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Pneumonia detection on chest X-ray images using segmentation technique and modified AlexNet-ML classifiers

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ABSTRACT

Worldwide, pneumonia is a serious health issue, and detecting pneumonia quickly and accurately is necessary for improving patient outcomes. This method seeks to save human labor, increase diagnostic efficiency, and eventually enhance patient outcomes in the healthcare system by automating the pneumonia detection process. This study aims to develop a robust pneumonia detection system using modified deep learning techniques followed by different classifiers such as kNN, DT, RF, and SVM applied to chest X-ray images. In the planned model, the images are processed beforehand to enhance the quality and clarity of the image for accurate prediction and are segmented utilizing the GrabCut algorithm to eliminate unwanted portions from the image. In this work, features are extracted utilizing a modified AlexNet architecture, and pneumonia disease is classified into pneumonia and normal images using different classifiers. The proposed method achieved optimal performance based on the testing accuracy, testing sensitivity, and testing specificity of 96%, 95.59%, and 96.15%, respectively, using the chest X-ray image dataset. According to the testing results, the most effective approach among the current methods with the highest accuracy was the combination of modified AlexNet models and the SVM classifier.

Contribution/Originality: In this proposed model, pneumonia is detected using the modified AlexNet-ML classifier with a given dataset of chest X-ray images. In this work, a modified AlexNet architecture with eight convolutional layers was developed to extract features.

1. INTRODUCTION

People of all ages are susceptible to pneumonia, a common worldwide health problem that may cause severe disease and even death among susceptible groups. Detecting pneumonia quickly and accurately is significant for improving patient outcomes. However, traditional diagnostic methods for pneumonia are often time-consuming and require multiple tests and examinations by healthcare professionals [1, 2]. To address this challenge, there is growing interest in using hybrid deep learning (DL) methodology for the automation of the examination of chest X-rays for detecting pneumonia.

The pneumonia disease is widespread, impacting individuals of all ages, but it has a greater impact on the elderly and young populations. Despite advancements in medical science, pneumonia diagnosis is still a challenge, particularly in settings with limited resources. Traditional diagnostic approaches are time-consuming and require a lot of manual labor [3], which can delay treatment and lead to harmful effects on patients. Moreover, the interpretation of diagnostic tests is subjective, which may result in variability and diagnostic errors. To streamline the pneumonia diagnosis procedure, increase diagnostic precision, and facilitate prompt intervention, creative solutions are therefore desperately needed. The prime goal of this work is to develop a system that applies DL models to examine chest X-ray images to automatically diagnose pneumonia [4]. By utilizing cutting-edge technology, this effort aims to improve diagnostic efficiency as well as accuracy while addressing the shortcomings of conventional diagnostic techniques. The specific goal of the system is to create DL algorithms that have high accuracy, sensitivity, and specificity to detect pneumonia in chest X-ray images [4]. By automating medical image analysis, the system aims to reduce the workload of healthcare professionals, speed up the diagnostic process, and enhance patient outcomes.

The most cutting-edge methods will be used in this study's DL models, which are intended for the detection of pneumonia from chest X-rays, to guarantee high detection accuracy and efficiency. The developed DL models will enable the rapid as well as accurate diagnosis of pneumonia by automating the analysis of chest X-ray images. This automation will reduce the need for healthcare professionals to perform manual interpretation, streamline diagnostic procedures, and lead to earlier treatment decisions and better patient outcomes. The investigation's prime goal is to examine the effect of DL models in this medical application and to appropriately determine whether the individual has pneumonia or not.

To provide a novel solution to this issue, a new modified architecture with eight convolutional layers was developed. In this proposed model, pneumonia is detected using the modified AlexNet-ML classifier with the given X-ray image dataset. The major contributions of the proposed model are.

- Detection of pneumonia using a modified AlexNet-ML Classifier model.
- Preprocessed images are segmented with the GrabCut algorithm to remove the unwanted portions of the image.
- The CNN-based modified AlexNet technique with eight convolutional layers is used to extract the features.
- In place of softmax, SVM, Random Forest, Decision Tree, and kNN classifiers are used to categorize pneumonia disease.

The following is the paper's next section: Section 2 outlines specific research publications pertaining to current methodologies. A brief description of the process is provided in Section 3. The performance and outcomes of the suggested work are detailed in Section 4. The entire study is concluded in Section 5.

2. LITERATURE SURVEY

This section provides an overview of some of the related works from the latest scientific articles.

2.1. Segmentation Based Approach

a) Shafi and Chinnappan [5] created a novel framework for lung disease segmentation along with classification utilizing M-Segnet and Hybrid Squeezenet-CNN architecture on CT images. To locate and distinguish the ROI from the lung picture's background items, the processed image is segmented. For efficient segmentation, it makes use of a suggested hard tanh-Softplus activation function in the M-Segnet (Modified Segnet) mechanism. Two classifiers are used in this hybrid model for classification: DCNN and SDPA-Squeezenet.

b) Vinta, et al. [6] presented a model based on a Hybrid Deep Learning Network and segmentation technique for the classification of Interstitial Lung Diseases. An enhanced U-Net++ model for efficient lung segmentation with lung abnormalities was first used in this work to segment the lung component of the HRCT images. A RAPNet (Refined Attention Pyramid Network) was then employed to extract the necessary features for classification. A MobileUNetV3 was subsequently created to categorize five ILD classes.

2.2. Machine Learning and Deep Learning Approach

a) Toğaçar, et al. [1] combined machine learning (ML) and mRMR feature selection to present a deep learning (DL) and ML model for pneumonia identification. Lung X-ray images were used in this investigation to diagnose pneumonia. Convolutional neural network models, including VGG-16, VGG-19, and AlexNet, were utilized as feature extractors. The number of deep features was then reduced from 1000 to 100 for each deep model using the lowest redundancy maximum relevance technique. This feature set was then supplied as input for the k-nearest neighbors, decision tree (DT), linear regression, linear discriminant analysis, and support vector machine learning models.

2.3. Deep Learning Approach

a) Mudasir, et al. [3] presented the innovative EfficientNetV2L for the detection of pneumonia by applying chest X-ray images. Furthermore, several cutting-edge CNN architectures, including InceptionResNetV2, VGG16, Xception, and ResNet50, are used for the diagnosis of pneumonia from chest X-ray images. The study also highlights how crucial it is to experiment with different CNN configurations and preprocessing methods for the enhancement of the models' performance. Furthermore, methods for data augmentation are suggested to expand the dataset's size, which may help with improved generalization.

b) Zadeh [4] developed a DL model for COVID-19 classification based on Hybrid Transfer Learning using chest X-ray images. The authors of this research proposed a method for diagnosing COVID-19 utilizing CXR images, based on the concatenated feature vector from three Deep Transfer Learning models and a soft-voting feature selection process that incorporates Entropy, ROC (Receiver Operating Characteristic), and SNR (Signal-to-Noise Ratio) techniques. The suggested approach achieved 99.34% accuracy, 99.48% sensitivity, and 99.27% specificity.

c) Zhang, et al. [7] created a CNN-based algorithm for pneumonia diagnosis in chest X-ray images. The authors of this investigation developed a simple, lower-layer model architecture based on VGG. Additionally, the DHE approach is utilized to preprocess the images in order to address the insufficient contrast of chest X-ray images, which results in unclear detection. The results show that the accuracy rate was 96.07%, and the precision rate was 94.41%.

d) Elshennawy and Ibrahim [8] proposed four effective CNN models. The components included a CNN architecture, an LSTM (Long Short-Term Memory) network, as well as two pre-trained models: ResNet152V2 and MobileNetV2. They also contrasted several parameters with which each model had been trained. Their four models achieved above 91% in F1-score, recall accuracy, precision, and AUC.

3. METHODS

Three distinct stages have been identified in the architecture of the suggested model: preprocessing, feature extraction, and classification. It investigates whether the classification outcome may be enhanced by altering the convolution layer in the original AlexNet architecture [9]. The suggested methodology aims to develop an intelligent system for automated pneumonia detection using a modified AlexNet-ML architecture utilized for chest X-ray images.

In this planned model, images are pre-processed using resizing, the Wiener filter, and the CLAHE method. The pre-processed images are segmented using the GrabCut algorithm [10]. After that, the appropriate features suitable for pneumonia classification are extracted by the modified AlexNet, ensuring that effective features are obtained. After extracting the relevant features, different classifiers are employed to determine whether an image is normal or contaminated with pneumonia. Figure 1 displays the block diagram of the devised modified AlexNet-ML classifier method for pneumonia detection.

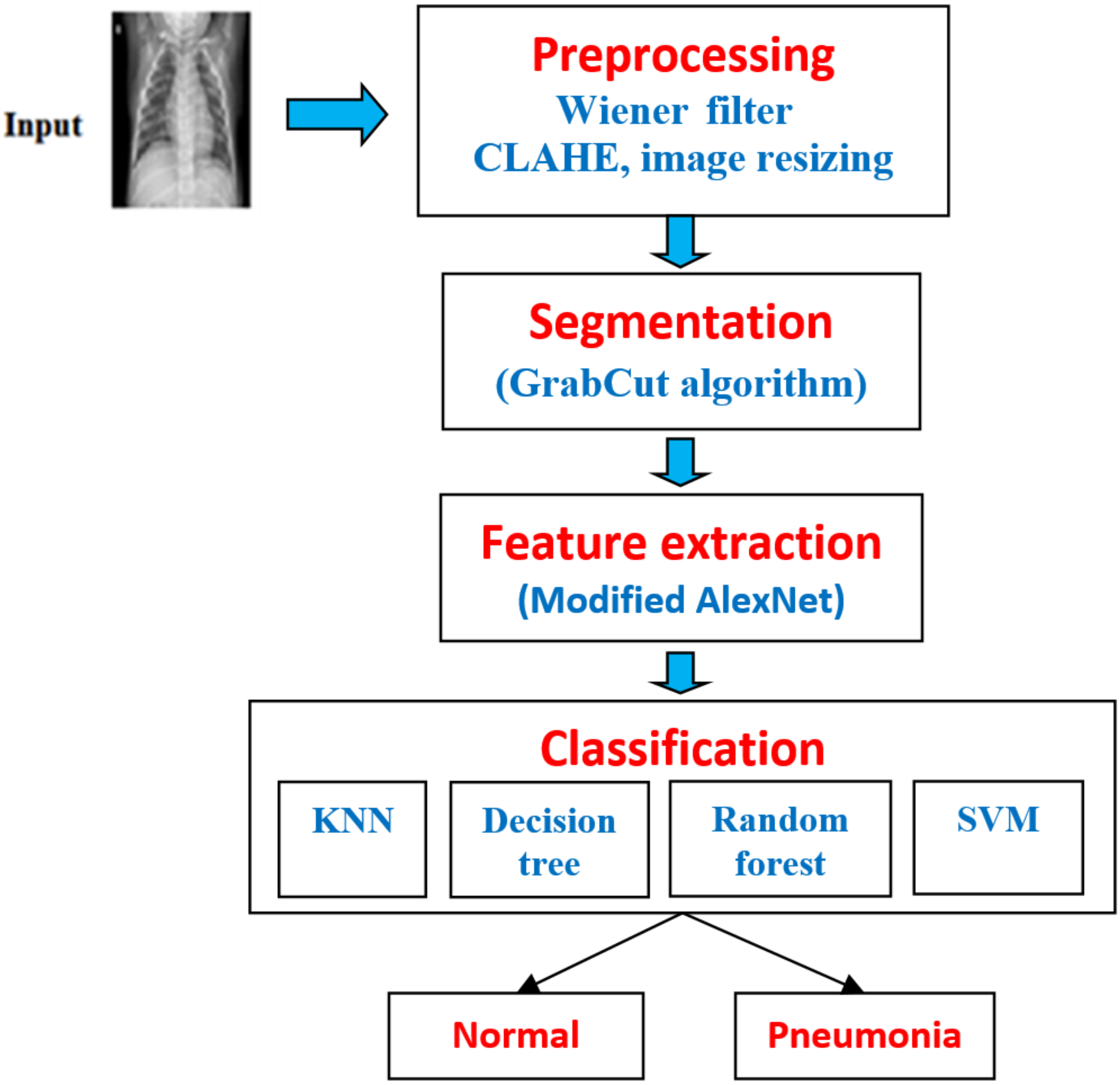


Figure 1. Block diagram of the proposed modified AlexNet-ML classifier model.

3.1. Pre-Processing

Preprocessing methods are essential for improving the generality and resilience of the model. These methods include downsizing to a uniform input size, noise reduction to enhance image quality, image normalization to standardize pixel values, and data augmentation to provide more training examples through transformations like flipping, zooming, and rotating. These preprocessing steps ensure that the model may learn relevant features as well as patterns from the input images effectively.

3.2. Segmentation using Grabcut Algorithm

After the image preprocessing, the segmentation phase is executed wherein the input considered is B_r. Here, the disease-affected region is segmented utilizing the GrabCut algorithm [10].

The GrabCut technique needs the initial form called trip, which comprises of input image partitioning into three areas namely foreground G_F, background G_B and the area having pixels, which resulted in the integration of foreground as well as background is denoted by G_H.

The image is indicated as array of values. $a = (a_1, \ldots, a_X)$and output obtained from segmentation can be the channel of values among 0 and 1 or hardest segmentation having binary allocation 0 or else 1. The segmentation may be denoted as $s = (s_1, \ldots, s_X)$ with $0 \leq s_x \leq 1$or $s_x = \{1,0\}$.

A GrabCut technique [10] also needs the model for distributing foreground or background colours as well as grey levels. This distribution is signified as a histogram in a direct manner collected from E and B as $б = \{\hbar(a; z), z = 0,1\}$. Under the trimap method, the segmentation technique evaluates the values of s from image a as well as distribution model $б$. The values of s are computed from the energy minimization function [10] is illustrated by .

$$X(s, б, a) = Y(s, б, a) + Z(s, a). \quad (1)$$

Here, $H$is the sub-function, which estimates fitness by allocating a lower score if segmentation $(\vartheta)$is consistent with an image a. It can be formulated by Chaudhari and Malathi, [10].

$$Y(s, б, a) = \sum_x - \ln \hbar\, (a_x; s_x). \quad (2)$$

Instead of utilizing a histogram as a probability density function estimator, an algorithm utilizes the Gaussian mixture method for taking into consideration about information approaching from every channel.

$$Z(s, a) = \varepsilon \sum_{(y,x) \in N} \left[s_x \neq s_y \right] e^{-\mu (a_y - a_x)^2}. \quad (3)$$

In the above equation, the sum set $N \in 3 \times 3$ signifies to neighbourhood pixels in the known window and μ is modelled by.

$$\mu = \frac{1}{\left(2Z \left| \langle (a_y - a_x)^2 \right| \rangle \right)}. \quad (4)$$

By utilizing global minimum, image segmentation is assessed by,

$$\hat{s} = \arg\min\, (X(s, б,\ a)) \quad (5)$$

To eliminate a third physical step of the algorithm, the permanent background image G_H mask is utilized at a time of iteration and the process of guided filter refinement is utilized for achieving an automated segmentation.

3.3. Feature Extraction

In this technique, a modified AlexNet CNN architecture is used to extract features. Feature extraction intends to decrease the number of features in a dataset by producing features from already available features.

3.3.1. Architecture of Modified AlexNet

AlexNet is an eight-layer CNN architecture that contains three fully connected layers and five convolutional layers. The initial five layers are convolutional layers, ending with three fully connected layers. In this research, a new modified AlexNet architecture [2] was proposed by improving the number of convolutional layers of the existing CNN-based AlexNet architecture. In fact, we used the modified AlexNet architecture because the architecture of the normal AlexNet is simpler compared to other available CNN architectures. It is a CNN architecture developed with an input image size of 227×227.

This modified AlexNet architecture has eight convolutional layers, three fully connected layers, and the final output layer replaced with ML classifiers. Image input is forwarded to the first convolutional layer, and the first six convolutional layers consist of batch normalization and a max pooling layer. The last two convolutional layers contain a max pooling layer [7] with a 3×3 filter size and a stride of 2. In this work, we employed 3x3 kernel layers with strides of size 1. In the convolutional layer of the modified architecture, the ReLU activation function is used. ReLU helps in increasing classification accuracy by removing the problem of gradient [8] and improves learning speed as well. A dropout layer is also added to reduce the overfitting problem. The appropriate features are extracted utilizing the modified AlexNet model and forwarded as input to the ML classifiers. In addition, the modified AlexNet architecture is investigated using both the Softmax classifier and the ML algorithm. Figure 2 illustrates the architecture of the proposed model developed for pneumonia detection. Figure 2 illustrates the architecture of the proposed model for the detection of pneumonia.

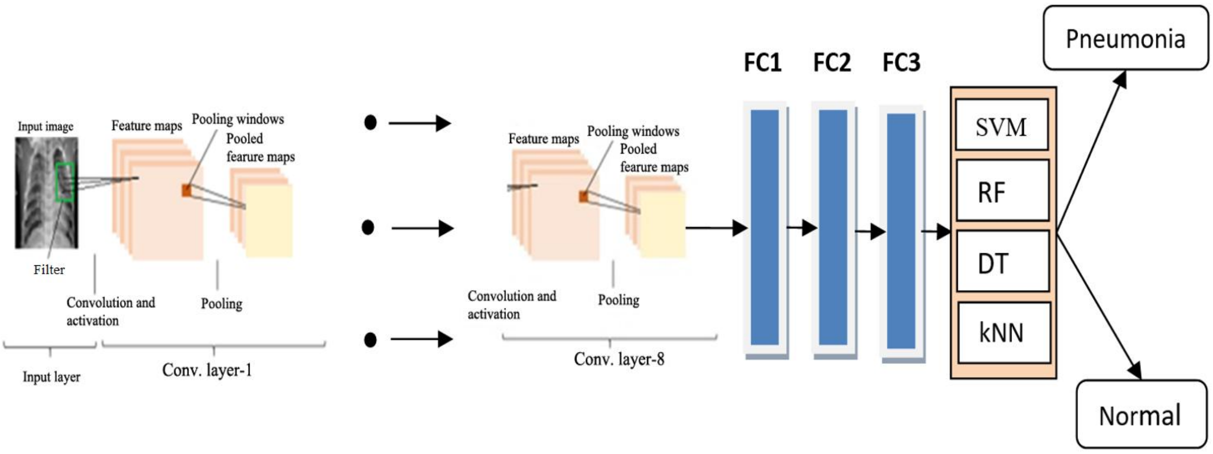


Figure 2. Architecture of modified AlexNet-ML classifier.

3.4. Pneumonia Classification

Features from the final fully connected layer are extracted and transmitted to different ML classifiers for classification in the proposed methodology utilizing a modified AlexNet network. Various ML classifiers were employed for the classification task following feature extraction. However, it was discovered that the best outcomes were obtained when the classifier for the problem was a Support Vector Machine (SVM). Therefore, to achieve better results, features taken from the modified AlexNet were combined with the SVM classifier in the proposed model.

SVM is an ML method for the classification of data by analyzing it and identifying patterns. It assigns a set of input data to one of two classes [11]. The distance from this hyperplane in the SVM model is the largest possible margin that separates the training set's data from one another. The SVM is a renowned learning approach for binary classification. Finding the optimal hyperplane for dividing data into two categories is the primary goal.

Let x is considered as input, j be the training instances $\{x_j, y_j\}, j = 1,..m$ and for each occurrence consist x_j and label $y_i \in \{-1,1\}$. Each hyperplane is parameterized using a weight vector (w) as well as a bias vector (b), which is written in equation (6) as shown below.

$$w.x + b = 0 \tag{6}$$

The hyperplane function that categorizes training and testing data can be defined using the following equation:

$$f(x) = sign(w.x + b) \tag{7}$$

When working with kernel functions, the prior function can be expressed as an equation,

$$f(x) = sign(\textstyle\sum_{j=1}^{N} \alpha_j y_j k(x_j, x) + b) \tag{8}$$

Where, b is the bias, the number of training instances denoted by N, $K(x_j, x)$ is the employed kernel function that translates the input vectors into an enlarged feature space and x_j is the input of training instance, $y_i$is its corresponding class label. Two restrictions apply while obtaining the coefficients α_j:

$$0 \leq \alpha_j, j = 1,..,N \tag{9}$$

$$\textstyle\sum_{j=1}^{N} \alpha_j y_j = 0 \tag{10}$$

Therefore, the aforementioned formulas are utilized to train and evaluate the pneumonia disease prediction feature that is taken from X-ray images.

4. RESULTS AND DISCUSSION

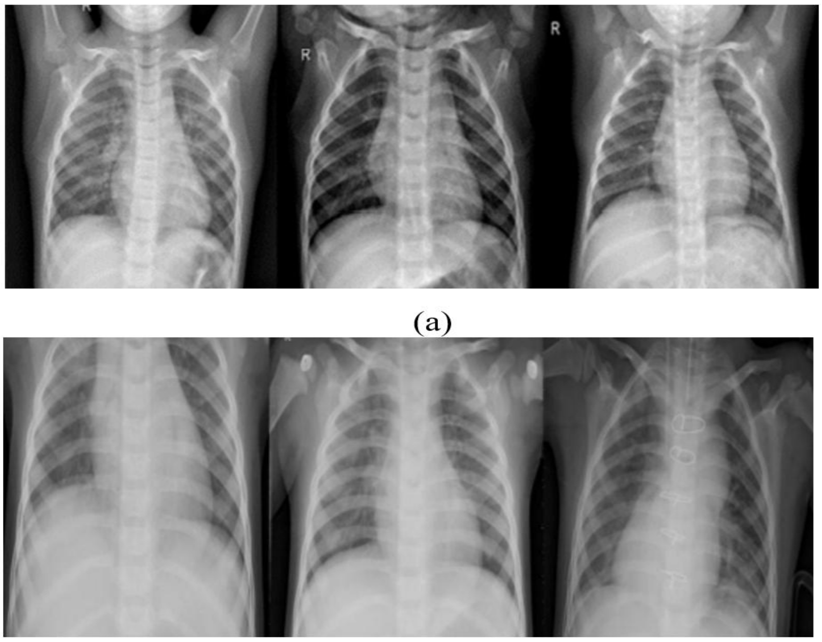
This segment explains on results obtained by the devised modified AlexNet-ML classifiers model for pneumonia detection by using performance matrix for evaluation such as accuracy, sensitivity and specificity. Furthermore, dataset description, the experiment setup, and outcomes of the newly introduced technique while compared with traditional approaches are also explained.

4.1. Dataset Description

5,863 chest X-ray images from the Kaggle dataset, which are used to assess the model's performance, make up the suggested dataset [12]. The three folders that comprise the database are Test, Train, and Val. Each of these folders contains subfolders for the Normal and Pneumonia image categories. There are 4,273 pneumonia images and 1,583 normal images among the 5,856 chest X-ray images (JPEG) in the collection. The images are categorized into two groups: pneumonia and normal, sourced from a diverse group of patients of different ages. An additional 15% of the training set is set aside for validation, and the dataset is divided into training and testing sets. Figure 3 shows several examples of both pneumonia and normal images. The number of images utilized for testing, training, and validation is displayed in Table 1.

Table 1. Dataset details for pneumonia and normal images

Set	Pneumonia	Normal	Total images
Training set	3875	1341	5216
Validation set	8	8	16
Testing set	390	234	624"



(a)

(b)

Figure 3. Examples from the dataset. (a) Normal cases (b) Pneumonia cases

4.2. Experimental Setup

All methods were implemented using the Python programming language. The experiment utilized an Intel(R) Core(TM) i5-10300H CPU operating at 2.50 GHz, a 4 GB (GDDR6) NVIDIA GTX 1650 graphics card, 32.0 GB of RAM, storage consisting of a 256 GB SSD and a 1 TB HDD, and a 64-bit operating system. Table 2 displays the hyperparameters applied in this experiment.

Table 2. Hyper-parameters of the model.

Parameters	Value
Number of data items	5863
Batch size	16
Epochs	15
Optimizer	Adam
Loss	"Categorical_crossentropy"
Learning rate	0.001
Learning rate decay per epoch	0.0001

4.3. Experimental Result

A comparison of the results is displayed in Table 3. The efficiency of the detection is investigated using performance metrics such as testing accuracy, testing sensitivity, and testing specificity. In addition, the confusion matrix (CM) and ROC curve were produced to assess the models' performance. From Figure 4a_c, we can see that the accuracy level is progressing, and finally, the accuracy has attained around 96.0%, which is quite impressive.

4.3.1. Evaluation Metrics

In this study, accuracy, sensitivity, and specificity are evaluation metrics used to assess the classification performance of the model. According to the outputs of the model, four indices—TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative)—are used to analyze and identify the performance of the model. The metrics are given as follows:

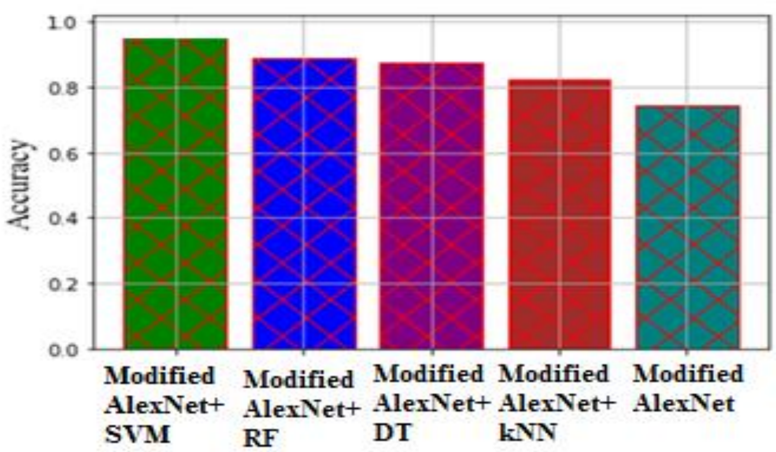
$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (11)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (12)$$

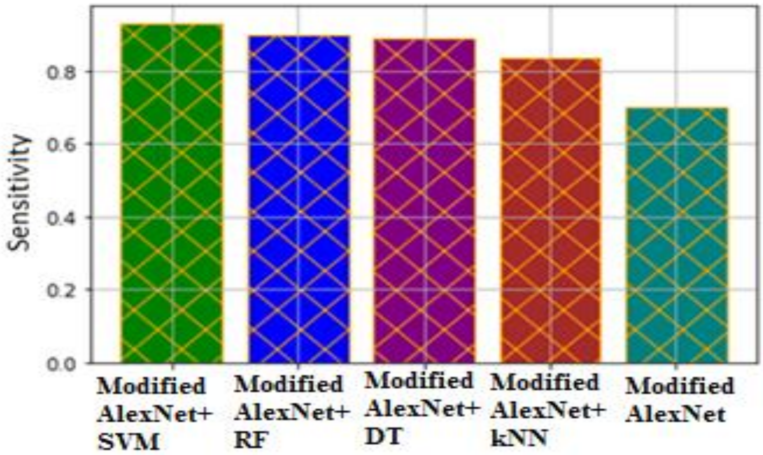
$$Specificity = \frac{TN}{TN+FP} \quad (13)$$

Table 3. Comparison of existing and proposed model based on Accuracy, Sensitivity and Specificity

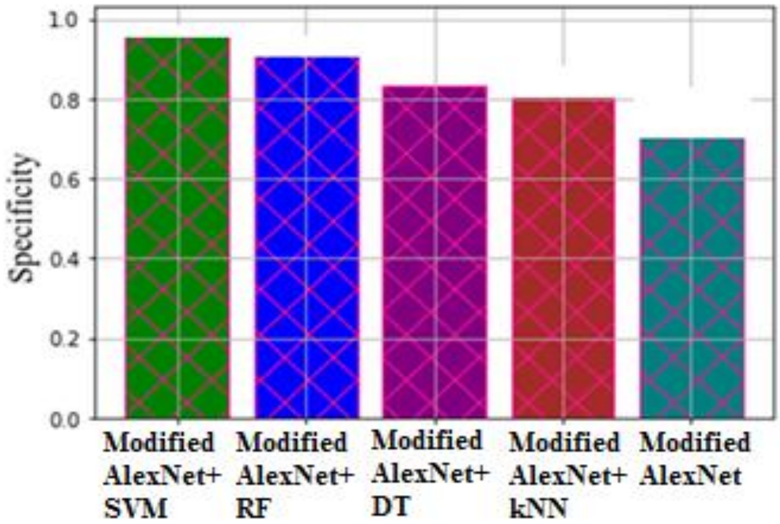
Model	Accuracy	Sensitivity	Specificity
Modified AlexNet without a classifier.	78.0	71.0	70.0
Modified AlexNet + kNN	82.0	81.90	80.10
Modified AlexNet + DT	92.70	89.50	87.10
Modified AlexNet + RF	93.80	93.70	93.50
Modified AlexNet + SVM	96.0	95.59	96.15



(a)



(b)



(c)

Figure 4. Comparison of models based on (a) Accuracy (b) Sensitivity (c) Specificity.

4.3.2. Confusion Matrix

An important visual tool to evaluate a classification model's performance, particularly in tasks like pneumonia diagnosis, is the confusion matrix. The confusion matrix is represented in Table 4.

Table 4. Confusion matrix.

Predicted/Actual	Normal lung (0)	Pneumonia (1)
Normal lung (0)	4102	164
Pneumonia (1)	70	1520

4.3.3. ROC Curve

Figure 5 illustrates the ROC curve, which appears to be a performance measure for categorization challenges at different levels. The following curve reaches '1', which means our system's performance measure is considered to be good.

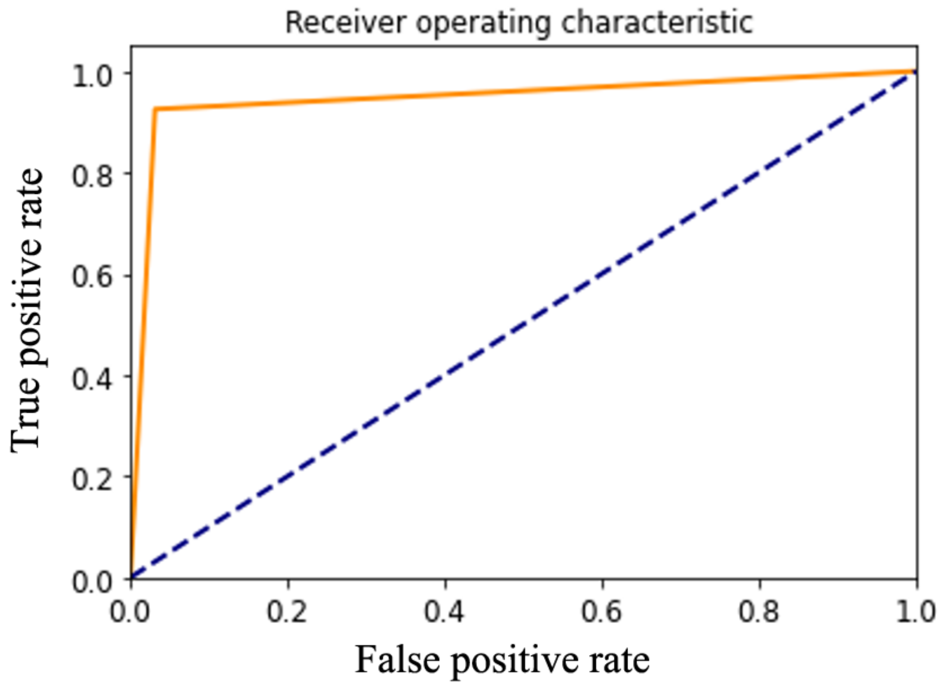


Figure 5. ROC Curve of the proposed method.

5. CONCLUSIONS

Detecting pneumonia quickly and accurately is crucial for improving patient outcomes. Improving clinical decision-making procedures greatly depends on achieving high classification accuracy for pneumonia images. By employing a dataset of chest X-ray images, this study presents a novel modified AlexNet-ML classifier model designed to identify pneumonia. In remote regions, our study facilitates the early detection of pneumonia to prevent adverse consequences, including mortality. In this paper, we modify the convolution layer of the existing AlexNet CNN architecture and replace the softmax classifier in the last classification layer with kNN, Decision Tree (DT), Random Forest (RF), and Support Vector Machine (SVM), and we obtained the results of the Modified AlexNet architecture with different ML classifiers. Additionally, to improve the classification results, the GrabCut segmentation method is used to exclude the undesirable regions from the provided image.

Increasing the quantity of convolutional layers in the present AlexNet architecture has been found to improve classification accuracy. The modified AlexNet model featuring eight convolutional layers and an SVM classifier demonstrated the most efficacy among the proposed methods, achieving 96% accuracy, 95.59% sensitivity, and 96.15% specificity. The performance metrics such as accuracy, sensitivity, and specificity of the proposed model are evaluated and compared with different ML classifiers and without a classifier. The suggested model's performance indicators are assessed and contrasted with those of the current methodologies. Furthermore, the obtained outcomes showed that the modified AlexNet-SVM model provided high performance against other architectures cited in this work.

To improve recognition performance, we want to apply other deep architectures and training algorithms in subsequent work.

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Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

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