PNEUMONIA DETECTION USING X-RAYS USING WATSON STUDIO

ABSTRACT

Pneumonia, an interstitial lung disease, is the leading cause of death in children under the age of five. It accounted for approximately 16% of the deaths of children under the age of five, killing around 880,000 children in 2016 according to a study conducted by UNICEF. Affected children were mostly less than two years old. Timely detection of pneumonia in children can help to fast-track the process of recovery. This paper presents convolutional neural network models to accurately detect pneumonic lungs from chest X-rays, which can be utilized in the real world by medical practitioners to treat pneumonia. Experimentation was conducted on Chest X-Ray Images (Pneumonia) dataset available on Kaggle. The first, second, third and fourth model consists of one, two, three and four convolutional layers, respectively. The first model achieves an accuracy of 89.74%, the second one reaches an accuracy of 85.26%, the third model achieves an accuracy of 92.31%, and lastly, the fourth model achieves an accuracy of 91.67%. Dropout regularization is employed in the second, third and fourth models to minimize overfitting in the fully connected layers. Furthermore, recall and F1 scores are calculated from the confusion matrix of each model for better evaluation.a potentially fatal infection and inflammation of the lower respiratory tract (i.e., bronchioles and alveoli) usually caused by inhaled bacteria and viruses has both properties (*Streptococcus pneumoniae*, aka pneumococcus). The illness is frequently characterized by high fever, shortness of breath, rapid breathing, sharp chest pain, and a productive cough with thick phlegm. Pneumonia that develops outside the hospital setting is commonly referred to as community-acquired pneumonia. Pneumonia that develops 48 hours or later after admission to the hospital is known as nosocomial or hospital acquired pneumonia. In this case report we review the presentation and management of pneumonia involving the respiratory system. The aim of this report is to alert the clinicians to the potential diagnosis of pneumonia treatment. This is the case report of 3 months old boy with Pneumonia. He was diagnosed with pneumonia. His treatment was starting and after 7 days, he became completely recovered. For his disease diagnosis different tests are also performed.At present, several prediction models have been proposed or validated. Biomarkers are not yet ready for routine use. The authors recommend careful consideration of the implications of any given definition of pneumonia severity. Outcome studies are needed to integrate human and health care system factors with the application of pneumonia severity definitions.

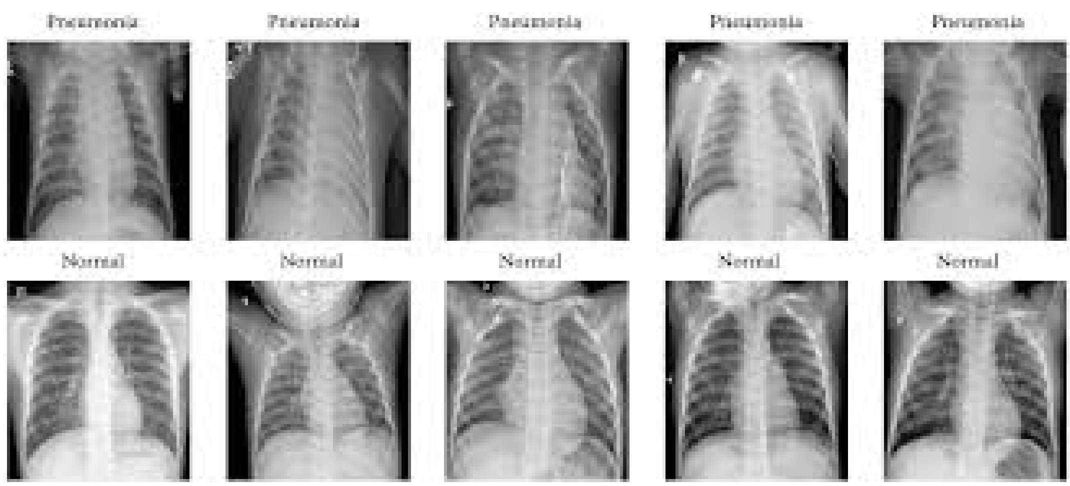
INTRODUCTION

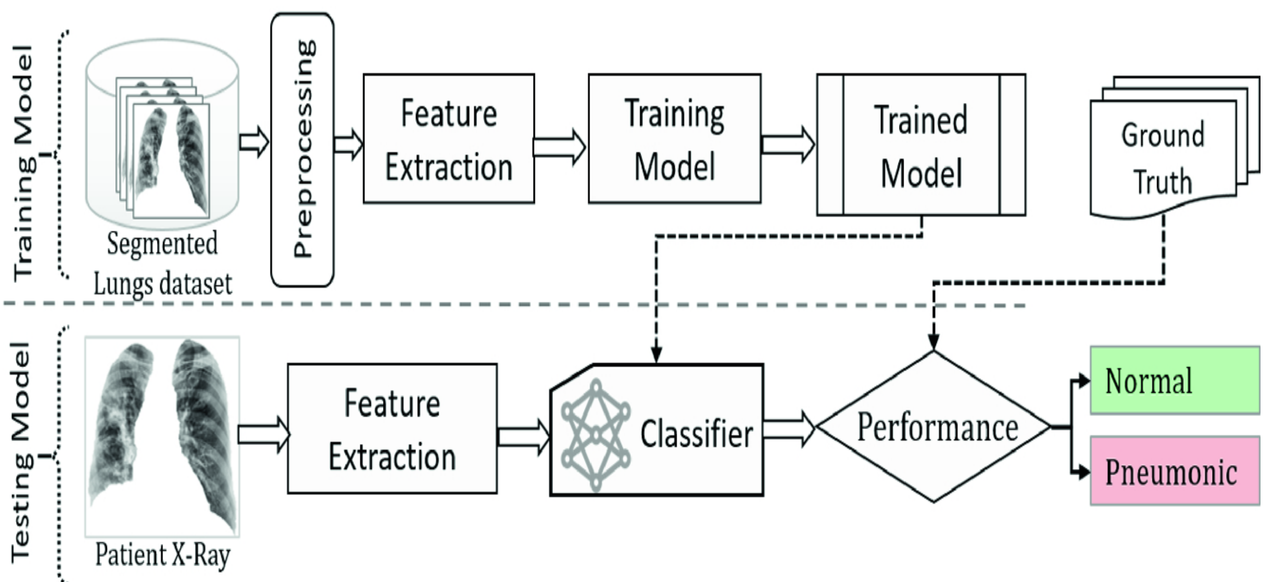
One of the major factors associated with pneumonia in children is indoor air pollution. Apart from this, under-nutrition, lack of safe water, sanitation and basic health facilities are also major factors. Pneumonia is an interstitial lung disease caused by bacteria, fungi or viruses. It accounted for approximately 16% of the 5.6 million under-five deaths, killing around 880,000 children in 2016 [1]. Affected victims were mostly less than two years old. Timely detection of pneumonia can help to prevent the deaths of children. This paper presents convolutional neural network models to accurately detect pneumonic lungs from chest X-rays, which can be utilized in the real world by medical practitioners to treat pneumonia [2]. These models have been trained to classify chest X-ray images into normal and pneumonia in a few seconds, hence serving the purpose of early detection of pneumonia. Although transfer learning models based on convolutional neural networks like AlexNet, ResNet50, InceptionV3, VGG16 and VGG19 are some of the most successful ImageNet dataset models with pre-trained weights, they were not trained on this dataset as the size of dataset taken for our research is not as extensive compared to ones which generally employ transfer learning [3]. Four classification models were built using CNN to detect pneumonia from chest X-ray images to help control this deadly infection in children and other age groups. Accuracy of the model is directly correlated with the size of the dataset, that is, the use of large datasets helps improve the accuracy of the model, but there is no direct correlation between the number of convolutional layers and the accuracy of the model. To obtain the best results, a certain number of combinations of convolution layers, dense layers, dropouts and learning rates have to be trained by evaluating the models after each execution. Initially, simple models with one convolution layer were trained on the dataset, and thereafter, the complexities were increased to get the model that not only achieved desired accuracies but also outperformed other models in terms of recall and F1 scores. The objective of the paper is to develop CNN models from scratch which can classify and thus detect pneumonic patients from their chest Xrays with high validation accuracy, recall and F1 scores. Recall is often favored in medical imaging cases over other performance evaluating parameters, as it gives a measure of false negatives in the results. The number of false negatives in the result is very crucial in determining the real-world performance of models. If a model achieves high accuracy but low recall values, it is termed as underperforming, inefficacious and even unsafe as higher false-negative values imply higher number of instances where the model is predicting a patient as normal, but in reality, the person is diseased. Hence, it would risk the patient's life. To prevent this, the focus would be only models with great recall values, decent accuracies . The paper is organized int introduces the subject of this research paper, addresses its importance and relevance, the purpose and motive to undertake this research work and the objective of the paper.explores the work related to this field that has been accomplished till now explains the methodology of the paper, explaining the architecture of the models, flowchart and the dataset used to train and test the four models.The results achieved by the various CNN models and compares the performance of each model using accuracy and loss graphs and confusion matrices provides a brief conclusion to the paper and delivers the best-suited model. Furthermore, the future scope of this research work has also been discussed. All the references which are cited in the paper have been listed in the end

LITERATURE SURVEY

Many researchers have tackled the problem of classifying images with high accuracy. Here are some citations related to our paper: Rubin et al. [6] developed a CNN model to detect common thorax disease from frontal and lateral chest X-ray images. MIMIC-CXR dataset was used to perform large-scale automated recognition of these images. The dataset was split into training, testing and validation sets as 70%, 20% and 10%, respectively. Data augmentation and pixel normalization were used to improve overall performance. Their DualNet CNN model achieved an average AUC of 0.72 and 0.688 for PA and AP, respectively. A deep convolutional neural network to classify pulmonary tuberculosis was developed by Lakhani et al. [7]. Transfer learning models such as AlexNet and GoogleNet were also used to classify chest X-ray images. The dataset was split into training, testing and validation sets as 68%, 14.9% and 17.1%, respectively. Data augmentation and pre-processing techniques were employed to get the best performing model achieving an AUC of 0.99. Precision and recall of the model were 100 and 97.3%. An AG-CNN model was developed by Guan et al. [8] to recognize thorax disease. ChestX-ray14 dataset was used to detect thorax disease from chest X-ray images. Global and local branch attention-guided CNN was used for classification purposes. Their model was better than other models mentioned in their research paper, achieving an AUC of 0.868. A deep convolutional neural network model was developed by Rajpurkar et al. [9] to classify chest X-ray images into pneumonia and other 14 diseases. ChestX-ray14 dataset was used for training the model. They compared their ChXNet model (121 layered model) with practicing academic radiologists. Their ChXNet model achieved an F1 score (95% CI) of 0.435 outperforming radiologists which achieved an F1 score (95% CI) of 0.387. A deep convolutional neural network model having five convolutional layers some followed by max-pooling layers, having three fully connected layers was trained by Krizhevsky et al. [10]. This network contained 60 million different parameters. By employing dropout, this model achieved a top-five error percent of 17%. Simonyan et al. [11] developed a highly accurate model employing multiple small kernel-sized filters to achieve top-five test accuracy 92.7%. This model was trained on the ImageNet dataset and submitted to the ILSVRC 2014 competition. A convolution neural network for classification and segmentation of brain tumor MRIs was developed by Xu et al. [12]. Multiple techniques such as data augmentation, feature selection and pooling techniques were employed in this model. The validation 474 V. accuracy for classification achieved by this model is 97.5%, and validation accuracy of segmentation is 84%, 256 × 256 pixels sized frontal chest radiographs which were fed to a deep convolution neural network to detect abnormalities. A convolutional neural network with five convolution layers employing leaky ReLU, average pooling and three fully connected layers was developed by Anthimopoulos et al. [13] to detect interstitial lung disease patterns in a dataset containing 14,696 images belonging to seven different classes. This model achieved a classification accuracy of 85.5%. He et al. [14] developed a residual neural network (RNN) to classify images present in the ImageNet dataset. RNN introduced the concept of shortcut connections to tackle the problem of vanishing gradients. This model which was submitted to ILSVRC 2015 attained state-of-the-art classification accuracy. A transfer learning model, extension of AlexNet using data augmentation techniques, was developed by Glozman et al. [15]. This model was trained on ADNI database. Two neural network models were presented by Hemanth et al. [16] which are MCPN and MKNN. These models classified MRIs with high accuracies and tackled high convergence time period for Artificial Neural Networks.

EXPERIMENTAL INVESTIGATIONS:





TESTING:

1.Depending on the affected person's medical history and the signs and symptoms that are present at the time of the physical exam, a number of laboratory tests may be performed to help make a
diagnosis.

2.The model is to be tested with different images to know if it is predicting correctly.

3.Pre-processing the image includes converting the image to array and resizing according to the model. And given pre-processed image to the model to know to which class your model belongs to

TRAINING:

1.Gather data.

2.Choose a measure of success.

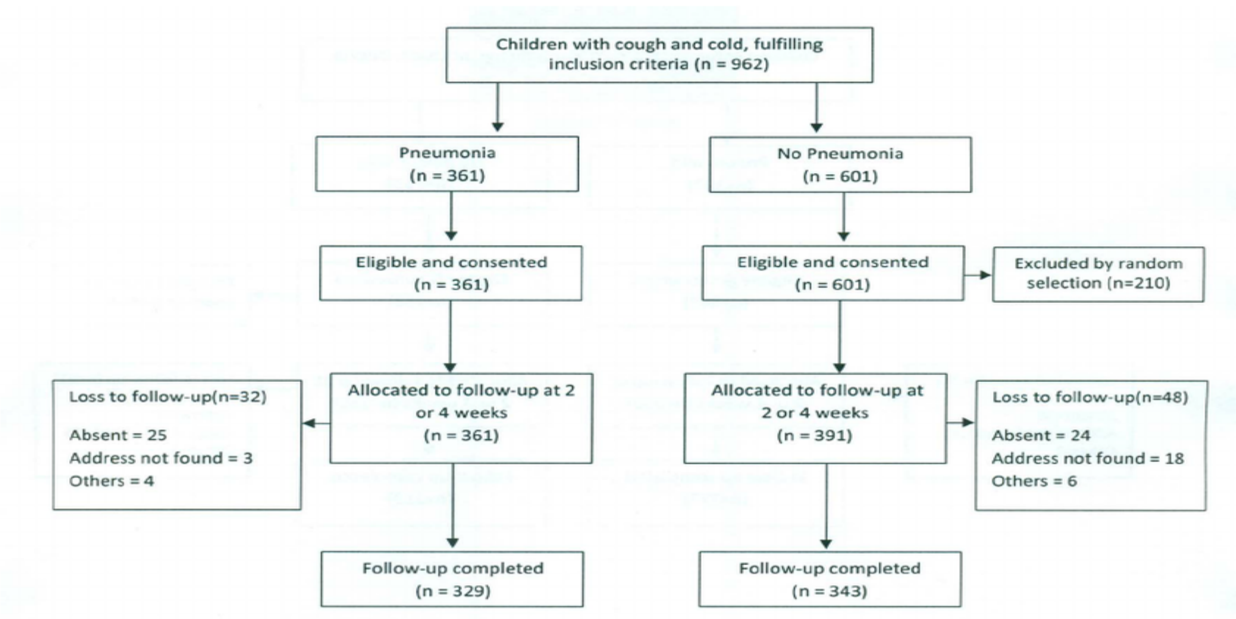
3.Set an evaluation protocol and the different protocols available.

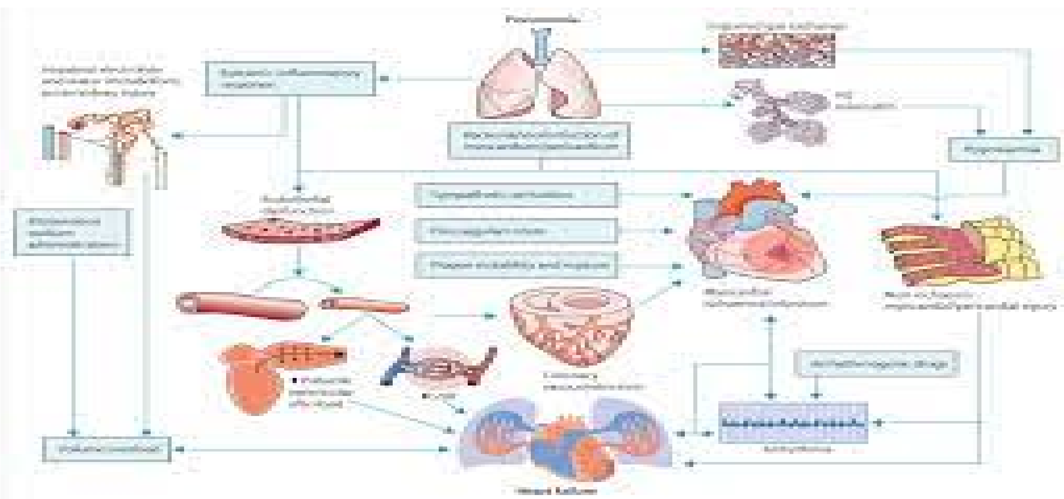
4. Prepare the data (dealing with missing values, with categorial values…).

5.Spilit correctly the data.

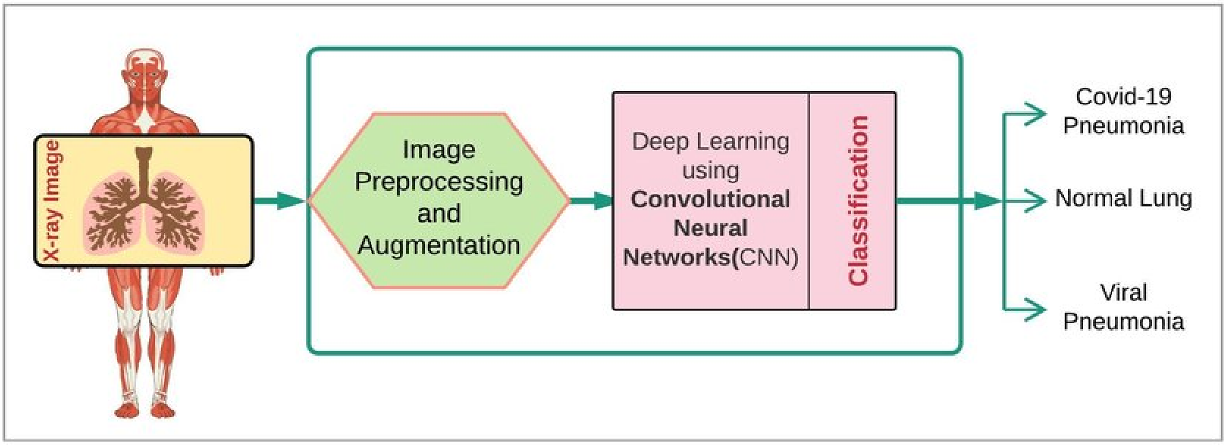
6.Differentiate between over and underfitting, defining what they are and explaining the best ways to avoid them.

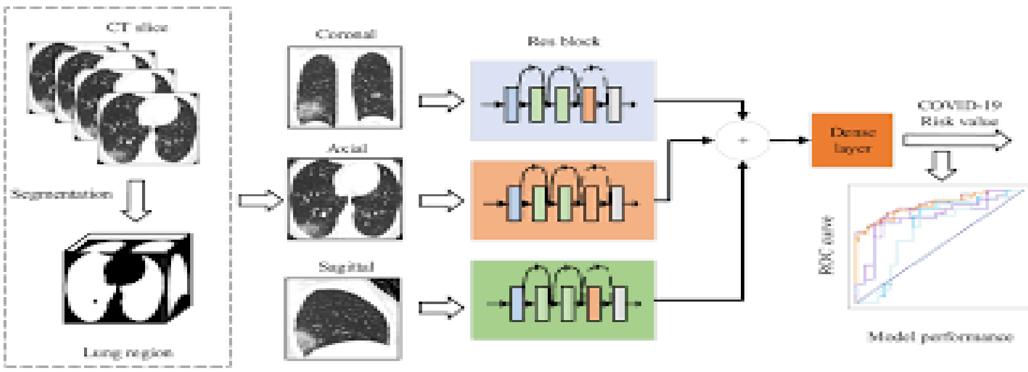
FLOW CHARTS:





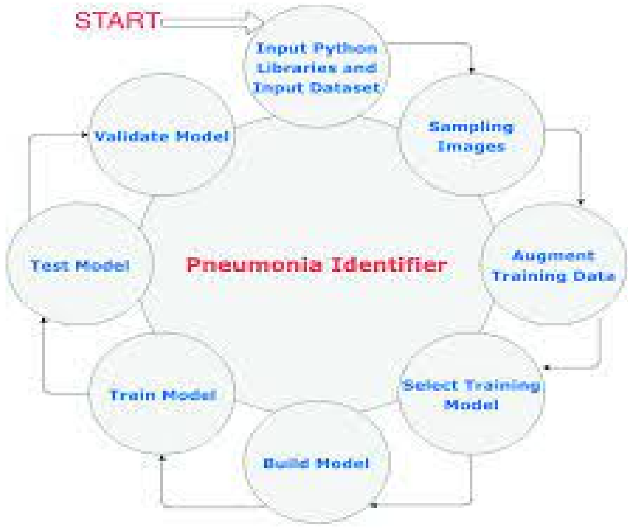
BLOCK DIAGRAM:





The results of deep learning models. Traditionally, deep learning based methods are considered to be a black-box approach. For clinical decision making, it is necessary that the results of the deep learning model can be interpreted. CAMs can help in identifying the parts of the image on which the model was focusing while making the final prediction and hence can provide insights into the working of the model. Such an analysis can further help in hyperparameter tuning and gain understanding of the reason behind the failure of the model. For obtaining the class activation map, the network needed to be trained with the global average pooling (GAP) layer. After the GAP layer, a fully connected network was maintained, which was followed by the softmax layer, providing the class, such as pneumonia,Currently, deep learning based methods cannot replace trained clinicians in medical diagnosis, and they aim to supplement clinical decision making. In this paper, a model is presented based on the applications of deep learning and convolutional neural networks that are capable of classifying automatically that the patient has pneumonia or not. The proposed methodology uses a deep transfer learning algorithm that extracts the features from the X-ray image that describes the presence of disease automatically and reports whether it is a case of pneumonia.

PNEUMONIA IDENTIFIER:



ADVANTAGES AND DIS-ADVANTAGES:

Advantages:

1. It is considered as the best ml technique for image classification due to high accuracy.

2. Image pre-processing required is much less compared to other algorithms.

3. It is used over feed forward neural networks as it can be trained better in case of complex images to have higher accuracies.

4. It reduces images to a form which is easier to process without losing features which are critical for a good prediction by applying relevant filters and reusability of weights

5. It can automatically learn to perform any task just by going through the training data i.e. there no need for prior knowledge

6. There is no need for specialised hand-crafted image features like that in case of SVM, Random Forest etc.

Disadvantages:

1. It requires a large training data.

2. It requires appropriate model.

3. It is time consuming.

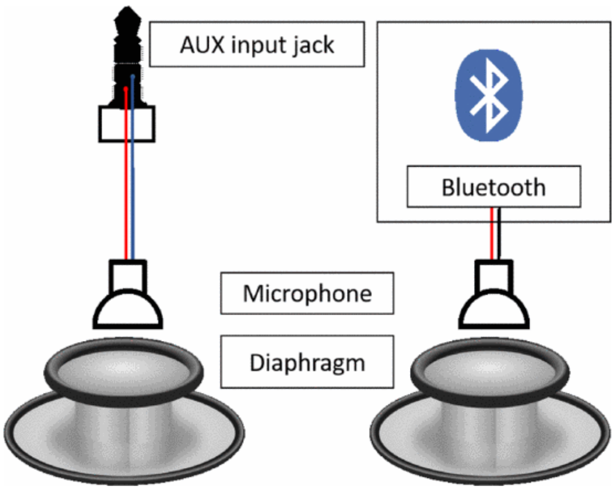
4. It is a tedious and exhaustive procedure.

5. While convolutional networks have already existed for a long time, their success was limited due to the size of the considered network.

APPLICATIONS:

The main application of this model is to predict the provided image is having brain tumor or not. It is well trained so that it will predict the correct data.

A. Design Methodology



Data collection is done using 157 X-ray images, of which 73 are X-ray images of pneumonia patients while 84 are Xray images of healthy individuals, through google search engine database, using a command-line Python program [19]. Subsequently, a refined dataset consisting of 84,495 Xray images based on two image categories of pneumonia-infected and normal X-rays, is procuree

Additionally, a module is developed to record the breathing patterns of pneumonia patients. This breathing pattern recorder module comprises a microphone, a diaphragm and an auxiliary audio input jack. This module has two variants - One is a low-cost wired module, and the other is a Bluetooth-based wireless module. The Trained ANN is used to predict the confidence level of the labels with the help of a known X-ray image of a pneumonia patient to verify the accuracy of the model. On verification, the level of confidence would predict the stage and the possible complications of pneumonia in the patient (fig. 4). A similar methodological framework could be followed to train the ANN for the breathing sound patterns of pneumonia affected persons. This ANN model is still under development and will be tested in the future.

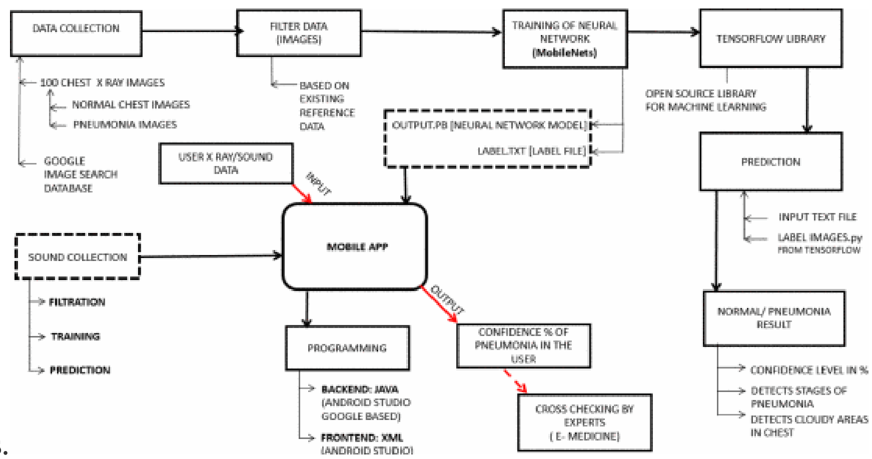
B. Development of the Mobile Application

A mobile application is developed in Android Studio 3.3.1 using Java at the backend and XML for the frontend. A test app, obtained from TensorFlow library is modified by adding the label and model files. Furthermore, three functionalities, namely; patient profile, X-ray analyser, and Emergency Reporting, are added. The input to the application is an uploaded X-ray image which gives the confidence level of pneumonia prevalent in the patients.

Additionally, there could be an option for uploading an audio file for analysing the breathing patterns of patients. An emergency reporting facility for pneumonia patients via e-diagnosis over the internet connection is also provided.

C. Development of Prototype

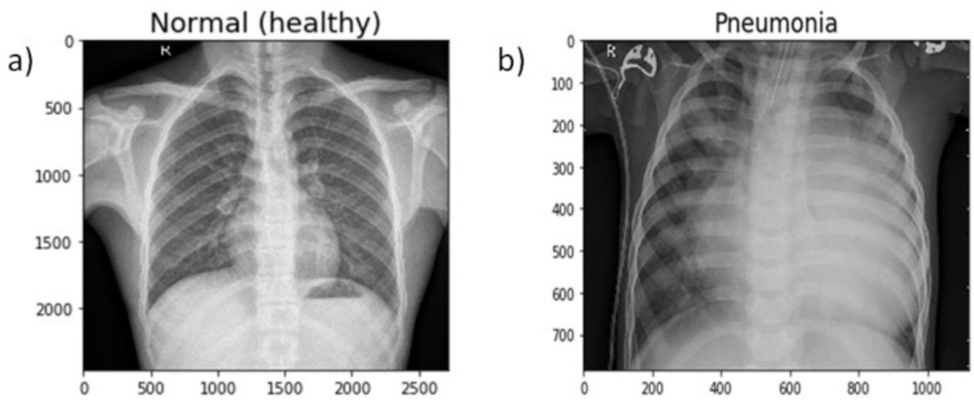
The confidence level of pneumonia is based on two labels defined as—'no pneumonia' or 'presence of pneumonia'—with the *stage* and *type* prediction. In addition, the results can be reaffirmed in coordination with medical experts available online who can act as an optional



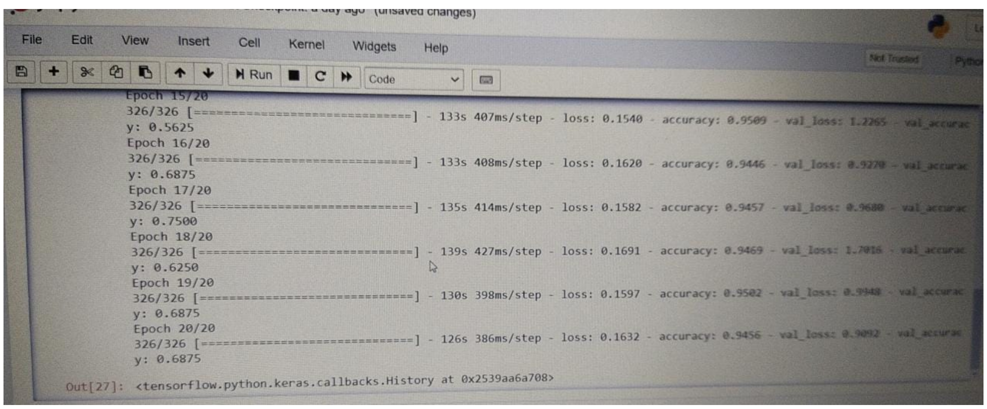
service to the users.

RESULT:

The dataset [55] comprised a total of 5836 images (Table 1) segmented into two main parts, a training set and a test set. Both bacterial and viral pneumonia were considered as a single category, pneumonia infected. The dataset used in this study did not include any case of viral and bacterial co-infection. All chest X-ray images were taken during the routine clinical care of the patients. Two expert physicians then graded the diagnoses for the images before being cleared for training the AI system. The evaluation set was also checked by a third expert to account for any grading errors. The proportion of data assigned to training and testing was highly imbalanced. Therefore, the dataset was shuffled and arranged into training and test sets only. Finally, there were 5136 images in the training set and 700 images in the test set. Eleven-point-nine-five percent of the complete dataset was used as the testing dataset. Figure 2 shows two chest X-ray images, one of a healthy person and the other of a person suffering from pneumonia.



Category	Training Set	Test Set
Normal (Healthy)	1283	300
Pneumonia (Viral + Bacteria)	3873	400
Total	5156	700
Percentage	88.05%	11.95%



CONCLUSTION:

Pneumonia constitutes a significant cause of morbidity and mortality. It accounts for a considerable number of adult hospital admissions, and a significant number of those patients ultimately die (with a mortality rate of 24.8% for patients over 75 years) [61]. According to the WHO, pneumonia can be prevented with a simple intervention and early diagnosis and treatment [4]. Nevertheless, the majority of the global population lacks access to radiology diagnostics [62]. Even when there is the availability of imaging equipment, there is a shortage of experts who can examine X-rays. Through this paper, the automatic detection of pneumonia in chest X-ray images using deep transfer learning techniques was proposed. The deep networks, which were used in our methodology, had more complex structures, but fewer parameters and, hence, required less computation power, but achieved higher accuracy.

FUTURE SCOPE:

Transfer learning and data augmentation were used to solve the problem of overfitting, which is seen when there is insufficient training data, as in the case of medical image processing. Further, to combine different architectures efficiently, a weighted classifier was proposed. The experiments were performed, and the different scores obtained, such as the accuracy, recall, precision, and AUC score, proved the robustness of the model. The proposed model was able to achieve an accuracy of 98.857%, and further, a high F1 score of 99.002 and AUC score of 99.809 affirmed the efficacy of the proposed model. Though many methods have been developed to work on this dataset, the proposed methodology achieved better results. In the future, it would be interesting to see approaches in which the weights corresponding to different models can be estimated more efficiently and a model that takes into account the patient’s history while making predictions.

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A Reliable Method for Brain Tumor Detection Using Cnn Technique NeethuOuseph C1, Asst. Prof. Mrs.Shruti K2 1(Digital electronics ECE, Malabar Institute of Technology, India) 2(Electronics and Communication Engineering, Malabar Institute of Technology, India)

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