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# Classification of Pneumonia in Chest X-Ray Images Using CNN and Varying Batch Size

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**ABSTRACT:** Pneumonia is one of the most common infectious diseases caused by bacteria or viruses; it affects many people, especially children and the elderly, all over the world in a short period due to the flow of fluid in the lungs. According to COVID-19 studies, aged people and people with a history of different medical issues, especially earlier cases of pneumonia, are at a greater risk of acquiring serious COVID-19 health complications. Because pneumonia is a common disease that affects the lungs, doctors frequently use a chest X-ray to identify high-risk lung areas. Early detection of pneumonia is essential for curative treatment and increasing survival rates. The goal of this study was to use CNN architecture and the Stochastic Gradient Descent (SGD) optimizer with batch sizes of 16 and 32 to detect the presence of pneumonia in input chest X-ray images. For predicting pneumonia, the model was evaluated and statistically validated. Several scores were computed to evaluate the effectiveness of the proposed model, including testing accuracy, precision, recall, and loss. The proposed model obtained a test recognition accuracy of 94.5%.

**KEYWORDS:** Pneumonia Detection; ResNet 50; Inception V3; Deep Learning; Adam Optimizer; Transfer Learning; Stochastic Gradient Descent Optimizer; Convolution Neural Networks; Accuracy; Radiological Society of North America (RSNA)

## I. INTRODUCTION

The WHO recently identified pneumonia as one of the most dangerous diseases, estimating over a million premature deaths worldwide. According to the World Health Organization, pneumonia is responsible for nearly 15% of all deaths in children under the age of five. As of 2017, this amounted to nearly 8,08,694 children. It affects approximately 450 million people worldwide each year. Pneumonia is becoming increasingly common in rapidly developing countries. Because pneumonia is caused by a variety of bacteria and viruses, X-rays are the primary diagnostic tool for detecting pneumonia.

Numerous research papers have been published in an attempt to solve the problem of pneumonia detection, and many of them have made improvements to the model. Typically, trained radiologists have diagnosed and classified pneumonia. Many researchers use deep learning methodologies to identify and recognize the type of pneumonia disease. A. Manickam et al. [1] proposed a Chest X-ray dataset containing 5232 X-ray images to detect the presence of pneumonia using U-Net structure segmentation and categorize pneumonia as normal, Bacteria, or viral using InceptionResNetV2, InceptionV3, and ResNet50. Additionally, Adam and Stochastic Gradient Descent (SGD) are used to extract useful features, and performance is evaluated with batch sizes of 16 and 32. Ayush Pant et al. [2] proposed a "ResNet-34 based U-Net" that is combined with an EfficientNet-B4 based U-Net, these features were fed to range optimizer and achieved recognition accuracy on chest X-ray image dataset as 93.3%. M. D. Kamrul Hasan et al. [3] developed a pneumonia detection model using CNN and VGG-16 transfer learning models. These features were then fed into hyper parameters such as Adam optimizer, achieving an average recognition accuracy of 91.69%. Hashmi et al. [4] presented compound scaled ResNET50 which is an upgraded version of ResNet 50. These features were then fed into an SGD optimizer with a learning rate of 0.01, achieving an average recognition accuracy of 89.19%. Shanay Shah et al. [5] developed a CNN model with four convolutional layers, ReLU activations, one dense layer, and sigmoid activation function. This model was created to detect pneumonia. These features were then fed into a 20-epoch Adam optimizer, obtaining an average recognition accuracy of 92.47%. Tatiana Gabruseva et al. [6] created an algorithm for detecting pneumonia regions using single-shot detection systems, squeeze-and-extinction deep CNN, multi-task learning, and augmentations, and the model was tested at the RSNA Pneumonia Detection Conference. A. Kareem et al. [7] studied Pneumonia using an X-ray image. This survey also looks into how k-nearest neighbor (KNN), deep learning models such as convolution neural network (CNN), CheXNet, RESNET, DECNET, and artificial neural network (ANN) can be used to detect pneumonia disease. A Sharma et al. [8] classified pneumonia infection using a CNN model based on a Chest X-ray dataset. A four-layer CNN model classifies pneumonia or non-pneumonia using extracted features



and achieves 84.1% recognition accuracy. Dirisala Yaowu Chen et al. [9] created pneumonia detection using faster R-CNN and transfer learning and a Deep Conv-DilatedNet-based methodology for analyzing and locating pneumonia in chest X-ray images.

The format of the research paper is as follows: The first section discusses the methodology of the paper to the proposed model. Section 2 outlines the experimental results and performance analysis, and Section 3 concludes this paper.

## II. METHODOLOGY

The pneumonia classification algorithm proposed in this paper classifies pneumonia from X-ray images of the chest. To learn more specific features from X-ray images of patients, a deep learning algorithm was used, allowing the model to detect pneumonia more accurately. The following working steps provide comprehensive knowledge of this research work using a flow chart as shown in Fig 1

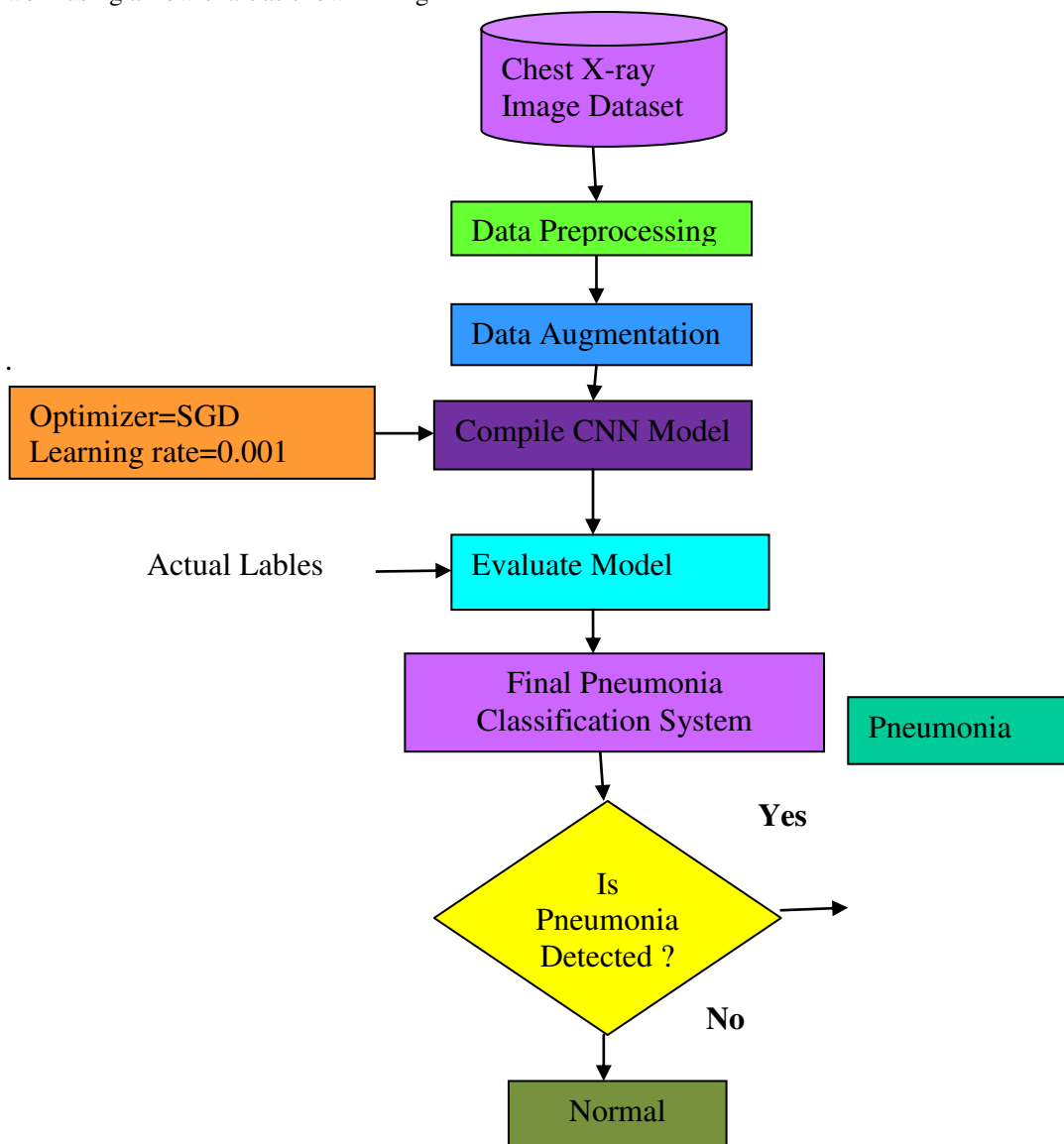


Fig 1: flow chart for pneumonia classification

1.1 Chest X-ray Data set

A publicly accessible Kaggle [10] dataset was utilized to evaluate the method. As shown in Table 2, this database contains 5,856 color chest x-ray images from Kaggle, including 3875 pneumonia images and 1341 normal image details presented in Table 1. The dataset has been divided into three sections, namely validation, training, and testing. Each image category has its subfolder, such as pneumonia and normal images. Fig.2 depicts the dataset's normal and pneumonia sample images. Data visualization of Chest X-ray imbalanced dataset as shown in Fig.3

Table 1: Chest X-ray Dataset information

Number of images in the Dataset	Normal
Train	1341
Test	234
Validation	8

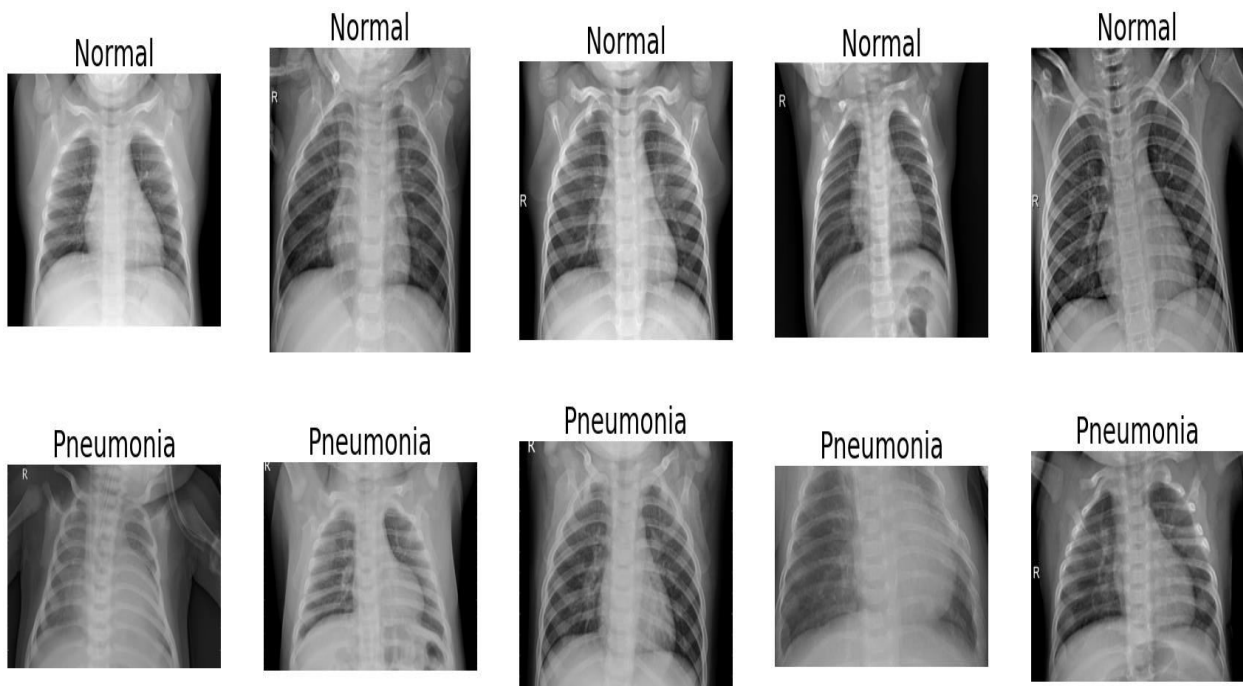
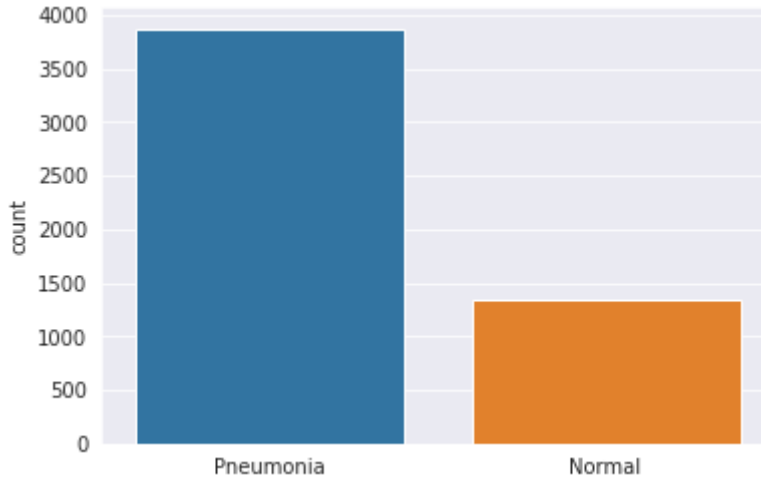


Fig 2: Chest X-ray normal and Pneumonia images



## 1.2 Data preprocessing

Image pre-processing is a common and helpful deep learning technique. For better computation, the input Chest X-ray images were resized to 160 x 160 x 3 and used to train the CNN model. The pixel intensity values were then normalized by dividing them by 255. The pixels in the chest X-ray image are thus represented by floating point numbers ranging from 0 to 1, rather than integer numbers ranging from 0 to 255. This should have a positive impact on CNN's performance.

## 1.3 Data Augmentation

Data augmentation was performed due to an imbalance in the number of training examples of images showing pneumonia versus those that were normal. One solution to the problem of overfitting is data augmentation. To train the model, a variety of data augmentation techniques such as height, width, and zoom were used, which may aid the model in correctly identifying the test image. Table 2 displays the hyperparameters for data augmentation settings. Fig.3 depicts the various augmentations applied to training sample images

Table: 2 Hyperparameters for data augmentation settings.

Hyperparameters for Data Augmentation	Values
Zoom range	0.2
Width shift range	0.1
Height shift range	0.1



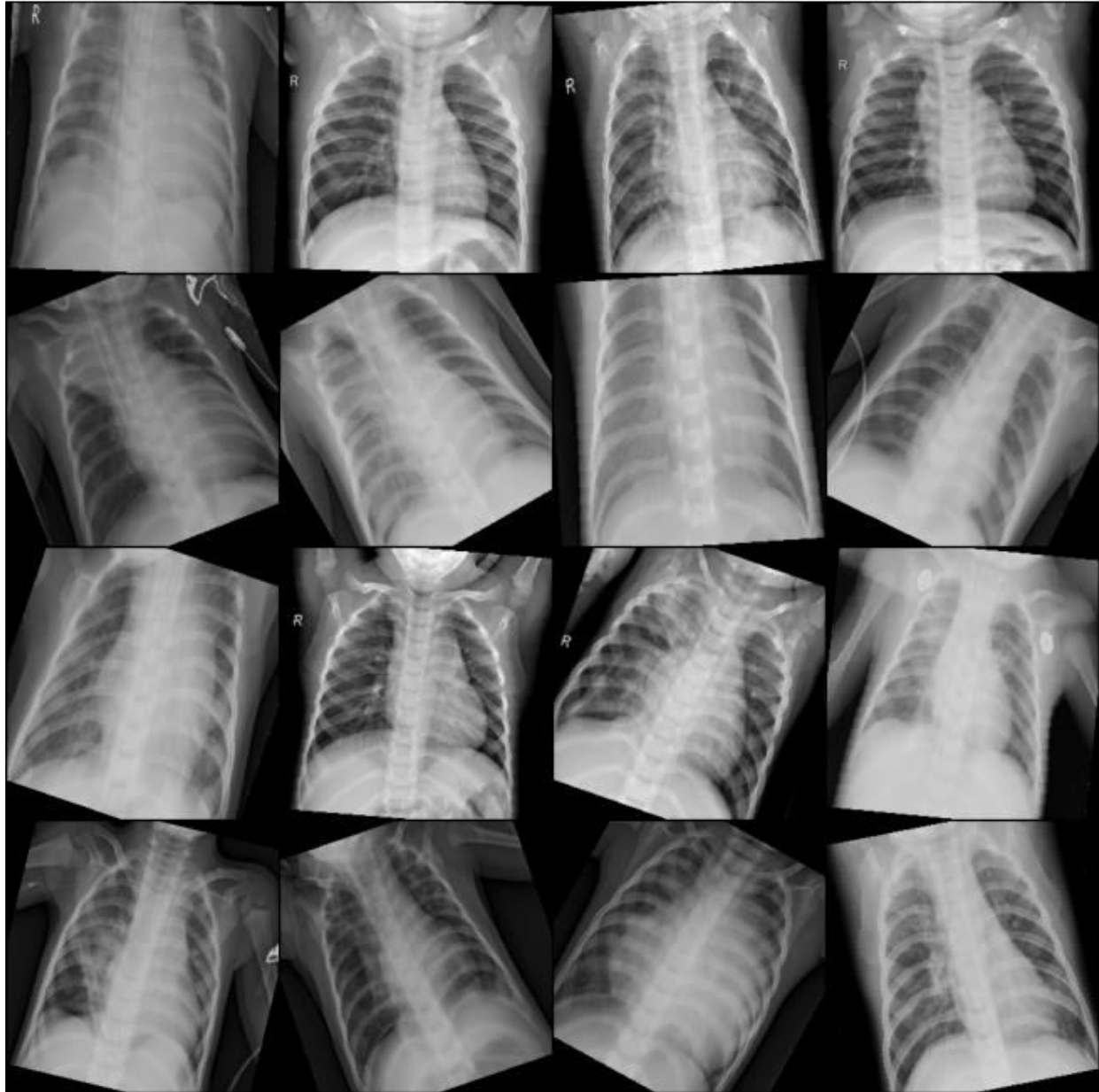


Fig: 3 various augmentations techniques on chest X-ray images.

#### 1.4 Architecture of the CNN model

CNN is made up of four layers of processing, namely a convolutional layer, a pooling layer, a flattening layer, and a fully-connected layer. Each layer is explained in detail in the following subsection.

The main building block of CNN is the convolution layer, which converts the image into a matrix on which the convolution operation is performed using a set of defined learnable filter parameters. The below figure demonstrates the architecture of the CNN model. The kernel is a simple square matrix that moves across the image from left to right and top to bottom. . In this paper, a 3 X 3 filter is used to extract the features from the input matrix to reduce the size of the image and thus make the processing function easier. To obtain a convolution feature layer, multiple filters are applied to the input matrix. This model is subjected to pooling, flattening, and fully-connected layers to produce the complete CNN. CNN employs stride and activation functions. Stride is a neural network filter parameter that modifies the amount of movement over the image or video. We could have stride 1, so we'll go one at a time.

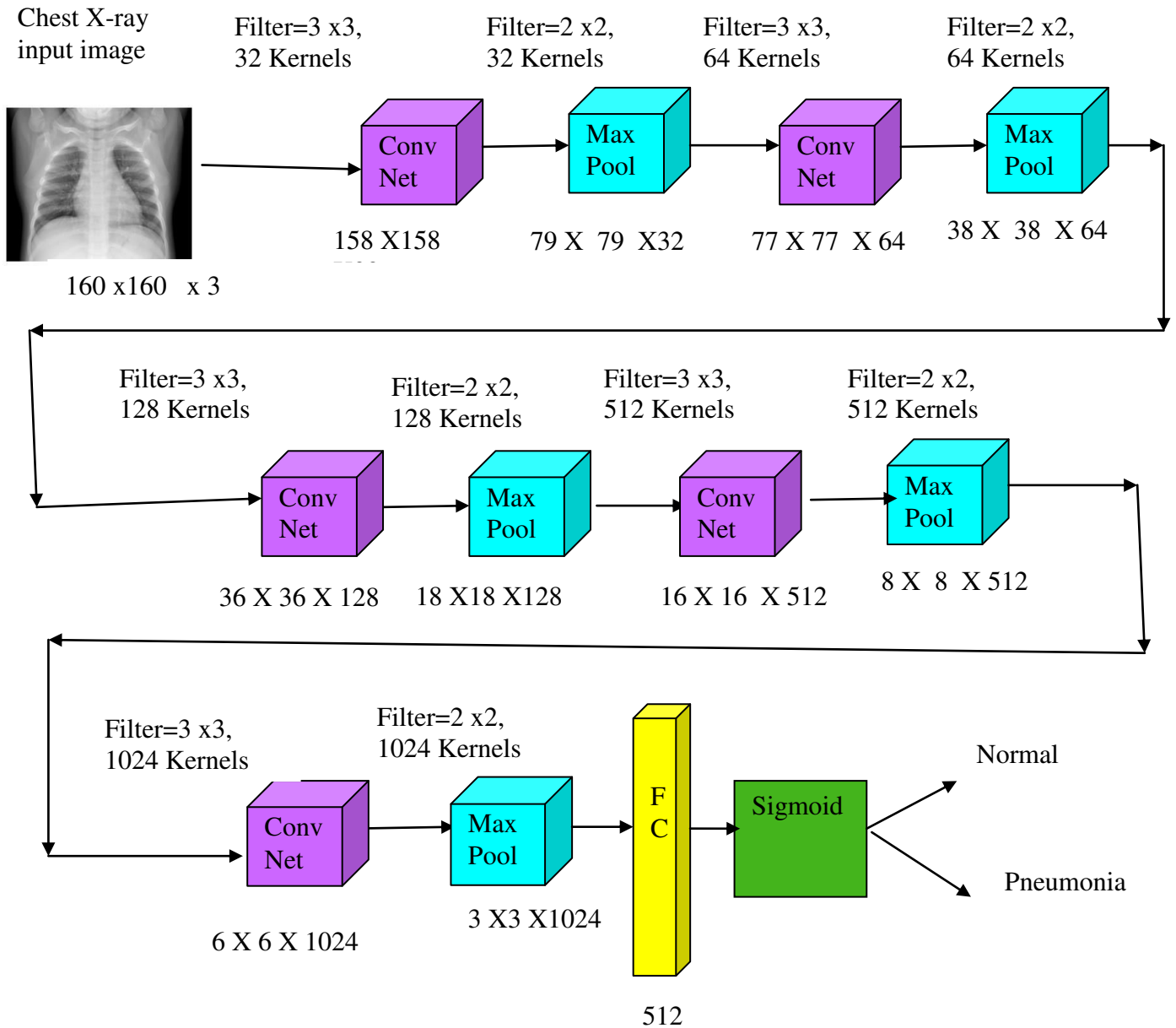


Fig 4 Architecture of the CNN model

Activation Function determines whether or not to initiate a neuron. This means that during the prediction process, it will determine whether the neuron's input to the network is important or not. Max Pooling is a pooling operation that computes the maximum value for a feature map. It is generally used following a convolutional layer. It tends to add a small amount of translation invariance. Fig 4 depicts the architecture of the CNN model. Initially, 160 x 160 x 3 Chest X-ray was used to train the CNN model. A 160x160 picture with valid padding, filter size =3x3, stride=1, and activation function="Relu" attributes is included in the input data. This produced 32 feature maps, indicating that it is convoluted across 32 channels, and the layer has padding=1, indicating that the output maintains the image size of 158 x 158, where max pooling is used after the CNN layer to reduce dimensionality to 79 x 79 x 32. Second layer 64 filters and maintains image size as 77 x 77 x 64. Then pooling layer is added to the new dimension will be 38 x 38 x 64. The third convolution layer employs 128 kernels with an image size of 36 x 36 x 128, followed by a max pooling layer with dimensions of 18 x 18 x 128. The fourth convolution layer employs 512 kernels with an image size of 16 x 16 x 512,



followed by a max pooling layer with dimensions 8 x 8 x 512. The fifth convolution layer employs 1024 kernels with an image size of 6 x 6 x 1024, followed by a max pooling layer with dimensions 3 x 3 x 1024. Finally, we have 3 x 3 x 1024 into a fully connected layer with 512 units with a sigmoid as the activation function and one of two classes. We extracted features from the Chest X-ray image and used them in the compilation. Following that, the model is optimized using stochastic gradient descent with a learning rate that decays exponentially from 0.01 and binary cross entropy as the loss function. We trained the model over 50 epochs, with steps per epoch equal to the number of images in the training set divided by batch size (16 or 32), allowing us to train the entire training set in each epoch. The optimizer has a major effect on the model's performance. Designing optimizers that improve practical convergence speed and generalize well across different settings is extremely difficult. In this paper, we have selected stochastic gradient descent (SGD) optimizers. stochastic gradient descent prioritizes data points. As a result, algorithms like SGD generalize data more effectively at the expense of slow computation speed. As a result, the optimization algorithms can be chosen based on the requirements and data type.

#### IV. CLASSIFIER EXPERIMENTAL RESULTS BASED ON THE CNN MODEL

This section presents the experimental results of chest x-ray image classification. The research was carried out in the Python environment. The proposed evaluation was conducted using performance metrics such as precision, recall, and accuracy. The best metric for a classification problem is accuracy for the balanced dataset. The accuracy rate in the test set across epochs ranges between 75% and 93 % as shown in Fig 5. The training set loss is decreasing, while the test set loss is hovering around 0.2 to 0.5 as shown in Fig 7. For imbalance data sets, precision and recall are better measures than accuracy.

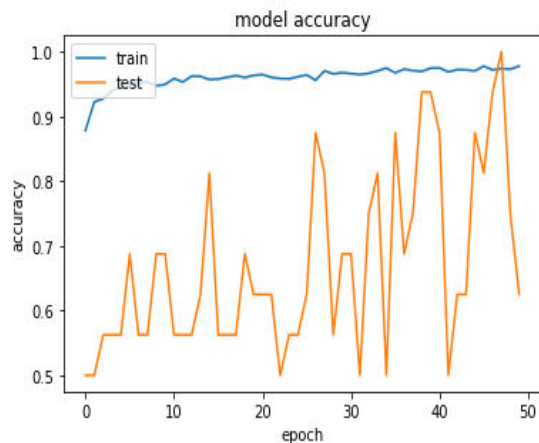


Fig. 6 Model accuracy against epoch

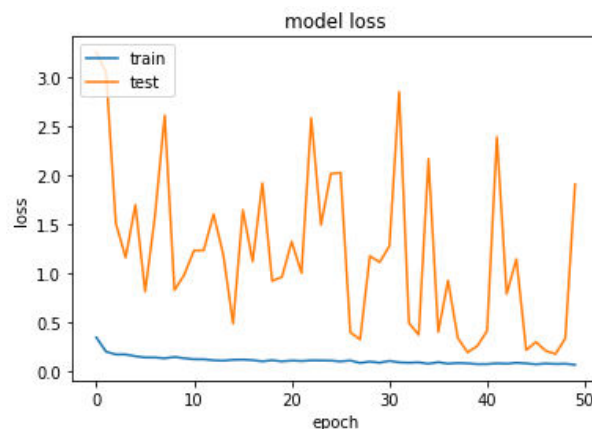


Fig. 7 Model loss against epochs

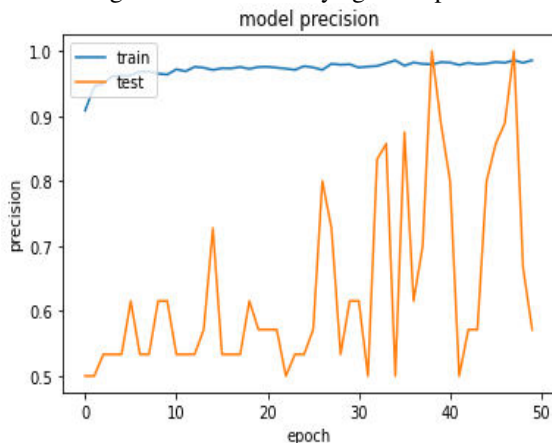


Fig. 8 Model Precision against epochs

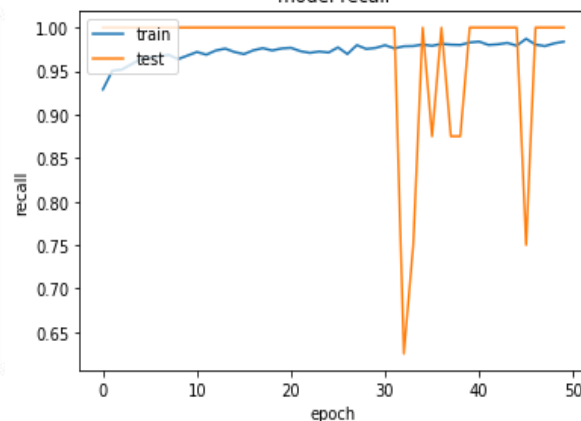


Fig. 9 Model Recall against epochs



Table 7: Comparison of different batch sizes on CNN model using evaluation metrics

Batch size	Accuracy	Test Loss	Precision	Recall
16	93.90%	0.254	94.50%	98.40%
32	94.50%	0.21	95.40%	98.80%

The recall is the percentage of positive events correctly predicted by the model. Precision is the ratio of predicted positive events that are positive. In this case, we would like to reduce the number of False Negatives because we do not want to miss any pneumonia patients in the batch. The perfect evaluation metric to use here is recall, which measures false negatives. The average precision rate in the test set across epochs is 95.4 % as shown in Fig 7. The average Recall rate in the test set across epochs is 98.8 % as shown in Fig 8. Table 7, compares the proposed model recognition accuracy, precision, and recall to two different batch sizes on the chest X-ray dataset. We concluded that the model evaluation metrics for batch size 32 were superior to those for batch size 16. Furthermore, the proposed method was compared to the previous research work on the pneumonic classification problem, with the results shown in Table 8. According to Table 8, the proposed method outperforms some of the existing methods.

Table 8  
Compare the proposed method to the existing techniques using accuracy metrics.

Methodology	Accuracy (%)
Inception ResNet V2 [1]	92.4
ResNet 34-based U-Net [2]	93.3
VGG-16 [3]	91.6
Upgraded ResNet [4]	89.19
CNN [5]	92.47
CNN [8]	84.1
Proposed method	94.5

## V. CONCLUSION

In this paper, we proposed a deep learning-based method for diagnostic testing and classifying pneumonia from Chest X-ray images using the CNN model. The extracted features have been classified using CNN architecture based on SGD optimization and a batch size of 32. The experimental results achieved 94.5 % testing accuracy, 0.21 errors, 95.4 % precision, and 98.8 % recall. Furthermore, it was demonstrated that the proposed work results were much better in terms of accuracy than other architectures, and the overall performance is much better than older works. A model is trained by using pre-trained architectures and the use of larger data sets can improve performance even more.

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