# Parameter Optimization in Convolution Neural Network Model to Accurately Predict Pneumonia in Chest X-ray Images

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*Abstract*—**Parameter optimization plays a major role in training any convolution neural network model. By effectively adjusting the network parameters, the feature learning capabilities and classification accuracy can be improved. In order to segregate the positive and the negative pneumonia infection using chest X-rays, this work seeks to investigate the ideal number of convolutional layers, filters,kernels activation functions and optimizers. The source of the dataset is pneumonia radiological society of North America challenge. Initially, the preprocessing stage uses the Contrast Limited Adaptive Histogram Equalization algorithm to improve the brightness and contrast of the chest X-ray images. Convolution neural network model with parameter optimization is employed for classification. Four activation functions and optimizers suitable for binary classification are chosen for experimentation. The efficiency of this model is tested by few metrics like accuracy, precision, recall, F1 score, area under the curve and receiver operating characteristics. The results obtained are compared with earlier research work available in literature. The comparative findings show that the proposed approach for classifying pneumonia performs better.**

*Index Terms*—**convolution neural network, parameter optimization, pneumonia, root mean square propagation optimizer, sigmoid activation function**

## I. Introduction

CONVOLUTION is one of the most important and a common technology used in computer vision. It is a regularized feedforward neural network model in which the model learns the features by itself [1]. CNN has achieved great appreciation in video recognition [2]–[4], recommender systems [5]–[7], natural language processing [8] and medical image analysis [9]- [10] through its automatic and adaptive learning capability. Pneumonia is a deadly infectious disease caused by bacterium called streptococcus pneumonia. It disturbs the human lungs making the infected person difficult to breathe [11]. This in turn makes the patient fatal. Pneumonia is initially analyzed by physical examination and then verified through chest radiographs by doctors [12]. In recent years, few researchers have introduced computer algorithms [13]- [14] and computer-aided diagnostic tools [15]- [16] to accurately detect the presence of pneumonia affected regions from chest radiographs. Convolution neural network model has also been used in recent times to examine pneumonia-affected lung region [17]- [18].

Detection of pneumonia and other similar lung disorder using convolution neural network is carried out by various researchers. Some of the pneumonia detection methods using CNN models are included in [17]- [19]- [20]. Ranjan et al., [17] employed three layer CNN model with softmax activation function for classifying eight lung diseases using front chest X-ray images. The work resulted in 0.54 classification accuracy. Varshini et al., [19] employed the DenseNet169. This model is used for feature extraction, while the support vector machine was utilized for classifications, which achieved an accuracy of 0.74. In [20] the researchers designed a customized CNN model to identify pneumonia in chest radiographs. The model gave a 0.93 validation accuracy. In [21] researchers performed an experimental analysis on 5856 chest radiographs to classify the images as pneumonia and no pneumonia. The model which consisted of three convolution and pooling layers, with ReLU activation and dropout rate of 0.3 gave 0.92 accuracy.

Convolution neural network consists of many hyperparameters like activation function, optimizers, number of layers, epochs, number of filers etc [22]. Each of these parameters affects the model performance. Thus selecting the right hyperparameters is important to help the network learn effectively and play a vital role in accurate classification. This paper conducts extensive experimentation to identify a suitable number of layers, filters, activation function and optimizer to classify pneumonia positive and pneumonia negative images from the dataset. The paper is structured as follows: Section II shows the materials and methodologies incorporated in the work. Section III demonstrates the results obtained and section IV draws conclusion from the obtained results.

## II. Materials and Methods

This section describes the dataset and discusses the preporcoessing steps, incorporated parameter optimizers and model design process.

### A. Dataset

This study used data from the ”ChestX-ray8” hospital-scale chest X-ray image database, which is part of the stage 2 pneumonia radiological society of North America (RSNA) challenge. [23]. Text mining and natural language processing tools are used to create chest radiographs based on X-rays and doctor’s reports. The compiled chest X-ray image dataset

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TABLE I
DEMOGRAPHIC DETAILS OF PARTICIPANTS USED IN THIS STUDY

| | Normal | Pneumonia |
|---|---|---|
| Number of subjects | 6000 | 6000 |
| Gender (Male/Female) | 3378/2622 | 3501/2499 |
| Age (Mean,Range) | (47,26-50) | (45,26-50) |

was authorized using 3851 chest X-ray images. Finally, the images are grouped as normal and pneumonia, and processed to digital imaging and communications in medicine (DICOM) format. In stage 2 dataset 26,684 images were used which includes 6,000 images of pneumonia cases and the normal control images. In order to balance samples, we utilized 6,000 pneumonia X-ray images and 6,000 healthy X-ray images. Totally 12,000 images were used for this study. Table. I shows the demographic data of the dataset. From Table. I, it is observed that number of persons affected by pneumonia are 6000. Number of males and female affected by pneumonia are 3501 and 2499 respectively. The average age of the number of affected persons is 45 years and they fall in the range of 26-50 years.

### *B. Pre-processing*

Data processing is an essential task while deploying a CNN model. Since the models takes input image of size $224X224$, the dataset is reshaped to a dimension of $224X224$ from $1024X1024$ dimensions. The normal lungs do not absorb X-rays, they look black in colour in any chest radiographs. Pneumonia can be located by identifying a hazy area or a gray dashed shadow. To these X-ray images, contrast and brightness enhancement applications are applied to increase the recognition rate. In this work, the contrast limited adaptive histogram equalization (CLAHE) algorithm is used to equalize the gray histogram and to enhance brightness and contrast [24]. The enhanced images are then loaded to the CNN model.

### *C. Parameter Optimizers*

This section discusses the hyper parameters that are used to train the CNN model. The parameters considered are number of layers and filters, activation functions and optimizers.

*1) Number of layers:* Number of convolution layers play an important role in the model design process and also for accurate classification [25]. An initial experiment is conducted to identify the optimum number of convolution layers that results in highest classification accuracy. The experiment started with 5 layers and was incremented gradually. The highest accuracy of 0.90 was observed for 19 convolution layers and the accuracy decreased for 20 layers and beyond due to overfitting. Thus CNN model with 19 layers is considered for further experimentation.

*2) Number of filters:* In a CNN model, filters are small matrices used to perform computational task. These filters are pivotal in extracting useful features from input image or from other multidimensional data. Filters slide over the input data performing element wise multiplication followed by summation of results. With the help of optimizers, the filters minimizes loss function and becomes better at extracting useful features that inturn help the network achieve good performance [26]. An initial investigation was conducted to identify the suitable number of filters which resulted in the highest classification accuracy. It is studied from [27]- [28]. A 3×3 filter has a huge receptive field compared to other filter sizes, which enable it to capture more accurate information from the input data. This helps in detecting more complex features, such as edges, textures, and patterns. Stacking multiple 3x3 convolutional layers can achieve a similar receptive field to a larger filter while maintaining fewer parameters. This hierarchical structure enables the network to learn features at different levels of abstraction. Thus, 64 filters of size 3X3 was found to be more appropriate and is been incorporated in this work. Accuracy obtained with various filter size is shown in Table III.

*3) Number of Kernels:* Kernel is a component of a filter where each kernel produces one feature map. For a grayscale X-ray images, the number of filters is equal to the number of kernels, as each filter corresponds to a single channel in the input [29]. Since our work includes X-ray dataset which is a greyscale image, the number of kernels used is same as the number of filters incorporated in the convolution layer.

*4) Activation function:* Activation function plays a key role in any convolutional neural network. An activation function in a CNN model adds nonlinearity to the model. The decision to update a neuron based on bias and weighted sum is done by an activation function. [30]. Few of the major activation functions are linear, softmax, sigmoid, swish, TanH, parametric ReLU, exponential linear unit, ReLu and leaky ReLu etc. Amongst these, the activation functions that are suitable for binary classification are sigmoid, TanH, ReLu and leaky ReLu.

**Sigmoid activation function:** generates values between 0 and 1 from a real value input. The range in (0,1) is obtained by translating the input range from $(-\infty,\infty)$ using the sigmoid activation function. Sigmoid activation function is calculated by equation 1.

$$f(x) = \frac{1}{1 + e^-x} \tag{1}$$

**TanH activation function:** is analogous to sigmoid activation function where it takes input values from $(-\infty,\infty)$ and outputs the values from -1 to 1 centered towards zero. Tanh activation function is shown in equation 2.

$$f(x) = \frac{e^x - e^-x}{e^x + e^-x} \tag{2}$$

**ReLU activation function:** it is the abbreviation for rectified linear inputs. It takes positive and negative input values and converts the negative values to 0, keeping the positive values. ReLu activation function is computed by the following formula in equation 3.

$$f(x) = max(0, x) \tag{3}$$

**Leaky ReLU:** is a variant of ReLU, instead of making the negative values 0 it submits a small constant of 0.01 to the negative values. Leaky ReLU is calculated by equation 4.

$$f(x) = max(0.01 * x, x) \tag{4}$$

*5) Optimizer:* is an algorithm that transforms the parameters of the model like weights and learning rates to improve the model's accuracy. The various optimizers that used in the CNN model are: gradiant descent, stocastic gradiant descent, RMSprop, Adam, Adgrad, Adadelta, AdaMax etc. Optimizers suitable for binary classifiers are : gradiant descent, stochastic gradient descent, RMSprop, and Adam. Thus these activation functions are explored in this study.

**Gradient Descent Optimizer:** It updates the weights value of the model by reducing the loss function using back propagation. Gradient descent is most commonly used in classification and regression task [31]. Gradient Descent optimizer is also found to produce high efficiency in large dataset, thus it is been used in the proposed work. Gradient descent optimizer is explained in algorithm 1.

**Algorithm 1** Gradiant descent

1:A learning rate $\alpha$ is selected.
2: An initial parameter $\theta$ is selected.
State 3: All the parameters from the gradiants are updated using the below equation.
$\theta_{i+1} = \theta_i - \alpha \text{ X } \Delta\theta \text{ J}(\theta)$
4: Step 3 is repeated until a local minima is reached

**Stochastic Gradient Descent:** is similar to the gradient descent algorithm where in it randomly selects the batches of data for each iteration to reach a minimum loss value [32]. Stochastic gradient helps to reduce over fitting of data. Thus it is been used in the deployed CNN model. Stochastic gradient descent optimizer is shown in algorithm 2.

**Algorithm 2** Stochastic gradient descent

1: Randomly suffle the dataset of size m.
2: Select a learning rate $\alpha$
3: Select an initial parameter value $\theta$
4: Update all parameters from the gradient of a single training example $x^j$, $y^j$ using the below formula
$\theta_{i+1} = \theta_i - \alpha \text{ X } \Delta\theta \text{ J}(\theta;\text{x}^j;y^j)$
5: Repeat Step 4 until a local minimum is reached.

**Root mean square propagation optimizer:** RMS prop calculates the exponentially weighted average of the gradients by updating the weights and bias of the CNN model to reach the local minima. RMS props adapts the learning rate for each parameter individually which helps convergence [33]. Thus, it is been used in the proposed CNN model. The RMS prop optimizer is demonstrated in algorithm 3.

**Algorithm 3** Root mean square propagation

1: For each parameter in the model, calculate the squared gradient $g^2$ at time step t
2: Calculate the exponential moving average of squared gradients
$\text{E}[\text{g}_t^2] = \beta * \text{E}[\text{g}_{t-1}] + (1-\beta)\text{g}_t^2$
$where \beta$ is a value between 0 to 1 usually 0.9
3: Update the weight and bias of the model using the following formula
$w_t = w_{t-1} - \frac{\alpha}{\sqrt{E[g_t^2]}} + \epsilon$
$b_t = b_{t-1} - \frac{\alpha}{\sqrt{E[g_t^2]}} + \epsilon$
where $\alpha$ is learning rate and $\epsilon$ is a constant$(10^{-6})$

**Adaptive moment estimation:** is an optimization technique which uses second order moments and exponential weighted average to optimize the weight and bias value of CNN model [34]. It is similar to RMS props which helps to smooth out the learning process and prevents optimizer from getting stuck in local minimum. Adam optimizer is shown in algorithm 4.

**Algorithm 4** Adam optimizer

1: Calculate the aggregates of gradiants $m_t$ and sum of squares of past gradiants $v_t$ at time t using the below formula
$m_t = \beta \text{m}_{t-1} + (1-\beta)\left[\ \partial L \partial w_t \right]$
$v_t = \beta \text{v}_{t-1} + (1-\beta)\left[\ \partial L \partial w_t \right]^2$
where $\partial L$ is derivative of loss function and $\partial w_t$ is derivative of weights at time t.
2: Calculate the bias corrected weights $\hat{m}_t$and $\hat{v}_t$ by the following equation $\hat{m}_t = \frac{m_t}{1-\beta_1}$
$\hat{v}_t = \frac{v_t}{1-\beta_1}$
$where \beta_1$ and $\beta_2$ are decay rates. 3: Using $\hat{m}_t$ and $\hat{v}_t$ update the general weight equation $w_{t+1}$
$w_{t+1} = w_t - \hat{m}\left( \frac{\alpha}{\sqrt{\hat{v}_t + \epsilon}} \right)$

### D. Model Design

Any CNN model is made up of three important layer, those are convolution layer, max pooling layer and a fully connected layer. The proposed CNN model contains 19 convolution layers and its architecture is illustrated in Fig 1.

The first layer is zero -padding layer, which adds a zero for the input data to preserve spatial dimensions. The second layer is convolution layer which consist of 64 filters with size 3X3. To obtain the feature map in the next layer the zero padding is incorporated. Convolution with 64 filters of size $3X3$ is applied in the fourth layer. Max pooling with stride 2 is applied in the next layer, to reduce spatial

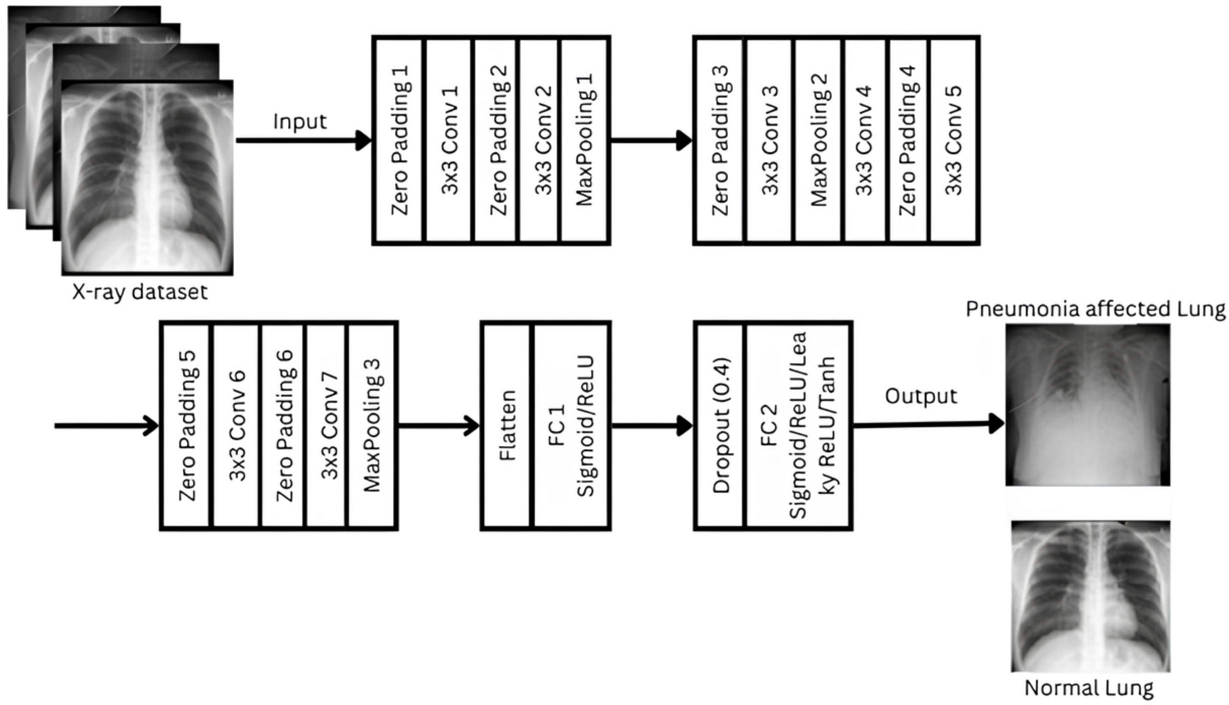


Fig. 1. Architecture of optimized convolutional neural network model.

dimensions. A convolution and pooling layer pair is applied in the next four layers. After this, a zero padding layer is applied, followed by convolution and max pooling layer. Next, a flatten layer is applied to convert the obtained feature map to one dimensional vector. The dense layer acts as the fully connected layer. A dropout rate of 0.4 is incorporated in the dropout layer to overcome overfitting. Lastly, the output layer is a fully connected layer with an activation function. The fully connected layer stores the obtained features. The optimizer is applied to the entire model to normalize the weight values of each layer.

TABLE II
ACCURACY OF CNN MODEL WITH VARYING NUMBER OF CONVOLUTION LAYERS

| CNN Layers | Accuracy |
|---|---|
| 5 | 0.78 |
| 10 | 0.82 |
| 15 | 0.85 |
| 16 | 0.86 |
| 17 | 0.87 |
| 18 | 0.89 |
| 19 | 0.90 |
| 20 | 0.88 |
| 22 | 0.87 |
| 25 | 0.85 |

## III. RESULTS

This section describes the obtained results based on the CNN model parameters like the number of convolution layers, the number of filters, activation function optimizer, and the combination of activation function and optimizers. It also draws inferences based on the obtained results.

### A. Obtained Results

For experimentation, the dataset is divided into 70% training data and 30% testing data. 8400 images are in training set and 3600 images are in testing set. The CNN model is built on training dataset and the model is validated on testing dataset. The obtained results based on optimized parameters are discussed as follows:

*1) Number of layers:* Number of convolution layers play a significant layer in the classifying the dataset accurately in a CNN model. An initial experiment was conducted to identify the optimum number of convolution layers that results in the highest classification accuracy. The experiment started with 5 layers and was incremented gradually and the highest accuracy of 0.90 was observed for 19 CNN layers. Thus the CNN model with 19 layers is considered for further experimentation. The accuracy measure for each of the convolution layers is been listed in Table II.

*2) Number of filters:* Filters are small matrices used to perform convolution operation on an input data. They are very effective in capturing useful information in the data. The $3X3$ filters are widely used filter size for binary classification. Thus the same as been incorporated in this work. Different results can be obtained for different number of filters, thus deciding the number of filters is equally important. Initial experimentation with different number of filters is conducted, so as to identify the number of filters that can accurately classify the dataset. The accuracy obtained for various number of filters is shown in Table III. Among these 64 filters of size 3 X 3 gave better results. Thus 64 filters are incorporated in this work.

TABLE III
ACCURACY OF CNN MODEL WITH VARYING NUMBER OF FILTERS OF SIZE 3 X 3

| Number of filters | Accuracy |
|---|---|
| 8 | 0.78 |
| 16 | 0.86 |
| 32 | 0.94 |
| 64 | 0.98 |
| 128 | 0.90 |

TABLE IV
ACCURACY OF CNN MODEL WITH DIFFERENT ACTIVATION FUNCTION

| CNN model with different activation function | Accuracy |
|---|---|
| Sigmoid | 0.96 |
| TanH | 0.90 |
| ReLu | 0.84 |
| Leaky RelU | 0.80 |

*3) Activation function:* Activation function which are suitable for binary classification are chosen for this study. The accuracy measure for selected activation function is shown in Table IV. Sigmoid activation function gave highest accuracy measure.

*4) Optimizer:* Optimizers are algorithms that updates the weights and bias values of the CNN model. Optimizers which are suitable for binary classification are chosen for this study. Accuracy measures of these optimizers are shown in table V. RMS prop optimizer gave better results.

*5) Combination of optimizer and activation function:* The efficiency of CNN model is assessed using a series of combination of activation functions and optimizers. Their effectiveness was measured based on the accuracy, precision, recall, F1 score, and the area under the curve scores. The confusion matrix, taken from the test data, provide a machine learning efficiency and also serves as a foundation for performance metrics. [35]. Accuracy measures the percentage of chest x-ray images provide the exact prediction of positive and negative results. Precision defines those chest X-ray images that are precisely predicted over correct and incorrect predictions. Recall shows those chest X-ray images that are correctly predicted over the entire the data set. F1 score is the harmonic mean of recall and precision. The diagnostic capacity of binary classifiers is demonstrated graphically by the receiver operator characteristic (ROC) curve. The false positive rate is plotted against the true positive rate to create a ROC curve. The area under the ROC curve determines how accurately the classifier performs at different thresholds. The efficiency of the proposed CNN model with various configurations of optimizer and activation function in terms of accuracy, F1-score, recall, precision and AUC score in shown in Table VI. The CNN model is built by considering the results obtained from Table II, III, IV, V.

TABLE V
ACCURACY OF CNN MODEL WITH DIFFERENT OPTIMIZER

| Optimizer | Accuracy |
|---|---|
| RMSprop | 0.94 |
| Adam | 0.92 |
| Gradient Descent | 0.84 |
| Stocastic Gradient Descent | 0.88 |

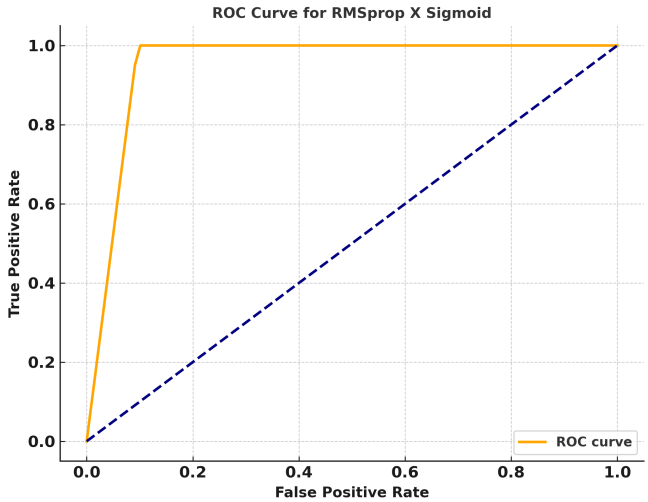


Fig. 2. ROC curve for RMS prop optimizer and Sigmoid activation function

The model is tested by considering the various combinations of the chosen activation function and optimizer. The obtained result is shown in Table VI. From, Table VI it is observed that results of RMS Prop optimizer with sigmoid activation function yields an accuracy, precision, recall, F1 Score 0.96 and AUC of 0.97, which are slightly better compared to other configurations of optimizer and activation function. Since RMS Props uses an exponentially weighted average for optimizing the CNN model, sigmoid activation function normalizes the input values from 0 to 1 range ensuring the uniform distribution. This combination of the optimizer and activation function gives a good performance result. The features stored in fully connected layer are obtained and plotted. The feature distribution fits the sigmoid activation function graph. This may be one of the reason that combination of RMS prop optimizer and sigmoid activation function configuration yields in better classification results.

The ROC curve of sigmoid activation function with RMS prop optimizer is shown in Fig.2. ROC curve which is closest to the top left corner shows better performance of any model. In Fig.2 it can been seen that ROC curve of RMS prop optimizer with sigmoid activation function moves up to top left corner and AUC of 0.97 is achieved indicating accurate classification.

The results of the proposed CNN model with sigmoid activation function and RMS prop optimizer is compared with other similar research work reported in the literature. The performance comparision results of the proposed approach is shown in Table VII. The research work reported in the literature include VGG based CNN model [36], ensemble deep learning [37], residual CNN network [38], CNN with ReLU activation function [39] and ResNet18 [40]. The comparision results from Table VII clearly shows better accuracy of deployed CNN model compared to other similar work. However in [36], a pretrained VGG model is used with limited training samples and gave the same accuracy value. The comparison results of proposed work with other existing work in literature suggest that on employing CNN model with parameter optimization on number of convolution layers and effectively choosing the number of filters, activation

TABLE VI
RESULTS OF CNN MODEL WITH VARIOUS COMBINATIONS OF OPTIMIZER AND ACTIVATION FUNCTION

| Optimizer and Activation function | Accuracy | Precision | Recall | F1 score | AUC score |
|---|---|---|---|---|---|
| RMS Prop and Sigmoid | 0.96 | 0.96 | 0.96 | 0.96 | 0.97 |
| RMS Prop and Tan h | 0.86 | 0.86 | 0.85 | 0.85 | 0.9 |
| RMS Prop and Relu | 0.95 | 0.94 | 0.96 | 0.95 | 0.95 |
| RMS Prop and Leaky Relu | 0.95 | 0.94 | 0.96 | 0.95 | 0.95 |
| Gradient Descent and Sigmoid | 0.95 | 0.95 | 0.96 | 0.95 | 0.96 |
| Gradient Descent and Tan h | 0.92 | 0.93 | 0.92 | 0.92 | 0.9 |
| Gradient Descent and Relu | 0.94 | 0.94 | 0.94 | 0.94 | 0.94 |
| Gradient Descent and Leaky Relu | 0.94 | 0.95 | 0.94 | 0.94 | 0.94 |
| Stochastic Gradient Descent and Sigmoid | 0.96 | 0.96 | 0.96 | 0.95 | 0.96 |
| Stochastic Gradient Descent and Tan h | 0.94 | 0.94 | 0.94 | 0.94 | 0.95 |
| Stochastic Gradient Descent and Relu | 0.95 | 0.95 | 0.93 | 0.94 | 0.95 |
| Stochastic Gradient Descent and Leaky Relu | 0.95 | 0.96 | 0.95 | 0.95 | 0.95 |
| Adam and Sigmoid | 0.95 | 0.96 | 0.95 | 0.95 | 0.95 |
| Adam and Tan h | 0.82 | 0.82 | 0.82 | 0.82 | 0.89 |
| Adam and Relu | 0.94 | 0.95 | 0.94 | 0.94 | 0.94 |
| Adam and Leaky Relu | 0.94 | 0.95 | 0.94 | 0.94 | 0.94 |

TABLE VII
PERFORMANCE COMPARISON OF PROPOSED APPROACH WITH SIMILAR WORK IN LITERATURE

| Approach | Accuracy |
|---|---|
| CNN with Sigmoid and RMS Prop | 0.96 |
| Zhang et al (2021) [36] | 0.96 |
| Kundu et al (2021) [37] | 0.86 |
| Al Munarok et al (2019) [38] | 0.85 |
| Shah et al (2020) [39] | 0.92 |
| Wang et al (2021) [40] | 0.92 |

function and optimizers a better pneumonia classification can be performed.

## IV. CONCLUSION

The parameters of a convolution neural network play a vital role in the performance of the model. This work aimed to identify the best CNN model parameters to classify pneumonia chest X-ray images as positive and negative. The appropriate hyper parameters for the work was determined by experimenting with the number of convolution layers, number of filters and with various combinations of activation function and optimizers. The experimental results indicated CNN model with RMS prop optimizer and sigmoid activation function gave an accuracy, precision, recall and F1 score of 0.96 respectively and area under the curve of 0.97. The comparison results of proposed work with other existing work in literature suggest that on employing CNN model with 19 convolution layers, 64 filters of $3X3$ size, RMS prop optimizer and sigmoid activation function better classifcation performance can be obtained.

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