep learning method of machine learning (ML) is predicated on the idea that computers may be taught to learn new things by looking at existing ones [17]. This is quite human-like. It is through observation and practice that humans learn. The more concrete and specific the examples a teacher, master, or scholar provides, the more the student learns. This is why there is a positive correlation between data size and DL algorithm performance. Since deep learning approaches employ neural network architectures, these models are often referred to as "deep neural networks" (DNNs) [16]. When referring to an ANN, "deep" indicates the number of hidden layers it possesses. Convolutional Neural Networks (CNN), a popular variant of DNN, are particularly suited for evaluating picture data.

2.3. CONVOLUTIONAL NEURAL NETWORK (CNN)

High-level physical traits including head shape, ears, eyes, mouth, legs, and other distinguishing aspects are what humans use to identify animals like dogs or cats. But computers choose a different strategy. In order to extract abstract notions, they first identify minute physical characteristics like corners and curves and then use a series of convolutional algorithms to do so. With the use of these procedures, the computer can elevate low-level physical characteristics into high-level ones, making item identification easier. Convolutional Neural Networks (CNNs), a deep learning architecture specifically created for image processing and classification, are used to do this task. CNNs are well known for their extensive use and ubiquity in deep learning. Convolutional layers and filters are essential components of CNNs for the extraction of spatial and temporal information from pictures. Within these levels, weight-sharing is a method used to lessen computing complexity [18]. A CNN is composed of three structural elements: (i) a convolution layer for learning features, (ii) a max-pooling (subsampling) layer for down sampling the image and reducing its dimensionality, which reduces computational effort, and (iii) a fully connected layer for providing classification capabilities to the network [19]. Figure 2.1 provides an illustration of CNN's overall architectural layout.

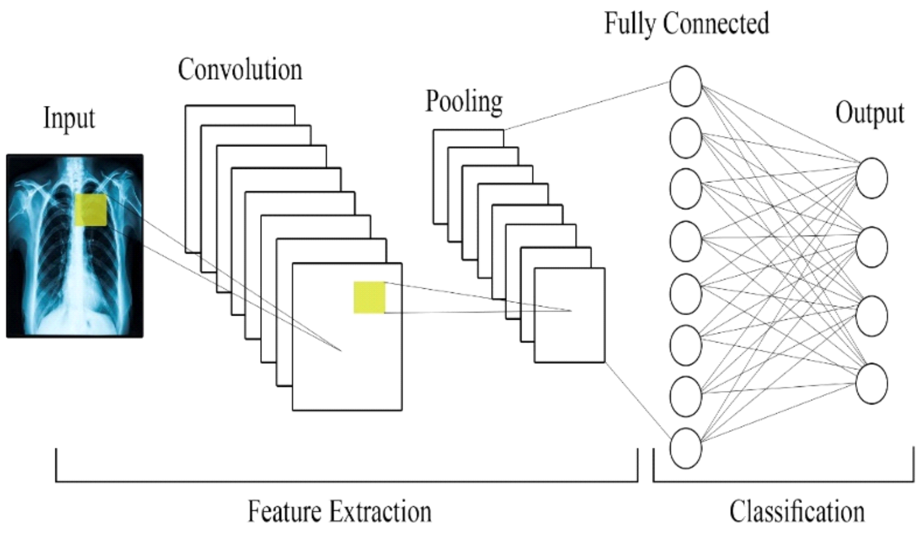


Figure 2.1: Architecture of Convolutional Neural Network (CNN)

2.4. PRE-TRAINED MODEL

A pre-trained model is one that has been developed by someone else. rather than creating and training a model from scratch. Although a pre-trained model rarely achieves perfect accuracy, It does save a significant amount of time. In this paper, four well-known pre-trained deep learning CNNs were used to diagnose pneumonia: DenseNet121, InceptionResNetV2, VGG16, and Xception. This is a high-level overview of pre-trained networks.

2.4.1. DENSENET121

It has been discovered by the researchers that convolutional networks perform better when connections are made between layers that are near to the input and layers that are close to the output. A popular kind of dense convolutional network that applies this idea is called DenseNet [20]. Traditional architectural convolutional networks have more parameters than DenseNet because of the latter's dense connection method, which does away with the requirement for a lot of feature map relearning. The network is split up into dense blocks, each of which has a fixed number of feature maps inside it but a variable number of filters overall. DenseNet has several noteworthy advantages, including as the efficient resolution of the vanishing gradient issue, the ease of feature repurposing, and the significant decrease in the number of parameters.

2.4.2. THE INCEPTIONRESNETV2

The InceptionResNetV2 Architecture is created by combining recent deep learning models residual connection and the Inception architecture [21]. This hybrid deep learning model retains the unique characteristics of the Inception network's multi-convolution kernel while getting the benefits of a residual network. The authors of [22] demonstrated how residual connections are implicit training methods for extremely deep topologies. The model ran faster thanks to this enhanced version of the Inception architecture, which also greatly increased performance. Initially, InceptionResNetV2 is composed of three blocks.

2.4.3. VGG-16

The 2014 ILSVR (ImageNet) competition was won by VGG16. It's been called the "most cutting-edge vision model design" currently on the market. The VGG-16 network was trained with data from the ImageNet database. VGG-16 [23] has 16 weighted layers, as indicated by the number 16. The VGG-16 network is highly accurate despite using small image datasets because of its extensive training.

2.4.4. THE XCEPTION

The Xception model was proposed by Francois Chollet [24]. Xception extends the Inception architecture, which performs better for the ImageNet ILSVRC and JFT datasets because modified depthwise separable convolutions are employed instead of the conventional Inception modules. Following the pointwise convolution comes a depthwise convolution, which is the modified depthwise separable convolution. The three building blocks that comprise the Xception architecture are the entry flow, middle flow, and exit flow.

2.5. CLASSIFICATION PERFORMANCE METRICS

The models were assessed using the test dataset after the training phase was completed. Performance indicators like area under the curve (AUC), precision, recall, and F1 scores were used to assess how well the models worked. All of the performance measurements used in this investigation are included in the discussion that follows. The number of photos with pneumonia that are accurately identified as such is called "true positive" (TP), while the number of images with normalcy that are correctly identified as normal (healthy) is called "true negative" (TN). The amount of normal images that are mistakenly categorized as pneumonia and the number of pneumonia images that are mistakenly labeled as normal are referred to as "false positive" (FP) and "false negative".

Accuracy: It indicates how near a measured value is to a known value.

$$Accuracy = \frac{TP+FN}{TP+TF+FP+FN} \qquad (1)$$

Precision: It indicates how accurate the model is in terms of positive predictions

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (2)$$

Recall: It computes the number of actual positives that the model was able to capture after labelling it as positive.

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (3)$$

F1-Score: It provides a good blend of precision and recall.

$$\text{F1} - \text{Score} = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} \qquad (4)$$

3.1 LITERATURE REVIEW

Many studies and publications on how to tackle the infection have been published as a result of the pneumonia outbreak. To categorize and evaluate medical images of pneumonia infections, Deep learning's accomplishment in the field of artificial intelligence has being used by researchers. This section looked at the application of AI-based models for pneumonia detection from chest X-rays, as well as previous research on this topic.

It was shown in a study by [25] that further research is still required to improve the effectiveness and precision of diagnostic systems, despite the present diagnostic approaches used to diagnose pneumonia. The current study uses radiographs to identify pneumonia in an effort to overcome this problem. Three distinct Convolutional Neural Network (CNN) variations, namely VGG16, Inceptionv3, and ResNet50, are used in this study. For model development, the strategy combines CNNs with Inception-V3, VGG-16, and ResNet50.

The introduction of a pneumonia detection algorithm trained on chest X-ray images in [26] has the potential to help radiologists in their decision-making. InceptionV3, ResNet18, Xception, Dense-Net121, and MobileNetV3 are just a few of the cutting-edge deep learning models that are used to create the study's novel weighted classifier technique. The performance of the model is then evaluated using test accuracy and AUC (Area Under the Curve) measures.

The goal of their study [27] is to develop a deep learning system (DLS) for the evaluation of chest X-ray pictures in order to detect lung problems. Working with both standard chest X-rays and chest X-rays that have been through a threshold filter is required for this activity. In the first round of the experiment, a softmax classifier is used in combination with popular DLS designs including ALexNet, VGG16, VGG19, and ResNet50. The results show that VGG19 performs better than the other approaches, with a much higher classification accuracy of 86.97%.

Every year, 700,000 children die from pneumonia, which affects 7% of the world's population. Pneumonia is a leading cause of death worldwide. X-ray imaging is widely used in the diagnosis of this condition [28]. In their research, a unique deep learning strategy that uses image processing and Transfer Learning techniques was developed to identify pneumonia. This novel approach produced astounding recall scores of 97.44% and accuracy scores of 96.00%.

The article by Kundu et al. [29] describes the development of a computer-assisted diagnostic system that autonomously identifies pneumonia using chest radiographs. To overcome the constraints

imposed by the data, the researchers implemented deep transfer learning to construct the convolutional neural network models GoogLeNet, ResNet-18, and DenseNet-121. By employing five-fold cross-validation on two publicly accessible X-ray pneumonia datasets from the Radiological Society of North America (RSNA) and Kermany et al., the proposed method was assessed. The accuracy and sensitivity values achieved by implementing this approach on the Kermany and RSNA datasets were 98.81% and 86.85%, respectively, and 87.02% and 98.80%.
The methodology employed by the authors [30] to accomplish transfer learning entailed the deployment of four unique deep convolutional neural networks (CNNs) that had been pre-trained: SqueezeNet, AlexNet, ResNet18, and DenseNet201. For their classification task based on transfer learning, they preprocessed and trained on a dataset of 5,247 chest radiographs that included bacterial, viral, and standard chest radiographs. The research study introduced three categorization scenarios: bacterial pneumonia in comparison to viral pneumonia, typical pneumonia in contrast to viral pneumonia, and typical pneumonia in contrast to viral pneumonia. It is noteworthy to remark that the reported categorization accuracy rates were 98%, 95%, and 93.3%, respectively, for images representing bacterial pneumonia, viral pneumonia, and normal pneumonia.
The research paper [31] examined the feasibility of utilizing pre-trained Convolutional Neural Network (CNN) models as feature extractors in combination with multiple classifiers for the purpose of categorizing chest radiographs as normal or pathological. To ascertain the most appropriate CNN model for the given task, a methodical inquiry was undertaken. The statistical results of this study indicate that the accuracy of chest X-ray image interpretation, specifically in the diagnosis of pneumonia, can be substantially improved by combining pre-trained CNN models with supervised classification methods. By utilizing a thoracic X-ray as its focal point, the aforementioned study ascertains the presence or absence of pneumonia by employing transfer learning and a CNN model.

As indicated in the cited source [32], machine learning and artificial intelligence are increasingly being implemented in the medical domain, particularly in areas that rely significantly on the analysis of extensive volumes of digital data and various biomedical imaging techniques. The implementation of machine learning techniques in the analysis of medical images improves the consistency and accuracy of diagnostic reports.
Convolutional neural network (CNN) models for the identification of pneumonia in X-ray images are presented in the study mentioned in [33]. These models could divide radiographs into pneumonia and non-pneumonia groups by adjusting a variety of parameters, hyperparameters, and convolutional layer combinations. Six different models are described in the article. The first two models each contain two or three convolutional layers. The last four models, VGG16, VGG19, ResNet50, and Inception-v3, are based on models that have already been trained.
The authors examine the processes and mechanisms involved in the use of deep learning for the creation of a pneumonia diagnosis model in their work published in [34]. The main objective is to develop a reliable and practical approach for pneumonia identification using X-ray pictures, with the intention of assisting chest physicians in performing quick, accurate, and time-saving evaluations. The method uses deep learning (DL) methods based on neural networks to build and apply a model that incorporates an image dataset for the diagnosis of pneumonia.
Convolutional neural networks (CNNs) have attracted a lot of interest in the field of disease classification [35] as a result of the success of deep learning algorithms in medical image analysis. Additionally, pre-trained CNN models that extract features from large datasets have great relevance for image classification applications.

The effectiveness of pre-trained CNN models as feature extractors, in conjunction with a variety of classifiers, is evaluated in the context of this study for the categorization of normal and abnormal chest radiographs. To choose the best CNN model for this purpose, careful investigation is used. The study's statistical results show how pre-trained CNN models may be used in combination with supervised classification algorithms, especially when analysing chest X-ray images for the purpose of detecting pneumonia.

The development of deep learning (DL) has significantly impacted how healthcare professionals make decisions, especially when it comes to diagnosing pneumonia in patients. For the prediction and discrimination of healthy and ill patients based on chest X-ray pictures, a comprehensive method including six different CNN models and adaptive, efficient deep learning algorithms was used in the work presented in [36].

For the goal of detecting pneumonia in their study [37], the scientists used two well-known convolutional neural network models, Xception and Vgg16. A mix of transfer learning and fine-tuning was used throughout the training phase. The test results showed that the Vgg16 network performed better than the Xception network in terms of accuracy, with accuracies of 0.87% and 0.82%, respectively. In contrast, the Xception network had a better percentage of success in identifying pneumonia patients. As a result, it was discovered that each network had unique strengths when used with the same dataset.

To conclude we can say that the given literatures has some distortion like the dataset and the improvement of Precision and accuracy, to improve the performance of CNN models, we need a huge dataset. So we collect the dataset from kaggle, first one dataset contains 5863 X-ray images and the second one we collect 2237 X-ray images from COVID-19 Radiography Database freely available on kaggle. After the dataset collection we get good accuracy and precision.

4.1 METHODOLOGY

This chapter describes the procedures utilized to conduct the research. As a study involving the creation of results from acquired data and the application of a deep learning algorithm to the data.

System training and testing are the two components of the suggested system. Before to segmenting images into small regions of interest (ROI) based segmentation during the training phase, images are preprocessed to improve contrast and noise reduction. To train the Deep Learning Neural Network, utilize this dataset (DNN). During the testing phase, ROIs are categorized using CNN models and assigned the status of normal or pneumonia. The entire image is then subjected to an aggregated decision-making process based on the identified ROIs.

The model implementation is divided into four major stages, which are as follows:

(i) Input-Stage
(ii) Pre-Processing Stage
(iii) Training-Stage
(iv)Output-Stage

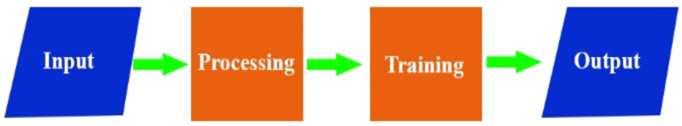


Figure 4.1: The proposed steps.

- **Input-Stage:** Red, green, and blue (RGB) color channels are present in the PNG/JPG format chest X-ray images that are sent to the model. The algorithm starts with the following step. The model's pre-processing phase will begin after the X-ray images have been loaded.

- **Pre-Processing Stage:** The algorithm's second stage involves checking the RGB format of the incoming chest X-ray images. They are converted to RGB format if they are not. The X-ray images are then downsized to 150 by 150 pixels. In order to normalise each image, each pixel's value in the input images is divided by 255. By using this normalisation technique, the original pixel value range of 0 to 255 is changed to the new range of 0 to 1. For the algorithm to effectively capture and extract important picture properties, the pre-processing stage is essential.
- **Training-Stage:** Training is the model's third stage. At this stage, the pre-processed chest X-ray images are fed into the input layer of the convolutional neural network (CNN), and the image is transferred to the output layer via the output of the final hidden layer after learning and extracting features from the hidden layers.
- **Output-Stage:** The model is at this stage, which is also the last stage. By creating two output classes, Normal and Pneumonia, the model reaches its final conclusion in this network layer (the output layer). This choice is determined in the final, probabilistic layer of the convolutional neural network.

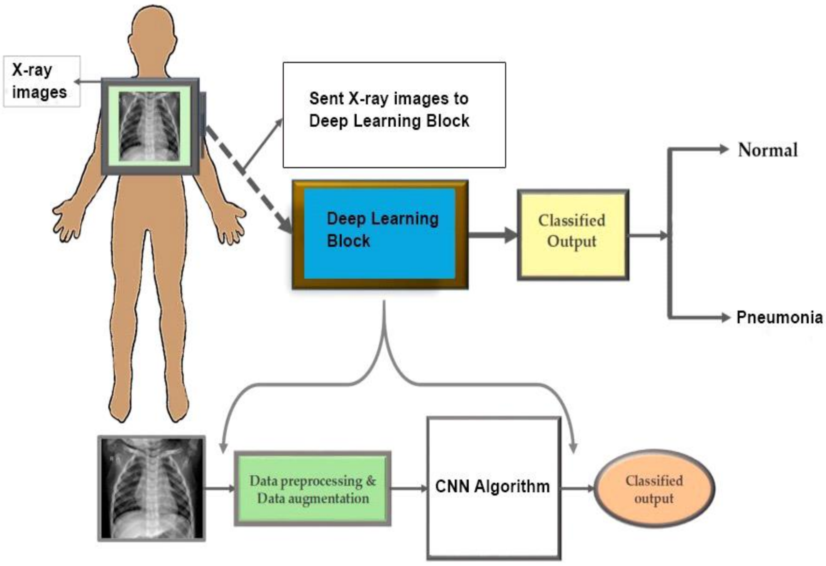


Figure 4.2: The deep learning system provided for detecting pneumonia illness.

4.2 DATASET DESCRIPTION

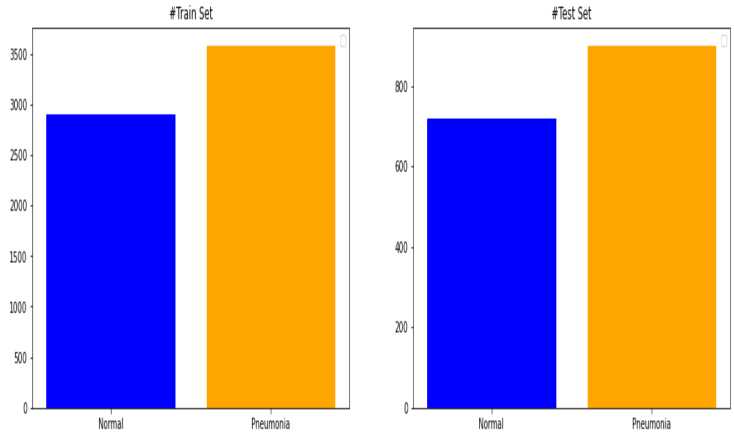
The dataset used in this research was obtained from the Guangzhou Women and Children's Medical Centre and the Guangzhou and COVID-19 Radiography Dataset, all of which are freely available on Kaggle [38-39]. According to Table 4.1, the collection includes 8100 chest X-ray images (JPEG). It is divided into two folders that are used for training and testing, respectively, and are titled train and test. In our experiment, there are 6480 images in the train folder and 1620 images in the test folder. Each of these two folders has two subfolders that each include photos that have been classified as either normal or pneumonia. Data labels are represented by subfolder names. Two chest X-ray pictures, one from the normal class and the other from the pneumonia class, are displayed in Figure 4.3.

Type	Number of X-ray images
Normal	3605
Pneumonia	4495
Total	8100

Table 4.1: Complete dataset details.

(a) Normal (b) Pneumonia

Figure 4.3: Chest X-ray with (a) healthy lungs and (b) pneumonia infected lungs



4.3 DATA PREPROCESSING

Data preparation is a crucial phase in the X-ray picture scaling process because each strategy requires a different set of image input. Depending on the deep neural network being used, each image had to be pre-processed. The normalization and shrinking phases were two important stages. Different kinds of neural networks require access to images with different sizes, depending on the details of their architecture. From then on, the X-rays will be classified as "0" for normal and "1" for pneumonitis. 150 by 150 pixel images were scaled for DenseNet121, InceptionResNetV2, VGG16, and Xception. Each and every image was compared to the requirements of a trained model.

4.4 DATA AUGMENTATION

Data augmentation is a technique for synthesizing artificially new training data from current training data. This is accomplished by employing specific procedures on training data examples to generate fresh and new training instances. The process of enhancing picture data entails producing altered duplicates of the training dataset's original image that belong to the same class. Transformations cover a wide range of image processing techniques, including flip, shift, zoom, and many others. We utilized the Image Data Generator function from the Keras package to enlarge and reduce the image.

Data augmentation is supposed to improve deep learning algorithms' categorization precision. Instead than obtaining new data, it is possible to improve the performance of deep learning models by enhancing existing data. In this study, however, the authors used three augmentation strategies to create new training sets (rotation, scaling and shear, and horizontal flip), as illustrated in Figure 4.5. Several deep learning frameworks include data augmentation techniques in their algorithms.

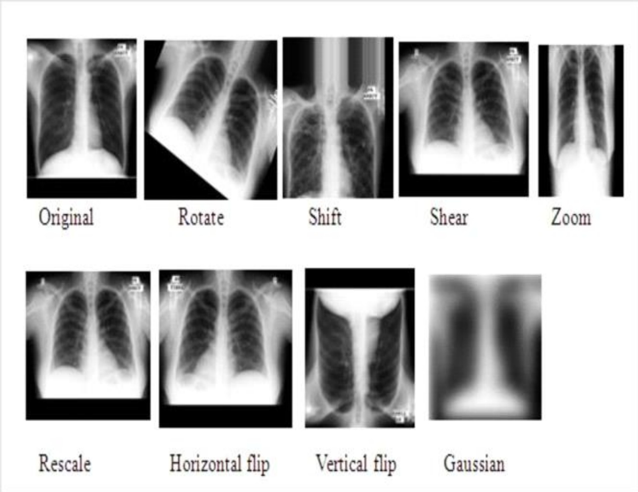


Figure 4.5: The final image following the enhancement procedure.

4.5 EXPERIMENTAL SETUP

In this study we used pre-trained algorithms and Google Colab, a free GPU cloud service offered by Google, the Python programming language was used to train, analyse, and test multiple algorithms. Each model was calibrated for 80 epochs and 32 batch sizes.

5.1. THE RESULTS AND DISCUSSION

This section outlines the methods and tests used to evaluate the suggested models' efficacy. In terms of training and testing accuracy, the performance of several CNNs for classification schemes. Among the four categorization techniques, InceptionResNetV2 yields the best results in terms of testing and training. While the training accuracy was 99.84%, the test accuracy for the classification of normal and pneumonia cases was 98.33%.

5.2. Training Results of given Algorithm

According to Table 5.1, InceptionResNetV2 outperformed other models in terms of training accuracy. With an accuracy of 99.84%, we discovered that InceptionResNetV2 does well in identifying pneumonia. 98.39% precision, 98.21% recall, and 98.30% F1 score were attained by this model.

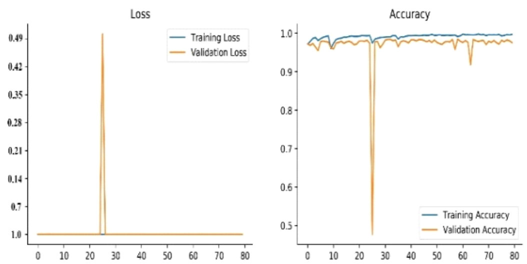
Model	Accuracy	Precision	Recall	F1-Score
InceptionResNetV2	99.84	98.39	98.21	98.30
DenseNet121	99.67	97.34	97.70	97.49
VGG16	98.53	96.73	96.73	96.73
Xception	99.75	97.40	97.60	97.49

Table 5.1: Accuracy, Precision, Recall, F1-Score of above Models

Figures 5.1–5.4 show the accuracy and loss per epoch for the proposed
Inception ResNetV2, DenseNet121, VGG16, and Xception models. The generated training-validation accuracy and training-validation loss curves for the suggested 80 epochs are depicted in Figure 5.1

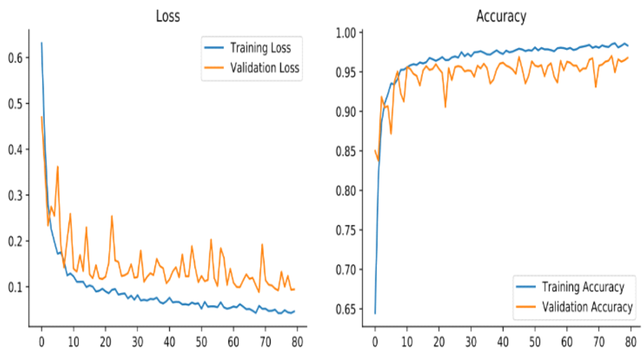
a b

Figure 5.1: InceptionResNetV2 based pneumonia disease Detection: (a) loss in keeping with epoch and (b) accuracy in keeping with epoch.



a b

Figure 5.2: DenseNet121 based pneumonia disease Detection: (a) loss per epoch and (b) accuracy per epoch.



a b

Figure 5.3: VGG-16 based pneumonia disease Detection: (a) loss per epoch and (b) accuracy per epoch.

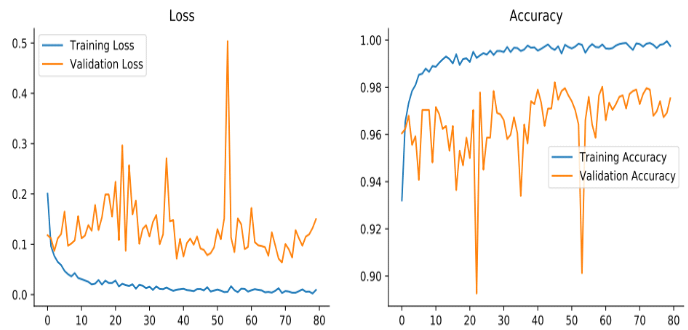


Figure 5.4: Xception based pneumonia disease Detection: (a) loss per epoch and (b) accuracy per epoch.

2. RESULT IN TERMS OF TESTING ACCURACY

The F1-score values for the four suggested CNN models—InceptionResNetV2, DenseNet121, VGG16, and Xception—as well as accuracy, precision, and recall are shown in Tables 5.2–5.5. According to Table 5.2, the InceptionResNetV2 model performs best in terms of accuracy, recall F1 score, precision, and 98.39%. The DenseNet121 model's accuracy, precision, recall, and F1-score were 97.53%, 97.70%, 97.49%, and 97.34%, in that order. The precision, recall, F1-score, and accuracy of the VGG16 model were 96.73%, 96.73%, 96.73%, and 96.79%, respectively. Table 5.5 displays the precision, recall, F1-score, and accuracy results for the Xception model, which were 97.33%, 97.40%, 97.60%, and 97.49%, respectively. The confusion matrix provides insight into the inaccuracy that the classifiers utilized produced. It is used to describe how well test photos were classified given true values that were known. With the "adam" optimizer, 80 epochs, and 32 batch sizes, experiments were successfully completed.

Pneumonia Classes	Precision	Recall	F1-Score	No of Tested Images
Normal	0.99	0.97	0.98	705
Abnormal	0.98	0.99	0.99	915
Accuracy			0.98	1620
Macroaverage	0.98	0.98	0.98	1620
Weighted	0.98	0.98	0.98	1620
Average				

Table 5.2: Precision, recall, F1-score, and accuracy metrics were achieved for the proposed InceptionResNet121 model.

Pneumonia Classes	Precision	Recall	F1-Score	No of Tested Images
Abnormal	0.95	0.99	0.97	705
Normal	0.99	0.96	0.98	915
Accuracy			0.98	1620
Macroaverage	0.97	0.98	0.97	1620
Weighted	0.98	0.98	0.98	1620
Average				

Table 5.3: Precision, recall, F1-score, and accuracy metrics for the DenseNet121 model were collected.

Pneumonia Classes	Precision	Recall	F1-Score	No of Tested Images
Abnormal	0.96	0.96	0.96	705
Normal	0.97	0.97	0.97	915
Accuracy			0.97	1620
Macroaverage	0.97	0.97	0.97	1620
Weighted	0.97	0.97	0.97	1620
Average				

Table 5.4: Precision, recall, F1-score, and accuracy metrics for the VGG16 model were collected.

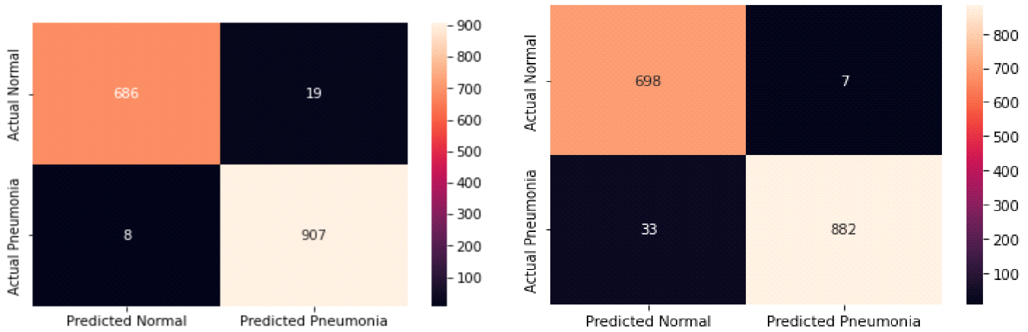
Pneumonia Classes	Precision	Recall	F1-Score	No of Tested Images
Abnormal	0.96	0.98	0.97	705
Normal	0.99	0.97	0.98	915
Accuracy			0.98	1620
Macroaverage	0.97	0.98	0.97	1620
Weighted	0.98	0.98	0.98	1620
Average				

Table 5.5: Precision, recall, F1-score, and accuracy metrics for the Xception model were collected.

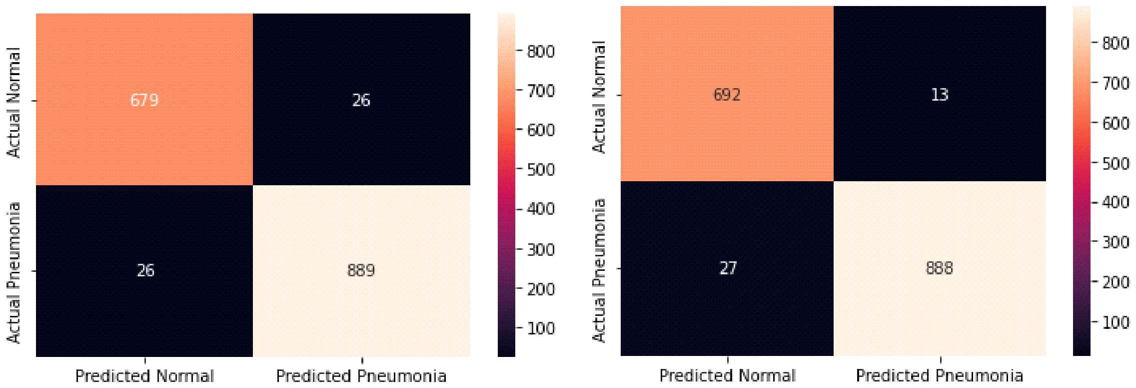
3. PERFORMANCE ANALYSIS

When assessing models, the confusion matrix is an invaluable resource. The performance of a classification model on test data is shown in a square matrix table. The numbers that create the shape of a cow along the off-diagonal represent the samples that were incorrectly detected. Our model's weaknesses and enhancements are illustrated in a confusion matrix. Numbers along the diagonal indicate samples that the model correctly identified, whereas numbers away from the diagonal indicate samples that the model incorrectly classified.

To further evaluate the reliability of the provided methodology, the accuracy, recall, precision, and F1-score of the proposed weighted classifier and individual models were ascertained. After acquiring confusion matrices for every design, we were able to compute the intended scores (Figure 5.5). We were able to determine the fraction of accurate classifications, incorrect classifications, false positives, and false negatives using the confusion matrix to evaluate the accuracy of the model.



(a) **InceptionResNetV2** **(b) DenseNet121**



(c) VGG16 **(d) Xception**

Figure 5.5: Confusion matrix for (a) InceptionResNetV2, (b) DenseNet121, (c) VGG16, (d) Xception.

CONCLUSION

Each year, pneumonia claims hundreds of thousands of lives, making it a primary cause of mortality in young children and the elderly. Pneumonia risk factors include smoking, drinking, having surgery, having asthma, having a weaker immune system, and being over 65. Potentially lowering pneumonia mortality is early diagnosis and timely treatment of pneumonia. Chest X-rays are often used by skilled specialists to detect pneumonia, but the scarcity of medical professionals and the recent rise in pneumonia cases have made treatment challenging.

This paper suggests a DL method for exploiting chest X-ray images to automatically detect pneumonia. In our studies, we used the Convolutional Neural Network CNN and the pre-trained models InceptionResNetV2, DenseNet121, VGG16, and Xception. Using chest X-ray pictures, four well-known CNN-based deep learning algorithms were developed and put to the test for the classification of normal and pneumonia patients. It was found that InceptionResNetV2 performed better than the other three deep CNNs. With scores of 98.33% accuracy, 98.31% precision, 98.73% recall, and 98.28% for F1, InceptionResNetV2 outperformed the other models in terms of accuracy.

FUTURE WORK

This proposed model can be used to identify COVID-19, as well as other diseases and pneumonia. This research will eventually be expanded to recognize and categorize X-ray images including lung cancer and Covid-19. We will address this issue in our future strategy because it has recently become a significant one.

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