



PNEUMONIA CLASSIFICATION ANALYSIS USING DEEP LEARNING IN HEALTHCARE

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Abstract

Pneumonia is a contagious disease that causes ulcers of the lungs, and is one of the main reasons for death among children and the elderly in the world. Several deep learning models for detecting pneumonia from chest X-ray images have been proposed. One of the extreme challenges has been to find an appropriate and efficient model that meets all performance metrics. Proposing efficient and powerful deep learning models for detecting and classifying pneumonia is the main purpose of this work. In this paper, four different models are developed by changing the used deep learning method; two pre-trained models, ResNet152V2 and MobileNetV2, a Convolutional Neural Network (CNN), and a Long Short-Term Memory (LSTM). The proposed models are implemented and evaluated using Python and compared with recent similar research. The results demonstrate that our proposed deep learning framework improves accuracy, precision, F1-score, recall, and Area under the Curve (AUC) by 99.22%, 99.43%, 99.44%, 99.44%, and 99.77%, respectively. As clearly illustrated from the results, the ResNet152V2 model outperforms other recently proposed works. Moreover, the other proposed models—MobileNetV2, CNN, and LSTM-CNN—achieved results with more than 91% in accuracy, recall, F1-score, precision, and AUC, and exceed the recently introduced models in the literature

1. INTRODUCTION

Pneumonia affects the lungs and causes about 18% of all deaths in children under five years old. Additionally, about two billion people worldwide suffer from pneumonia every year, and death can occur if action is not taken. Early diagnosis of pneumonia is a vital matter. Therefore, rapid diagnosis by an expert radiologist using chest X-rays is required to avoid misdiagnosis. Chest X-rays are the most common and cheapest way to detect pneumonia. Likewise, there is a shortage of radiologist experts, especially in low-resource countries and in rural regions, causing long waits for diagnoses, which increases the death rate. Because of the nature of chest X-ray image analysis, pneumonia diagnoses by X-ray images are often unclear and can be confused with other diseases that have similar features, such as opacity, cavity, and pleural effusions. Thus, chest X-rays cannot be as easily used for detecting diseases. Accordingly, many computer-aided diagnosis (CAD) systems and computer algorithm diagnostic tools have been proposed by researchers for X-ray image analysis; these proposed systems help radiologists discover various types of chest X-ray pneumonia immediately after acquisition. Recently, various biomedical problems, such as skin cancer detection, brain tumor detection, and breast cancer detection are using solutions based on Artificial Intelligence (AI) approaches as handcrafted techniques, deep learning, and machine learning techniques. As a matter of fact, deep learning is a subsection of AI and machine learning that utilizes multi-layered artificial neural networks to provide the latest technology in many topics, such as speech recognition, language translation, and others. There is a difference between traditional machine learning techniques and deep learning in that the latter can automatically learn representations from data, such as videos, images, or text, without entering manually coded rules or direct human intervention. Their architectures are highly flexible, and thus can learn immediately from the data and raise their predictive

Accuracy by providing it with more data. The main objective of this work was to develop a deep learning framework to automatically diagnose pneumonia using chest X-ray images and to classify the result as normal cases or pneumonia cases, which will help in quickly and easily diagnosing the disease.

2. LITERATURE SURVEY

Research	Author	Technique	Accuracy	Recall	F1-Score	Precision	AUC
R1	Antin B. et al. [12]	CNN+Adam (DenseNet 121)	—	—	—	—	60.9 %

R2	Rajpurkar P. et al. [13]	CNN (DensNet121)	—	—	43.5%	—	—
R3	Donthi A. et al. [15]	CNN	78.9%	90.7%	—	—	71.7%
R4	Almubarak A. et al. [16]	(deep ResNet), mask RCNN +Adam + FPN	85.60%	51.52%	—	—	—
R5	Li B. et al. [17]	CNN (RetinaNet, Mask R-CNN)	26.2%	83.5%	—	61.1%	—
R6	Sirazitdinov I. et al. [18]	CNN (RetinaNet, Mask R-CNN) + FPN principle	—	79.3%	77.5%	75.8%	—
R7	Sharma H. et al. [19]	CNN (4 models)	90.68%	—	—	—	—

Table 1: Summary of recent work used in detecting pneumonia using a convolutional neural network (CNN).

3. PROPOSED METHDOLOGY

3.1 Convolutional Neural Networks (CNNs)

In recent years, the use of deep learning in clinical diagnosis and medical images has increased rapidly; specifically, CNNs can be considered a special type of multi-layer neural network that was built to directly identify visual patterns in pixel images with minimal preprocessing. CNNs have many benefits, such as an ability to extract more significant features from images rather than handcrafted features. Researchers have proposed different CNN-based deep networks for achieving image classification, image segmentation, object detection, and localization in computer vision.

Besides solving natural computer vision problems, CNNs have also been very successful and efficient in solving medical problems, such as breast cancer detection, brain tumor segmentation, diagnosing Alzheimer's disease, and classifications of skin lesions. In addition, detailed reviews about deep learning in medical image analysis have been presented. Various CNN models, such as ResNet, AlexNet, LeNet, VGGNet, and Inception were developed as pre-trained models on millions of images and can be used for image classification using transfer learning. These models have disadvantages—a very large architecture, millions of trainable parameters that require substantial computing power, and high time consumption. Moreover, when the used dataset size is small, these models may overfit the training data, resulting in poor

classification accuracy.

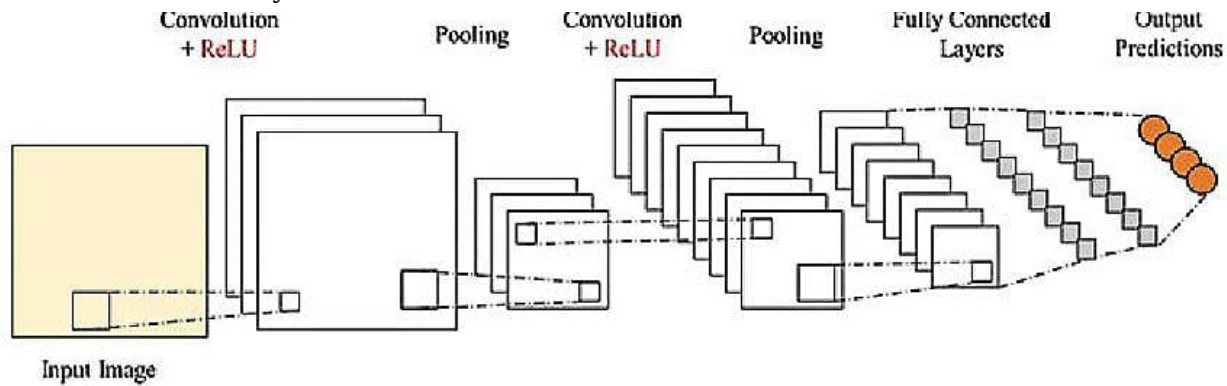


Fig7 CNN Model architecture.

3.2. Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNNs) are the other type of deep learning technique and are mainly used for prediction purposes. They feed the output from the previous step and use it as an input for the current step. In this case, the networks themselves have repetitive loops. These loops, which are in the hidden neurons, allow for the storing of previous input information for a while so that the system can predict future outputs. Its most important feature is the hidden state, which remembers information about the sequence.

They are also powerful tools for obtaining healthier modeling and prediction performance. The problem is that, when the network contains a large number of deep layers, they become untrained, which is called the vanishing gradient problem.

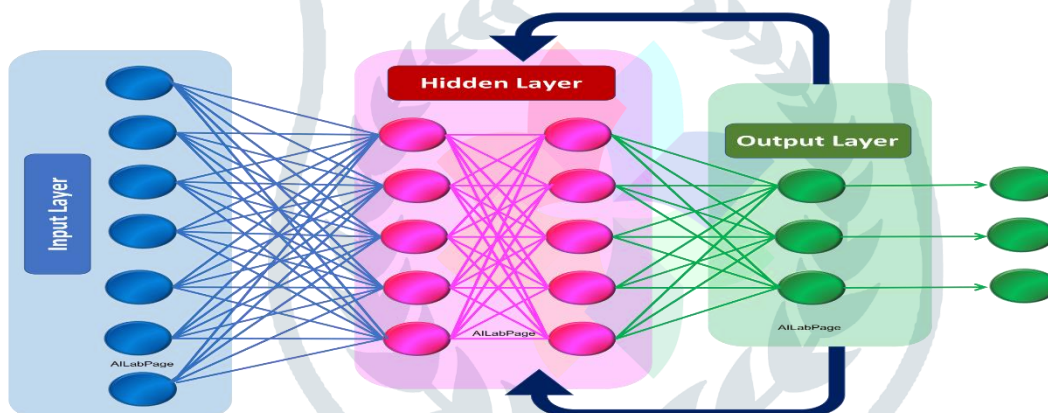


Fig 8. Recurrent Neural Networks.

3.3. Long Short-Term Memory (LSTM)

One of the most famous types of RNN is the Long Short-Term Memory (LSTM) technique, which can be used mainly for large neural networks. The main benefit of the LSTM is that it can model both short- and long-term memory and can address the disappearance of the vanishing gradient problem that appears in RNNs by training on long strings and keeping them in memory. These are the main types of deep learning techniques. These motivated us to build a CNN and LSTM combination architecture that helps to extract features and image classification, using the advantages of both types.

A common LSTM unit is composed of a **cell**, an **input gate**, an **output gate** and a **forget gate**. The cell remembers values over arbitrary time intervals and the three regulate the flow of information into and out of the cell.

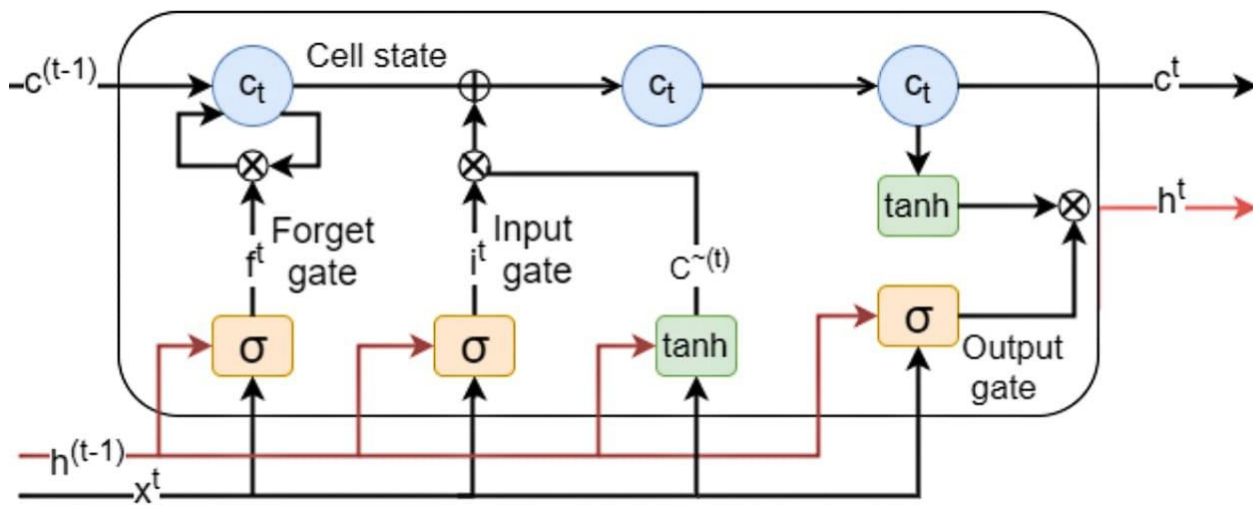


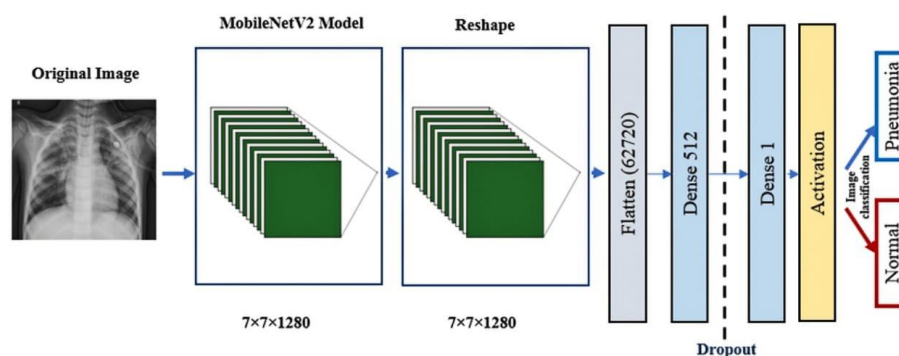
Fig 9 LSTM working procedure.

3.4. Pre-Trained Convolutional Neural Networks

There are two well-known pre-trained deep learning methods based on CNNs: ResNet152v2 and MobileNetv2. These models have many applications, such as classification, feature extraction, and prediction.

• ResNet152v2 Architecture

Residual Network (ResNet) is a CNN architecture with hundreds or thousands of convolutional layers. Previous CNN structures decreased the efficacy of additional layers. ResNet contains a huge number of layers, with strong performance. The primary difference between ResNetV2 and the original (V1) is that V2 uses batch normalization before each weight layer. In the field of image recognition and localization tasks, ResNet has strong performance that demonstrates the importance of many visual recognition tasks.



ResNet152V2 architecture.

Fig 10 Resnet architecture.

• MobileNetV2 Architecture

The architecture of MobileNetV2 is based on a between the thin bottleneck layers. The intermediate expansion layer of the MobileNetV2 uses lightweight depth-wise convolutions in order to filter the features. In traditional residual models, expanded representations in the input are used. MobileNetV2 consists of the primary full convolution layer through 32 filters, followed by 19 residual bottleneck layers.

3.5 Used Machine Learning Algorithms

3.5.1 K-MEANS Algorithm

K-means clustering is one of the simplest and popular unsupervised machine learning algorithms. A cluster refers to a collection of data points aggregated together because of certain similarities. You'll define a target number k , which refers to the number of centroids you need in the dataset. A centroid is the imaginary or real location representing the center of the cluster. Every data point is allocated to each of the clusters through reducing the in-cluster sum of squares.

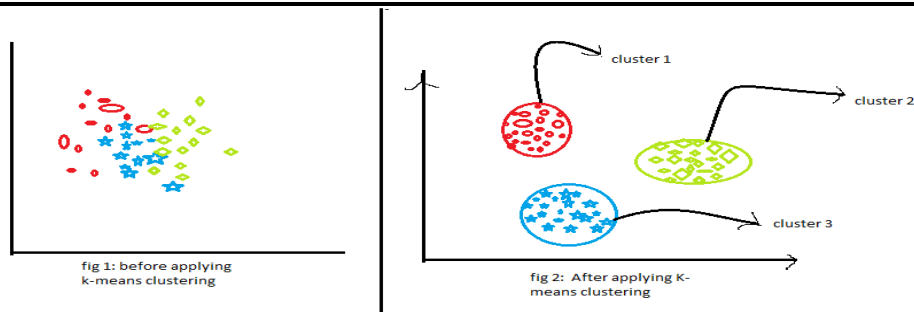


Fig 11 K Means clustering.

In other words, the K-means algorithm identifies k number of centroids, and then allocates every data point to the nearest cluster, while keeping the centroids as small as possible

How the K-means algorithm works

To process the learning data, the K-means algorithm in data mining starts with a first group of randomly selected centroids, which are used as the beginning points for every cluster, and then performs iterative (repetitive) calculations to optimize the positions of the centroids

It halts creating and optimizing clusters when either:

1. The centroids have stabilized — there is no change in their values because the clustering has been successful.
2. The defined number of iterations has been achieved.

3.5.2 Support Vector Machine

“Support Vector Machine” (SVM) is a supervised machine learning algorithm which can be used for both classification or regression challenges. However, it is mostly used in classification problems. In the SVM algorithm, we plot each data item as a point in n dimensional space (where n is number of features you have) with the value of each feature

being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiates the two classes very well

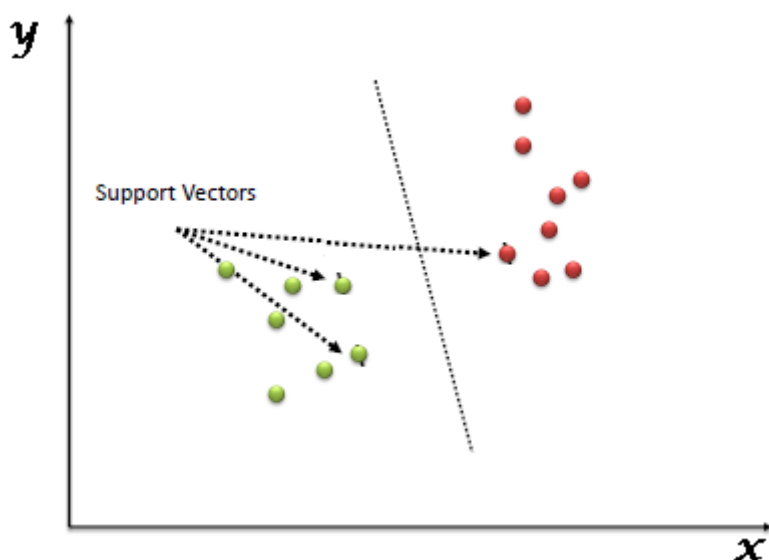


Fig 12 support vector machine

SVM can be of two types:

- o **Linear SVM:** Linear SVM is used for linearly separable data, which means if a dataset can be classified into two classes by using a single straight line, then such data is termed as linearly separable data, and classifier is used called as Linear SVM classifier.
- o **Non-linear SVM:** Non-Linear SVM is used for non-linearly separated data, which means if a dataset cannot be classified by using a straight line, then such data is termed as non-linear data and classifier used is called as Non-linear SVM classifier.

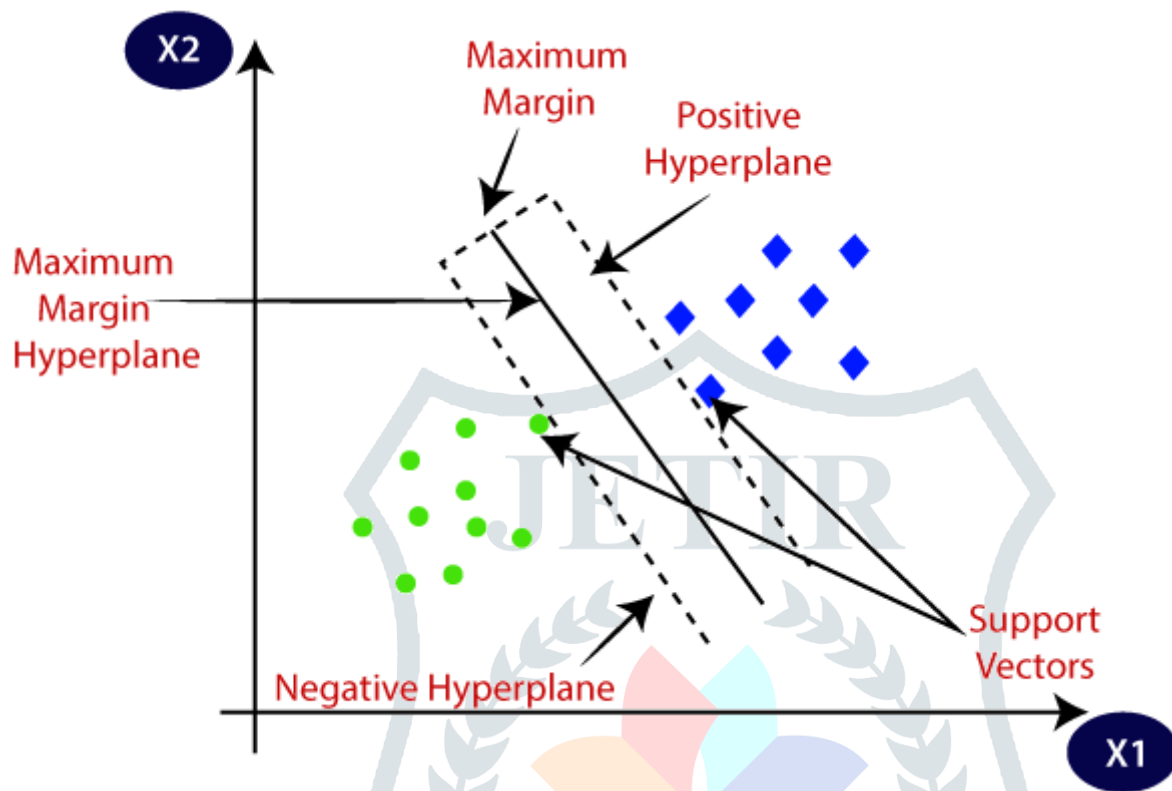


Fig 13 Detailed View of SVM.

3.6 Impact of Pneumonia on children

Most deaths occurred among children under the age of two. India accounts for 1.27 lakh deaths owing to pneumonia, ahead of Pakistan and Bangladesh. Only Nigeria is ahead of our country with 1.62 lakh such deaths.

Globally, the disease accounts for 8 lakh deaths, one child every 39 seconds and just five countries are responsible for more than half of child pneumonia deaths — Nigeria (1,62,000), India (1,27,000), Pakistan (58,000), Democratic Republic of Congo (40,000) and Ethiopia (32,000).

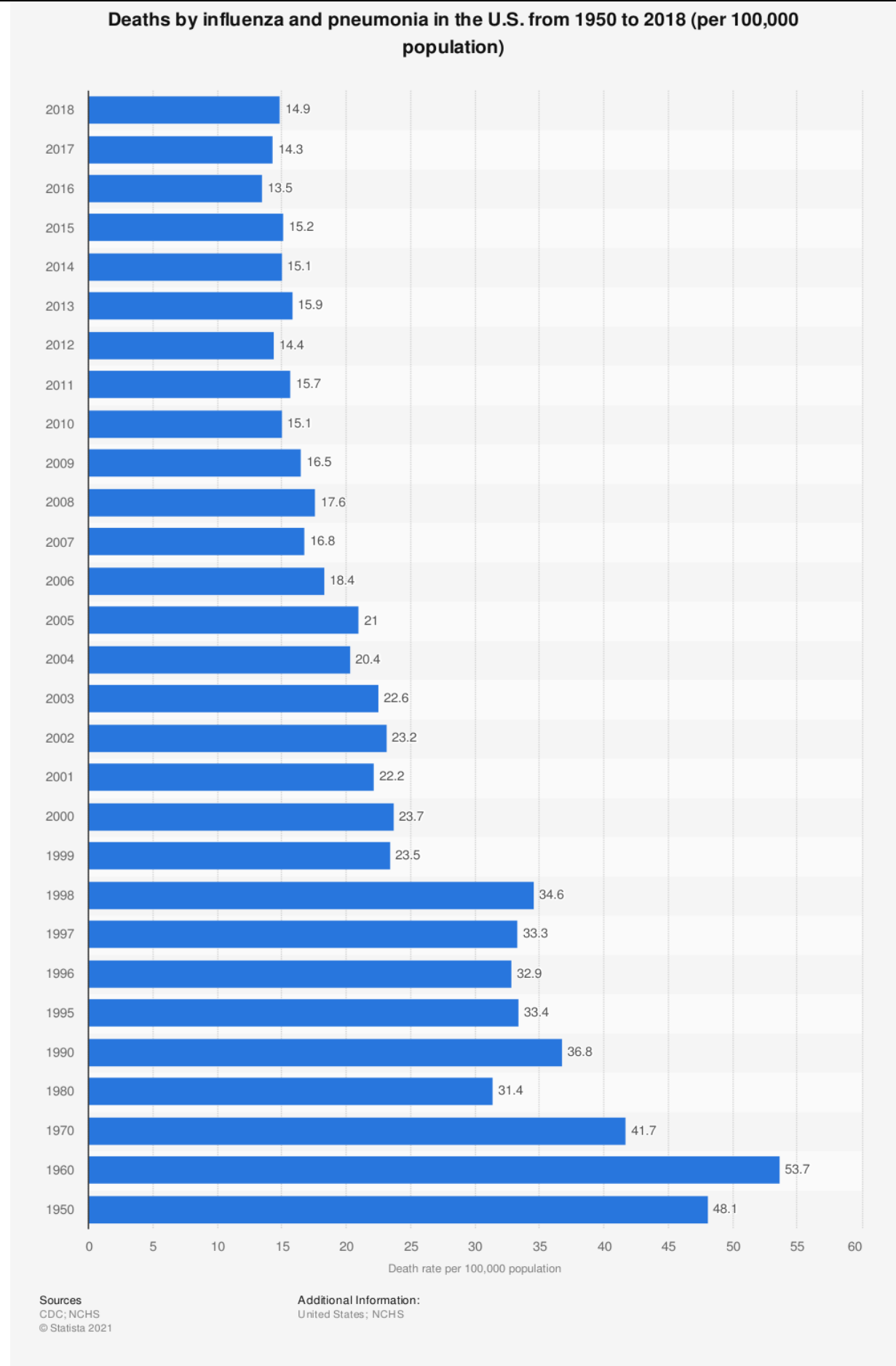


Fig14 Graph representing the Impact of pneumonia on Children.

3.7 INPUT AND OUTPUT DESIGN

3.7.1 INPUT DESIGN

The input design is the link between the information system and the user. It comprises the developing specification and procedures for data preparation and those steps are necessary to put transaction data in to a usable form for processing can be achieved by

inspecting the computer to read data from a written or printed document or it can occur by having people keying the data directly into the system. The design of input focuses on controlling the amount of input required, controlling the errors, avoiding delay, avoiding extra steps and keeping the process simple. The input is designed in such a way so that it provides security and ease of use with retaining the privacy. Input Design considered the following things:

- What data should be given as input?
- How the data should be arranged or coded?
- The dialog to guide the operating personnel in providing input.
- Methods for preparing input validations and steps to follow when error occur.

OBJECTIVES

1. Input Design is the process of converting a user-oriented description of the input into a computer-based system. This design is important to avoid errors in the data input process and show the correct direction to the management for getting correct information from the computerized system.

2. It is achieved by creating user-friendly screens for the data entry to handle large volume of data. The goal of designing input is to make data entry easier and to be free from errors. The data entry screen is designed in such a way that all the data manipulates can be performed. It also provides record viewing facilities.

3. When the data is entered it will check for its validity. Data can be entered with the help of screens. Appropriate messages are provided as when needed so that the user will not be in maize of instant. Thus, the objective of input design is to create an input layout that is easy to follow

3.7.2 OUTPUT DESIGN

A quality output is one, which meets the requirements of the end user and presents the information clearly. In any system results of processing are communicated to the users and to other system through outputs. In output design it is determined how the information is to be displaced for immediate need and also the hard copy output. It is the most important and direct source information to the user. Efficient and intelligent output design improves the system's relationship to help user decision-making.

1. Designing computer output should proceed in an organized, well thought out manner; the right output must be developed while ensuring that each output element is designed so that people will find the system can use easily and effectively. When analysis

design computer output, they should Identify the specific output that is needed to meet the requirements.

2. Select methods for presenting information.

3. Create document, report, or other formats that contain information produced by the system.

The output form of an information system should accomplish one or more of the following objectives.

- Convey information about past activities, current status or projections of the · Future.
- Signal important events, opportunities, problems, or warnings.
- Trigger an action.
- Confirm an action.

4. RESULTS ANALYSIS

4.1. CONFUSION MATRIX

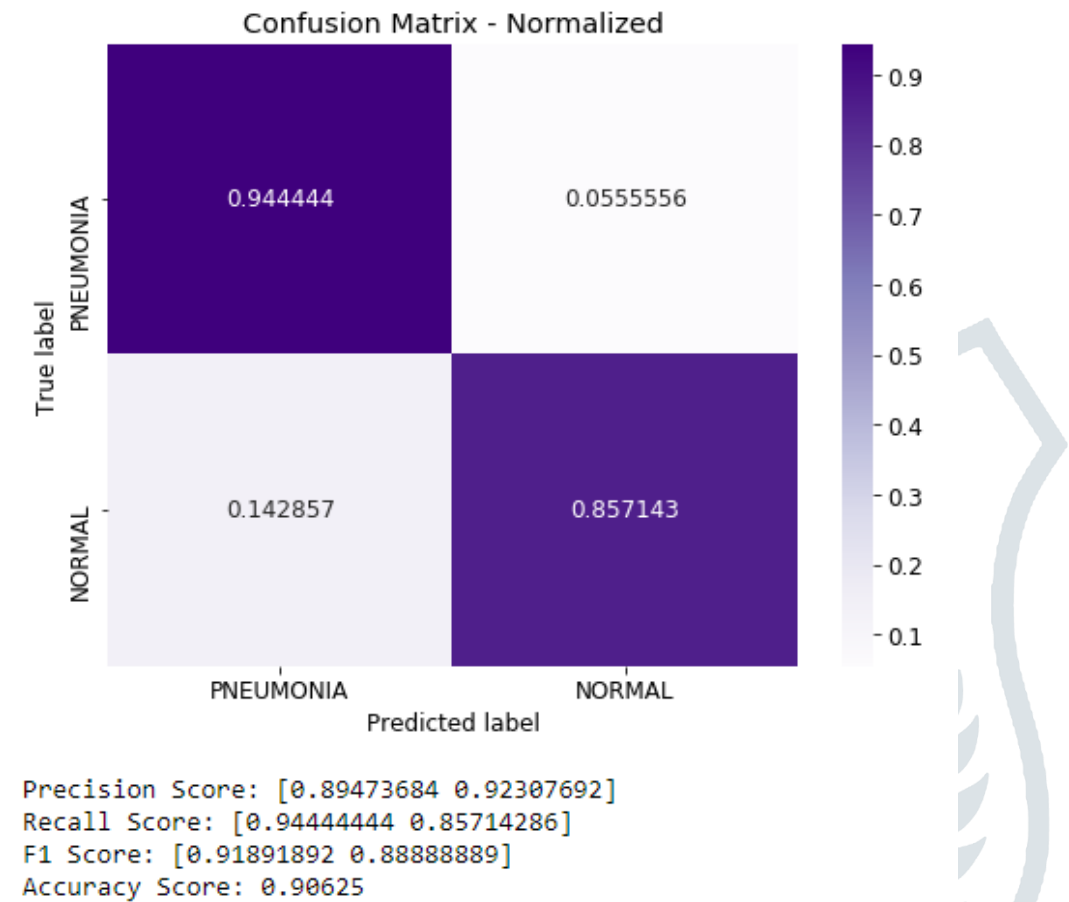
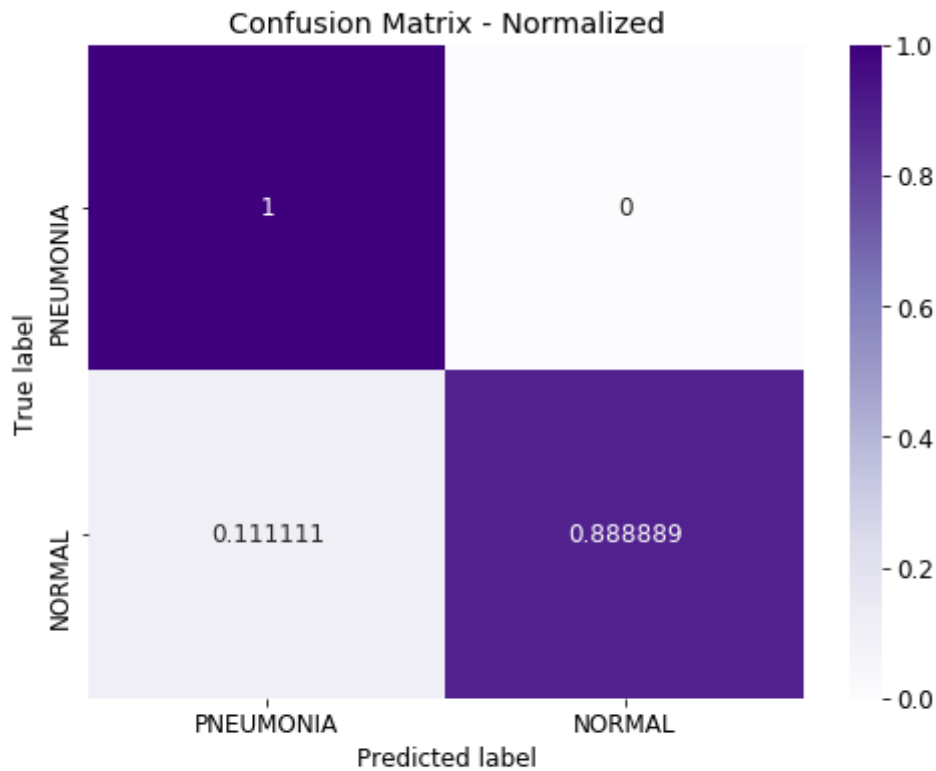


Fig 15 Confusion Matrix 1.

Confusion Matrix



Precision Score: [0.875 1.]
 Recall Score: [1. 0.88888889]
 F1 Score: [0.93333333 0.94117647]
 Accuracy Score: 0.9375

Fig 16 confusion matrix 2.

4.2 MODEL LOSS AND ACCURACY

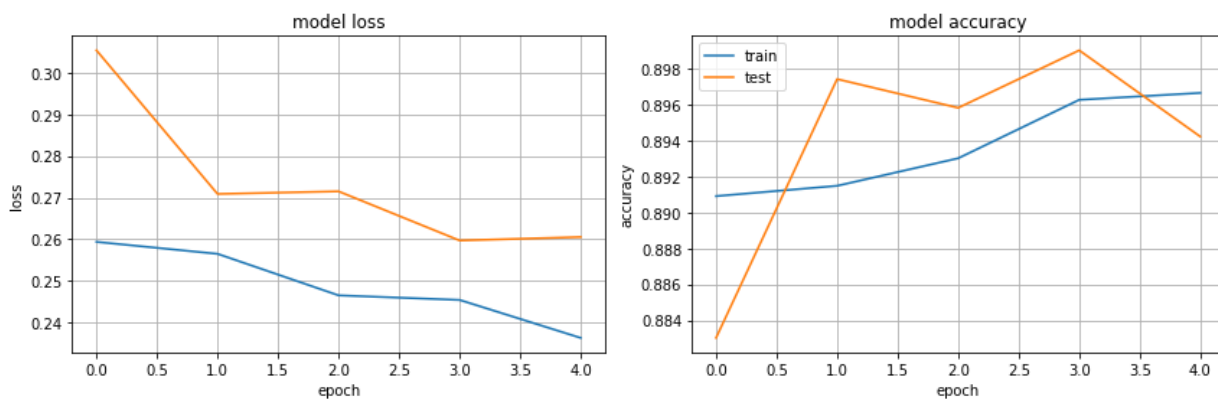


Fig 18 Model loss and accuracy.

4.3 ROC CURVE

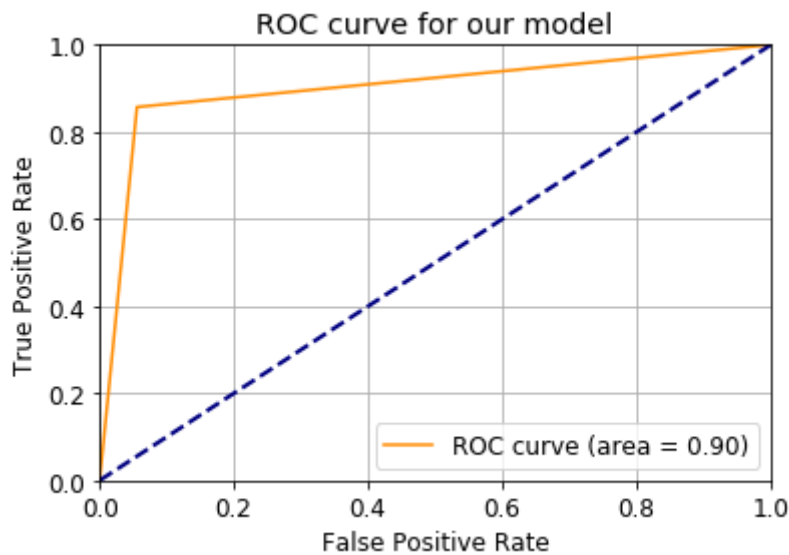


Fig 19 Graph Representing the Roc curve.

4.4 X RAY

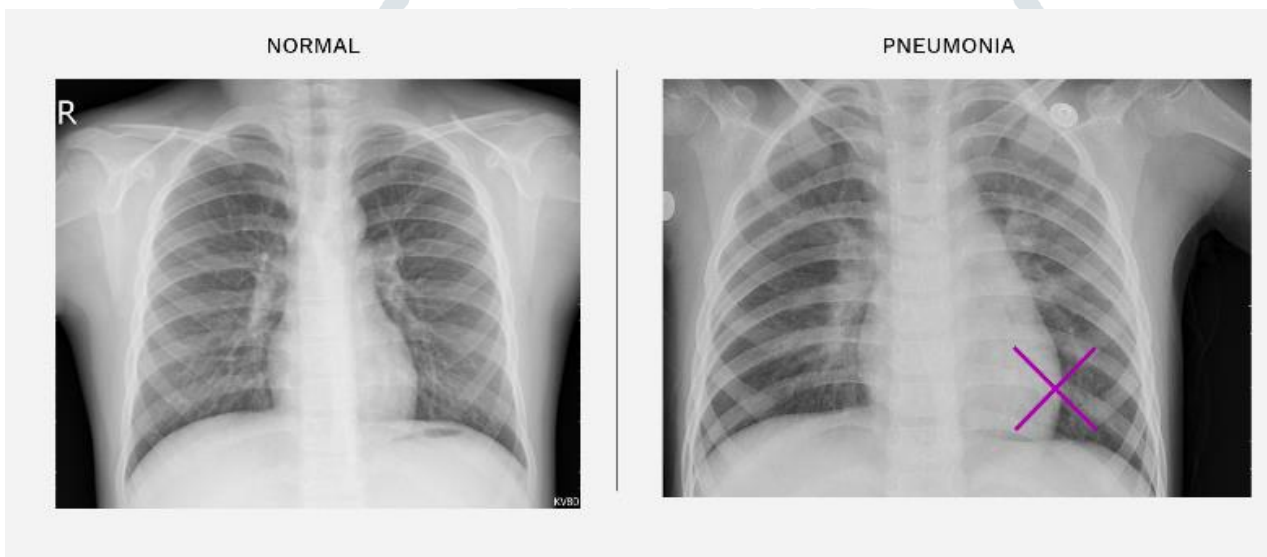


Fig 20 X Ray Representing of Normal and Infected Person

CONCLUSION

A deep learning framework for pneumonia classification with four different CNN models was proposed. Two of them were pre-trained models, ResNet152V2 and MobileNetV2, and the others were designed from scratch. We evaluated the proposed models by comparing them with recent, similar research. The experiment performance of our proposed deep learning framework was assessed based on accuracy, precision, F1-score, recall, and AUC, and our model showed values of 99.22%, 99.43%, 99.44%, 99.44%, and 99.77%, respectively. It is evident that our proposed ResNet152V2 model accomplished the highest results compared with the others. Moreover, the other three proposed models, MobileNetV2, CNN, and LSTM CNN, achieved results of more than 91% in accuracy, recall, F1-score, precision, and AUC.

For future work, we plan to apply other CNNs and RNNs as bidirectional LSTM architectures and pre-trained models for detecting pneumonia using chest X-ray images.

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