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Pneumonia Detection using Deep Learning Approach

Sukhada Raut[1], Veena Kulkarni[2]
[1]Student, [2]Professor, Department of Computer Engineering, Thakur College of Engineering and Technology, Mumbai, India

Abstract*: Pneumonia is a lung infection; it is one such form of lung disease where viruses or bacteria cause inflammation or infection in the lungs. The air sacs of the patient's lungs are filled with liquid substance in the event of pneumonia, which does not allow the lungs to function properly. Radiology is a field of medical science where x-ray image is used to diagnose this disease. As an efficient way to automate the analysis and diagnosis of medical photos, machine learning has been encouraged. The widely used method of detecting pneumonia is the use of chest X-rays, which involve a specialist to closely analyse X-ray images. Human aided diagnosis has its drawbacks such as an expert's inaccessibility, high cost, false negative detections etc., and thus there is a need for an efficiently automated system that is invariant to several factors that can influence the diagnosis of the radiologist, such as eyestrain, distraction, stress, etc. The purpose of the automated system is to increase the efficiency and effectiveness of the work of a radiologist by helping to identify and diagnose diseases more precisely, regardless of the doctor's experience. The purpose of the proposed paper is a comparative study of four different Deep Learning's Convolution Neural Network algorithms which are: Basic CNN, AlexNet, VGG16 and VGG19. The layers of these algorithms are customized to optimize the results. Also, the algorithms are combined with different image augmentation techniques to find out the best working combinations. The final results of the algorithms are compared using the parameters such as: Accuracy, Precision, Recall, F1 Score and Specificity.

Keywords: Artificial Intelligence, Machine learning, Pneumonia, Image Classification, Deep Learning, Chest X-Ray, Healthcare, Convolution Neural Network

I. INTRODUCTION

Pneumonia is a type of lung disease, in which there is inflammation or infection in the lungs caused by viruses or bacteria. The air sacs of the patient's lungs are filled with mucus substance in the event of pneumonia, which does not allow the lungs to function properly. Pneumonia diagnosis mainly requires exams by a doctor that may require blood tests, such as a full blood count (CBC) to see whether the immune system of the patient is battling an infection. This will then lead to x-ray tests to determine whether or not the patient is suffering from pneumonia. A chest x-ray image of the patient can be used to diagnose pneumonia. In the x-ray picture, the radiologist will search for white spots in the lungs that identify an infection while analysing the x-ray. [1]

The main purpose of the automatic classification system for pneumonia is to enhance the efficiency and effectiveness of the radiologist's job by providing an assistance of a computer system for disease detection and classification. And for a professional radiologist, analysing chest X-rays is a difficult task. In order to improve the accuracy and reduce the time taken, which is very necessary in the healthcare sector, the automated system may help the radiologist in their decision-making process. The automated system can be used to enhance diagnostic accuracy, not as a way to replace the specialist, but rather as a second system, which is invariant to several factors that can influence the radiologist's, such as eyestrain, distraction, stress and others. [2]

II. ARTIFICIAL INTELLIGENCE IN COMPUTER AIDED DIAGNOSIS

Radiology is a branch of medical science that uses imaging technology and radiation to diagnose a disease and treat it. An active field of study is Chest X-Rays image classification in medical image analysis and computer-aided diagnosis for radiology. The primary objective is to improve the quality and productivity of the work of radiologists by providing a computer system for diagnosis and classification of the disease. [2]

A Computer-Aided Diagnosis (CAD) is an automated system that helps the main radiologist or assists him. This type of software is used not as a means of replacing the specialist, but rather as a second one, which is invariant to many variables that can affect the diagnosis of the radiologist, such as eyestrain, distraction, stress and others, to improve diagnostic accuracy. Currently pneumonia is detected using chest radiographs. As an efficient way to automate the analysis and diagnosis of medical photos, machine learning has been encouraged. Thus, ML leads to CAD improvement. In addition, deep learning has been investigated and proven to be the most effective medical image analysis Machine Learning model.

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Machine learning is a subset of artificial intelligence that, from empirical evidence, can learn complex relationships or patterns and make precise decisions. ML algorithms are classified predominantly into three types: supervised learning, semi-supervised learning, and unsupervised learning. Classification, regression, and reinforcement learning provide examples of supervised learning. Machine Learning offers an important way to automate the study and diagnosis of medical images in the sense of radiology. With an automated device, the radiologist can support. [3] In medical image processing, there are a few Machine Learning algorithms which have been implemented. The techniques that are most used are known as deep learning. The foundation of most methods of deep learning is focused on neural networks. With certain activations and parameters, a neural network consists of neurons. There are several layers in the Neural Network that relate to the input layer, output layer, and hidden layers. (i.e., layers in between input and output). Meanwhile, Convolutional Neural Networks is the most common deep learning architecture in medical image analysis (CNNs). The key explanation is that when filtering input files, CNNs maintain feature relationships. [4]

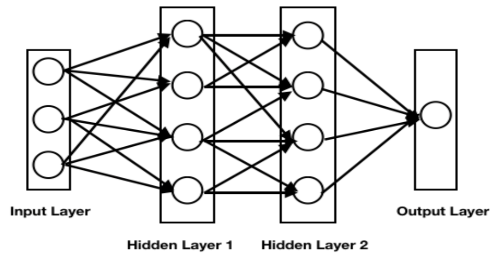

Fig 1. Architecture of Neural Network

An input is taken as an image by CNNs and results in class scores or probabilities being allocated. This implies that for a given input, the class with the highest probability is the correct class. As well as the implementation of the backpropagation algorithm, the method of translating the inputs into the chosen groups has layers close to the neural network. [4]

III.LITERATURE REVIEW

Pneumonia is a lung disease that can be identified by an x-ray scan of the chest. I reviewed different pneumonia detection system algorithms used for computer assisted diagnostics in this literature review.

A. Technique 1: X-ray image classification using Machine Learning Algorithms

In this technique Support Vector Machine (SVM) and K-nearest neighbours (KNN) scheme is used to detect the pneumonia. SVM is a classification method in which all types of problems can be solved, i.e., classification and regression (curve fitting). It is a supervised method of machine learning. In this method, data in space is plotted and the dimension of space is taken equal to the number of characteristics. By finding the hyper plane that differentiates between classes quite accurately, we carry out classification problem. Based on the equation of hyper plane (kernel) SVM are classified as linear, quadratic, cubic and fine Gaussian SVM etc.

KNN, the technique is example-based learning, where function approximation is determined locally and the computational process is continued until the correct classification is performed. It is a type of non-parametric technique that is used for problems of classification and regression. K-NN is graded as Fine, Medium, Coarse, Cosine, Cubic and Weighted K-NNN, depending on the number of neighbours. [6]

B. Technique 2: X-ray image classification using Deep Learning

The Convolution Neural Network of this deep convolution neural network system uses architectures to extract features from chest X-ray images and categorize the images to detect whether an individual has pneumonia. CNN is a subset of deep neural networks, such as image segmentation, image recognition, object detection, etc., which have achieved tremendous success in the field of computer vision. A CNN have convolution layers, pooling layers and a fully-connected layer.

The Convolution Neural Network of this deep convolution neural network system uses architectures to extract characteristics from chest X-ray images and identify the images to detect whether a person has pneumonia. CNN is a subset of deep neural networks, such as image segmentation, image recognition, object detection, etc., which have achieved tremendous success in the field of computer vision. By having a visual processing system that is close to that of humans and an incredibly optimized structure for handling images, as well as the ability to extract features by studying, CNNs presides over the DNNs. In training CNNs models, gradient-based A are used and are less vulnerable to decreasing gradient problem. During training, CNN frameworks often need pictures of fixed sizes. [2]

In this system, a model is developed to detect and classify pneumonia at high validity precision from chest X-ray images taken from frontal views. The initial algorithm process involves the conversion of chest X-ray images into sizes smaller than the original. Then, the convolutions neural network architecture, which extracts characteristics from images and images, recognizes and classifies images. This approach has been shown to distinguish positive and negative data on pneumonia from a series of X-ray pictures. In this, the model is developed from scratch, which distinguishes it from other strategies that depend heavily on the approach to transfer learning. To detect and recognize X-ray images consisting of lung cancer and pneumonia, this study can be expanded. In recent times, separating X-ray images containing lung cancer and pneumonia has been a major problem and our next approach will resolve this question. [7]

C. Technique 3: X-ray image classification using Deep Convolution Architecture

Deep convolution architecture has led to a number of breakthroughs in image classification and object detection because it can combine lower and higher characteristics of the image details. With the addition of stacked layers, the data can be enriched. There are several distinct architectures that are commonly used to identify images. R-CNN is used as the name suggests Regional Convolution Neural Network for object detection, i.e., a specific area. These networks were optimized to preside over the success of previous architectural innovations. The two commonly known deep convolution architectures are studied in classifying and detecting pneumonia, such as residual network and mask-RCNN.

A further development of the Faster Regional CNN algorithm is the Mask Regional CNN (mask-RCNN). This algorithm is widely used to locate and identify objects in an image by integrating object detection and semantic segmentation. [7]. The aim of object detection is to use a bounding box to localize each object in the image. Meanwhile, the purpose of semantic segmentation is to use object delineation to classify each pixel into a defined set of categories. In the object detection process, the Faster Regional CNN algorithm is involved. This algorithm consists of two stages, the Area Proposal Network (RPN) proposing candidates for a region of interest (RoI). The second stage uses RoI-align to extract the characteristics and identify the class of the item within RoI. [9]

IV. PROPOSED METHODOLOGY

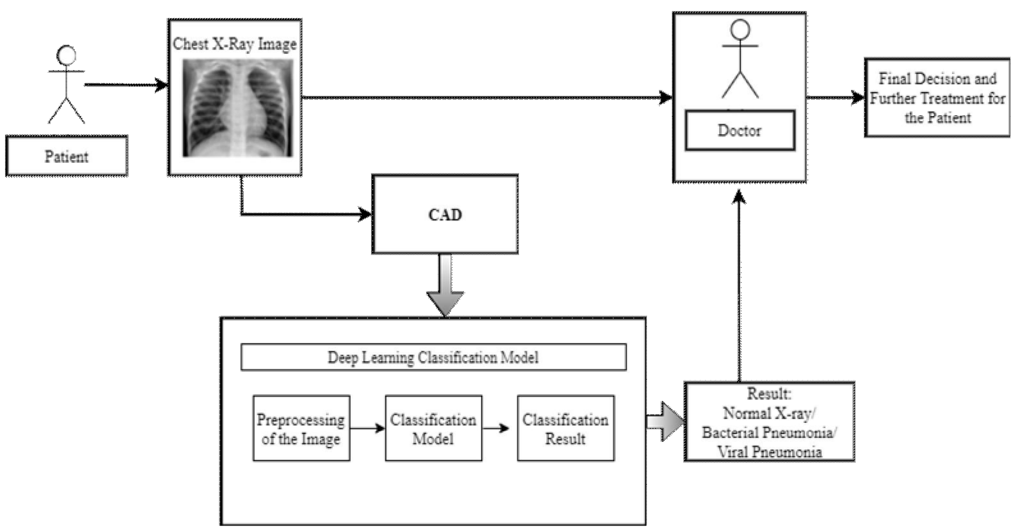

Fig 2. Proposed Methodology

As shown in above diagram, as an input the x-ray image of the patient's chest x-ray will be taken. The X-ray will be immediately given to the CAD system. The CAD system is built on the Deep Learning Algorithms. I will take the image of X-ray as input, the image will be preprocessed and then classified in one of the three classes: Normal, Bacterial Pneumonia or Viral Pneumonia. Along with the detection, the System will suggest an immediate course of action to be followed by the Patient.

The doctor will receive the X-ray image along with the output of the CAD system. After examining the x-ray and considering the CAD system's output, the doctor will give the final decision and the further treatment for the patient. This system will accelerate the process, will help to reduce false negative rate and will improve the diagnosis quality.

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A. Proposed Deep Learning System for Pneumonia Detection

The Computer Aided Diagnosis System will have a Deep Learning model, for image classification of the chest X-ray. To find out the best working model for the CAD System, each model will be built using the algorithms combining then with different augmentation techniques.

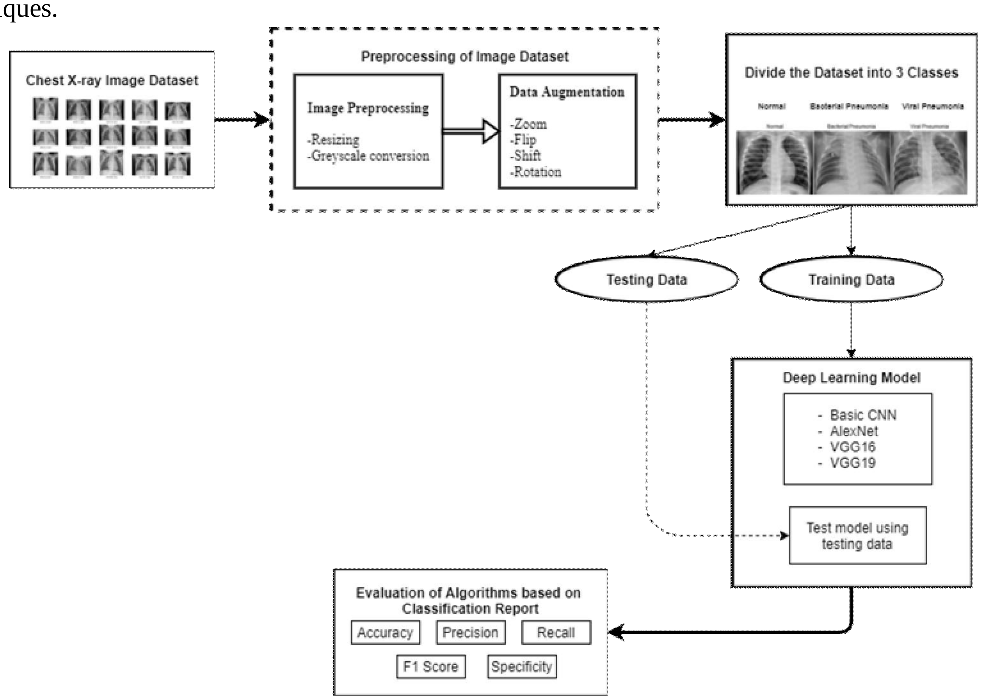

Fig 3. Deep Learning System

As shown in above diagram, first the Chest X-ray image dataset will be obtained from Kaggle. Then the dataset will be preprocessed using image processing techniques such as Resizing, Greyscale conversion etc. The preprocessed images will then be augmented using Image Augmentation techniques such as Zoom, Flip, Shift, Rotation etc. Then the dataset will be divided into three different classes as Normal, Viral Pneumonia and Bacterial Pneumonia. Further the dataset will be split into training dataset and testing dataset. Using the training dataset, the Deep Learning model will be trained by applying Basic CNN, AlexNet, VGG16 or VGG19. After training the model it will be tested using the testing dataset. The model will be evaluated based on the parameters such as Accuracy, Precision, Recall, F1 Score and Specificity.

B. Dataset

The dataset is obtained from Kaggle which has almost 6000 images of chest X-ray. Initially it has images of two classes: Normal and Pneumonia. To give the more diversified result the dataset in Pneumonia class is further divided to Viral Pneumonia and Bacterial Pneumonia. [16]

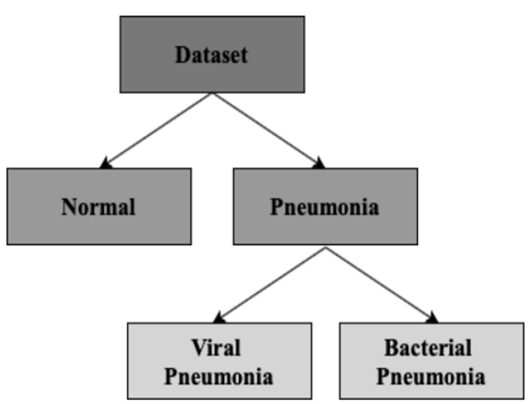

Fig 4. New Classes are: Normal, Viral Pneumonia and Bacterial Pneumonia

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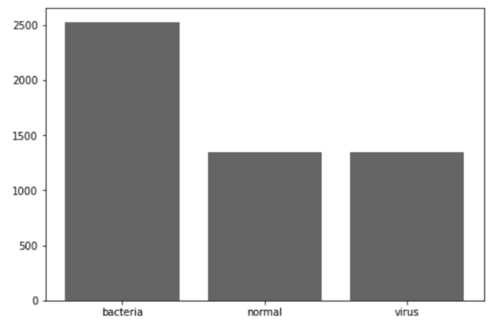

Fig 5. Images Available for Each Class

C. Image Processing:

Imaging plays an important role in the identification and diagnosis of patients infected with pneumonia. X-Ray, which is more precise, painless, more precise and non-invasive, is the most available imagery. There are various image preprocessing techniques which can be applied on a x-ray image dataset. The techniques used in the proposed system are resizing, greyscale conversion. [13]

D. Data Augmentation:

Data augmentation is a technique that allows researchers, without necessarily obtaining new data, to greatly expand the variety of data available for training models. In the above graph, it can be concluded that the images available for each class are not balanced hence data augmentation will be used to balance the dataset. For the training of large neural networks, data augmentation techniques are used.

Normally used Data Augmentation Techniques:

1) *Flipping:* Vertically or horizontally flipping the image.
2) *Rotation:* Rotates the image by a degree defined.
3) *Shearing:* One section of the picture moves like a parallelogram.
4) *Cropping:* Objects appear in various proportions in the image at different locations.
5) Zoom in, Zoom out.

In the proposed system, these data augmentation techniques are used in different combinations with different algorithms to find out the best working combination.

E. Convolution Neural network:

CNNs are a class of Deep Neural Networks that can recognize and identify specific features from images and are commonly used for analyzing visual images. Their applications range from image and video recognition, image detection, medical image analysis, computer vision etc.

1) *CNN Architecture has 2 main Parts*
   a) A convolution method that separates the different features of the image for analysis and defines them in a process called Feature Extraction
   b) A fully connected layer that uses the output from the convolution process and predicts the image [15]

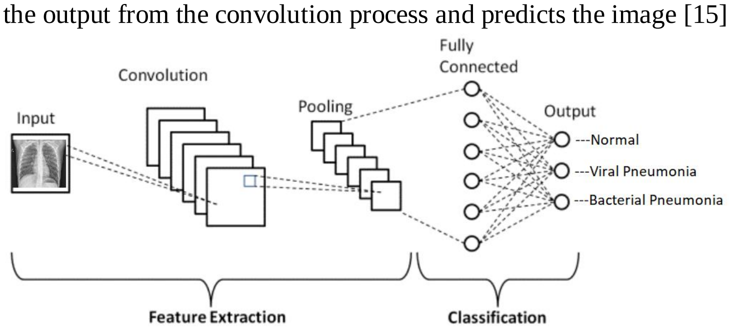

Fig 6. CNN Architecture

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F. Layers of CNN

1) *Convolution Layer:* The first layer that is used to separate the different features from the input images is this layer. In this layer, between the input image and a filter of a specific size MxM, the mathematical convolution operation is carried out. The dot product is taken between the filter and the sections of the input image by moving the filter over the input image with respect to the filter size (MxM). The output is called as the Feature map.
2) *Pooling Layer:* A Convolutional Layer is preceded by a Pooling Layer in most instances. The primary objective of this layer is to minimize the size of the transformed feature map in order to reduce the cost of computing.
3) *Fully Connected Layer:* Usually, these layers are positioned before the output layer. In this, the input image is flattened and fed to the FC layer from the previous layers. The flattened vector then undergoes a few additional FC layers where the operations of mathematical functions normally take place.
4) *Dropout:* Overfitting occurs when a particular model works so well on the training data that when used on new data, it causes a negative impact on the performance of the model. A dropout layer is used to overcome this issue.
5) *Batchnormalization:* Batchnormalization is used to normalize the output of each layer, it adjusts the data input to next layer. Batchnormalization is a layer, which allows each layer of network to do learning more independently.
6) *Activation Function:* It decides which information of the model should fire in the forward direction and which ones should not at the end of the network. In the proposed system, the Softmax activation function is used just before the output layer. Softmax Activation function assigns decimal probabilities to each class, the class with maximum probability is given in the output layer. [25]

G. Evaluation Parameters

1) *Accuracy:* It is the ratio of correct predictions to the total number of predictions.
   Accuracy = (TP+TN)/(TP+FP+TN+FN)

2) *Precision:* It is the ratio of correct positive predictions to total positive predictions.
   Precision = TP/(TP+FP)

3) *Recall:* Also known as Sensitivity. It is the ratio of correct positive predictions to total correct positives.
   Recall = TP/(TP+FN)

4) *F1 Score:* It can be said as the mean of Precision and Recall.
   F1 Score = 2(Precision*Recall) / (Precision+Recall)

5) *Specificity:* It is a ratio of correct negative predictions to total number of negative predictions.
   Specificity = TN/(TN+FP)

(TP-True Positive, FP-False Positive, TN-True Negative, FN-False Negative)

V. IMPLEMENTATION OF DEEP LEARNING ALGORITHMS

A. Applying Deep Learning Algorithms

On the available dataset, that is the chest x-ray images, first the image preprocessing techniques resizing and Greyscale conversion are applied. Then the dataset is augmented using augmentation technique. After preprocessing the dataset, the deep learning algorithms can be applied on the clean image for further processing.

Basic CNN: In Basic CNN algorithms, the first layer is input layer, next there are 1 or 2 convolution layers and equal FC layers. At the end there is activation function Softmax and finally output layer.

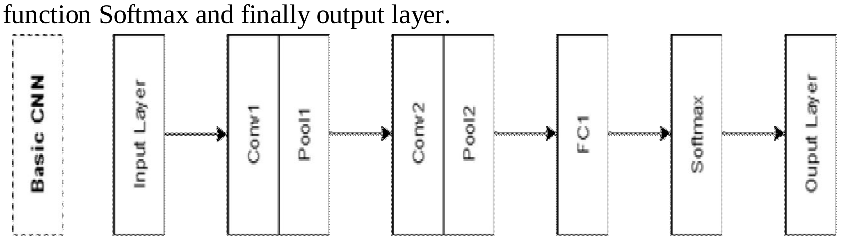

Fig 7. Basic CNN Architecture

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1) Implementation Output for Basic CNN

TABLE I
Basic CNN Architecture

Algorithm		Data Augmentation	Accuracy	Precision	Recall	F1 Score	Specificity
Basic CNN	model 1	zoom_range=0.2, horizontal flip=True	81.89	81.79	79.83	80.81	79.05
	mode 2	zoom_range = 0.2, width_shift_range = 0.1, height_shift_range = 0.1	81.73	81.72	80.02	80.86	81.9
	model 3	zoom_range = 0.2, rotation_range=5	77.08	77.84	75.56	76.81	78.67

- *AlexNet:* In AlexNet algorithms, the first layer is input layer, next there are 5 convolution layers and 3 FC layers in total 8 layers. At the end there is activation function Softmax is used and finally output layer.

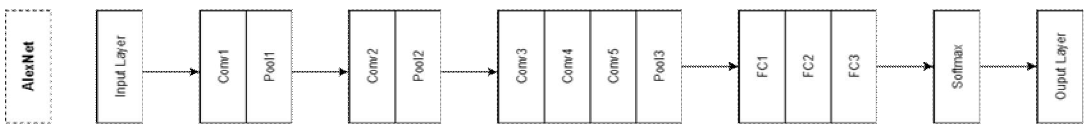

Fig 8. AlexNet Architecture

2) Implementation output for basic AlexNet

TABLE III
AlexNet Architecture

Algorithm		Data Augmentation	Accuracy	Precision	Recall	F1 Score	Specificity
AlexNet	Model 1	rotation_range = 10, zoom_range = 0.1, width_shift_range = 0.1, height_shift_range = 0.1	70.19	74.63	69.62	72.05	67.65
	Model 2	zoom_range = 0.1, Vertical_flip = True	68.1	70.42	67.15	68.99	66.97

- *VGG16:* In VGG16 algorithms, the first layer is input layer, next there are 13 convolution layers and 3 FC layers in total 16 layers. At the end there is activation function Softmax is used and finally output layer.

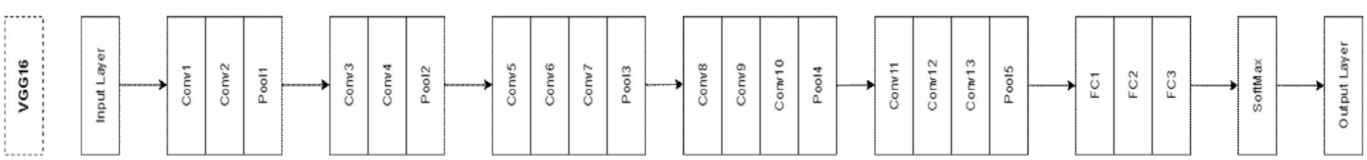

Fig 9. VGG16 Architecture

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3) Implementation output for basic VGG16

TABLE IIIII
VGG16 Architecture

Algorithm		Data Augmentation	Accuracy	Precision	Recall	F1 Score	Specificity
VGG16	model 1	rotation_range = 10, zoom_range = 0.1, width_shift_range = 0.1, horizontal_flip = True	82.85	82.81	81.99	82.4	83.07
	Model 2	zoom_range=0.3, horizontal_flip=True	78.84	80.62	76.92	78.73	80.88
	Model 3	rotation_range = 10, zoom_range = 0.1, width_shift_range = 0.1, horizontal_flip = True	76.64	79.32	75.84	77.54	79.34

- *VGG19:* In VGG19 algorithms, the first layer is input layer, next there are 16 convolution layers and 3 FC layers in total 19 layers. At the end there is activation function Softmax is used and finally output layer.

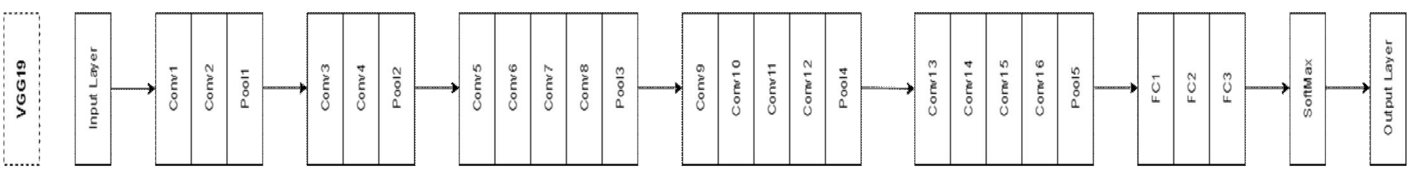

Fig 10. VGG19 Architecture

4) Implementation output for basic VGG19

TABLE IVV
Basic CNN Architecture

Algorithm		Data Augmentation	Accuracy	Precision	Recall	F1 Score	Specificity
VGG19	Model 1	rotation_range = 10, zoom_range = 0.1, width_shift_range = 0.1, height_shift_range = 0.1, vertical_flip = True	75.64	77.61	73.31	75.4	74.88
	Model 2	rotation_range = 10, zoom_range = 0.1, vertical_flip = True	75	74.32	69.23	71.69	73.66

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VI. USER INTERFACE

The UI is built using python open-source application framework, Streamlit. Streamlit is a python library used for building Machine Learning and Data Science Applications.

In the proposed system, to build a user interface the best working algorithm is used, which is VGG16 (Model 1). Below are the screenshots of my UI:

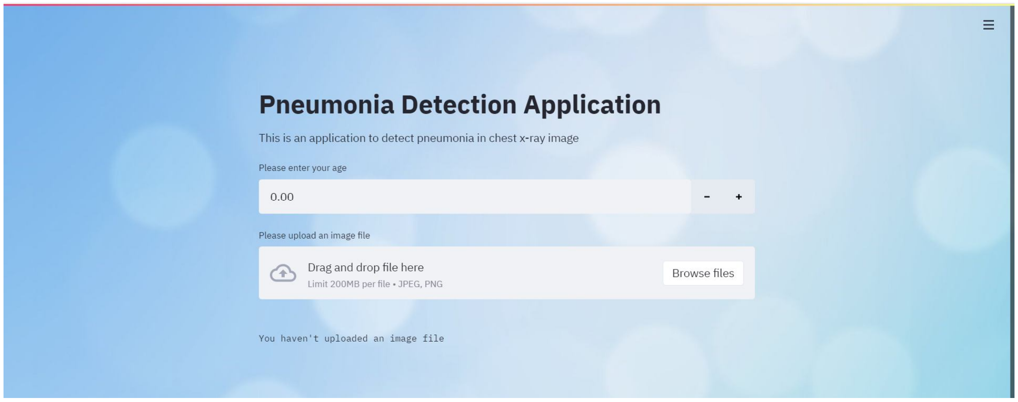

Fig 11. User Interface (1)

The UI takes age of the patient and the X-ray image of the patient as input. The age above 65 and below 2 years comes under the high risk group of Pneumonia.

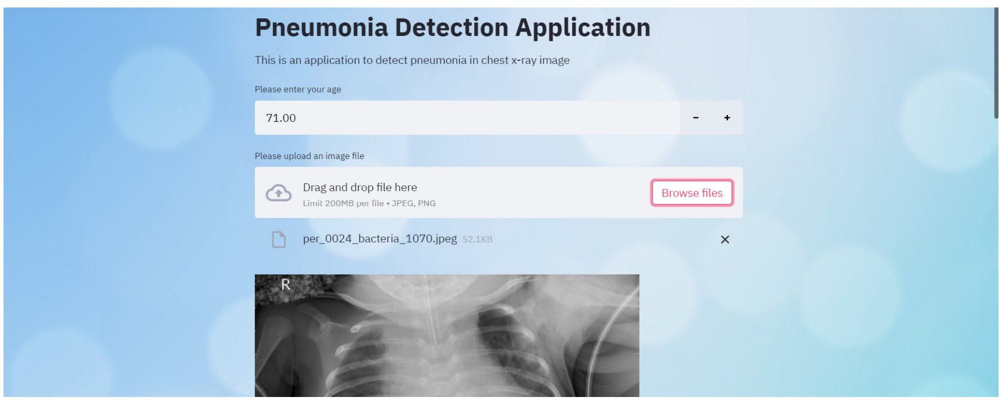

Fig 12. User Interface (2)

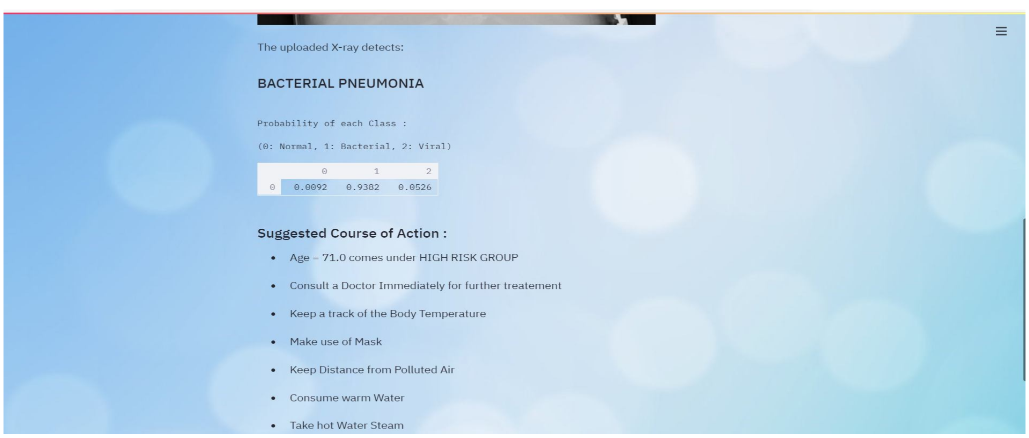

Fig 13. User Interface (3)

Hence, Considering the age entered and the class detected by the application. The UI will suggest the further course of action to be taken. The Suggested Course of Actions mentioned here in the UI is validated from a Doctor.

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VII. RESULT AND DISCUSSION

Below are the results of implementations done till now. The mentioned algorithms are the best working models of each algorithm, which are compared using the evaluation parameters: Accuracy, Precision, Recall and F1 Score.

TABLE V
Comparison of the Algorithms

Model	Accuracy	Precision	Recall	F1 Score	Specificity
Basic CNN	81.89	81.79	79.83	80.81	79.05
AlexNet	70.19	74.63	69.62	72.05	67.65
VGG16	82.85	82.81	81.99	82.4	83.07
VGG19	75.64	77.61	73.31	75.4	74.88

1) Below Is The Graph Of Evaluation Of Each Implemented Algorithm

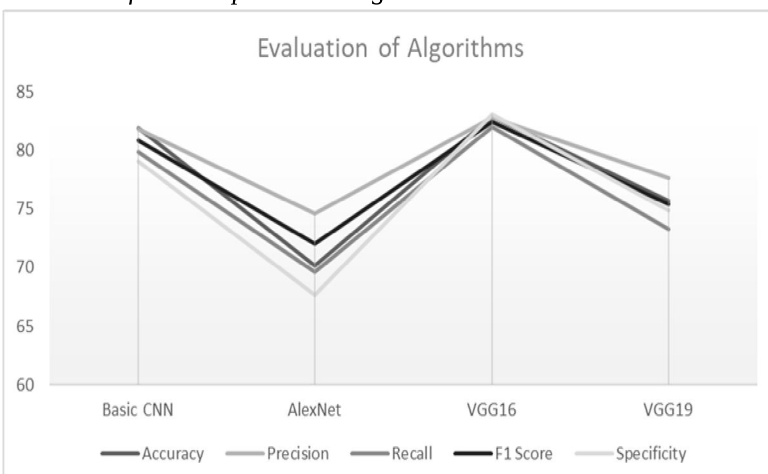

Fig 14. Evaluation Graph of the Algorithms

2) Accuracy Is The Parameters Which Takes All The Predictions In Consideration

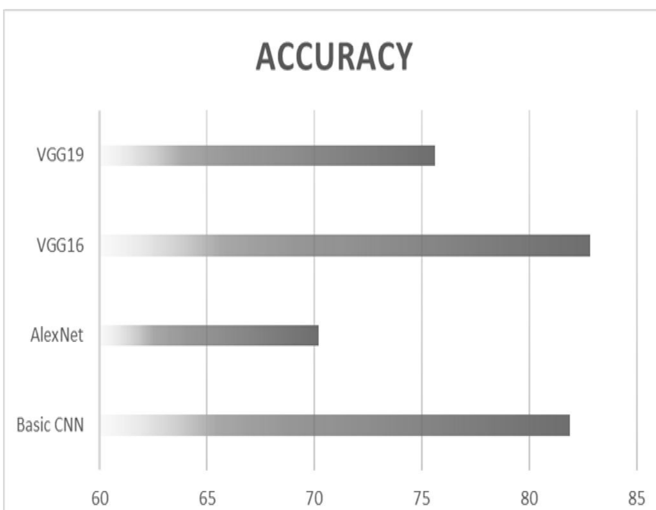

Fig 15. Comparison of Algorithms based on Accuracy

For this problem statement, based on the implementations performed, it can be stated that the two algorithms Basic CNN and VGG16 are working better than the other two algorithms.

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A. Best Working Basic CNN Model

The number of Convolution layers used in this model are 2. Also, the dropout and batchnormalization layers are used to avoid overfitting of the model. Before the output layer Softmax Activation function is used.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 62, 62, 16)        160
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 31, 31, 16)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 29, 29, 32)        4640
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 14, 14, 32)        0
_________________________________________________________________
flatten (Flatten)            (None, 6272)              0
_________________________________________________________________
dense (Dense)                (None, 128)               802944
_________________________________________________________________
dense_1 (Dense)              (None, 128)               16512
_________________________________________________________________
dense_2 (Dense)              (None, 3)                 387
=================================================================
Total params: 824,643
Trainable params: 824,643
Non-trainable params: 0
_________________________________________________________________
```

Fig 16. Model Summary of Basic CNN Model

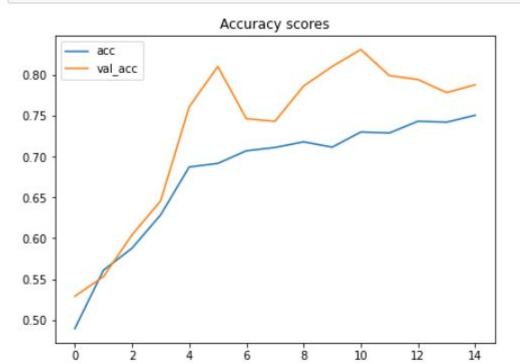

Fig 17. Accuracy Graph of Basic CNN Model

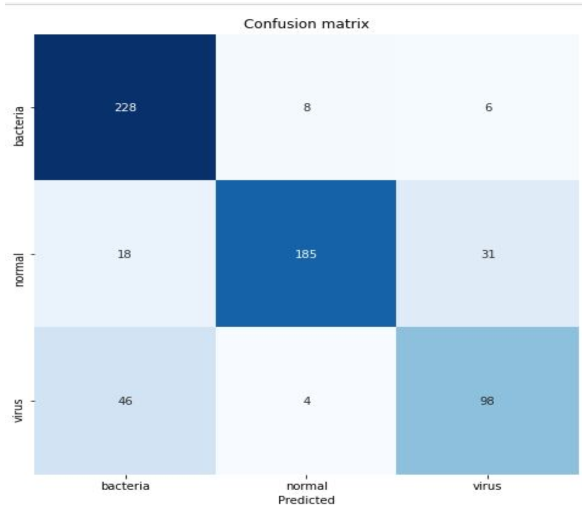

Fig 18. Confusion Matrix of basic CNN Model

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B. Best Working VGG16 Model:

The number of Convolution layers used in this model are 13 and 3 Dense Layers are used. Also, the dropout and batchnormalization layers are used to avoid overfitting of the model. Before the output layer Softmax Activation function is used.

Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 200, 200, 1)]	0
conv2d (Conv2D)	(None, 200, 200, 16)	160
conv2d_1 (Conv2D)	(None, 200, 200, 32)	4640
max_pooling2d (MaxPooling2D)	(None, 100, 100, 32)	0
conv2d_2 (Conv2D)	(None, 100, 100, 16)	2064
conv2d_3 (Conv2D)	(None, 100, 100, 32)	2080
max_pooling2d_1 (MaxPooling2	(None, 50, 50, 32)	0
conv2d_4 (Conv2D)	(None, 50, 50, 16)	2064
conv2d_5 (Conv2D)	(None, 50, 50, 32)	2080
conv2d_6 (Conv2D)	(None, 50, 50, 64)	8256
max_pooling2d_2 (MaxPooling2	(None, 25, 25, 64)	0
conv2d_7 (Conv2D)	(None, 25, 25, 16)	4112
conv2d_8 (Conv2D)	(None, 25, 25, 32)	2080
conv2d_9 (Conv2D)	(None, 25, 25, 64)	8256
max_pooling2d_3 (MaxPooling2	(None, 12, 12, 64)	0
conv2d_10 (Conv2D)	(None, 12, 12, 16)	4112
conv2d_11 (Conv2D)	(None, 12, 12, 32)	2080
conv2d_12 (Conv2D)	(None, 12, 12, 64)	8256
max_pooling2d_4 (MaxPooling2	(None, 6, 6, 64)	0
flatten (Flatten)	(None, 2304)	0
dense (Dense)	(None, 100)	230500
dense_1 (Dense)	(None, 50)	5050
dense_2 (Dense)	(None, 3)	153

Total params: 285,943
Trainable params: 285,943
Non-trainable params: 0

Fig 19. Model Summary of VGG16 Model

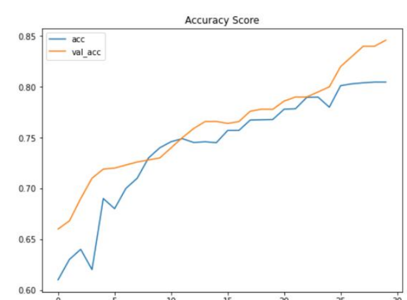

Fig 20. Accuracy Graph of VGG16 Model

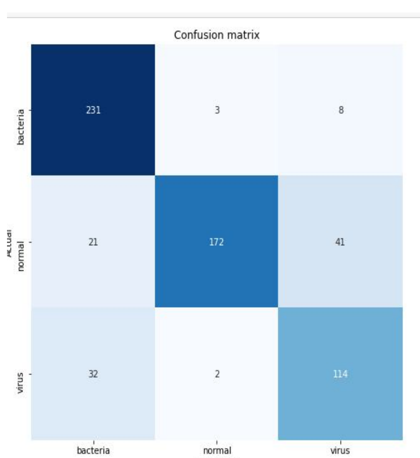

Fig 21. Confusion Matrix of VGG16 Model

VIII. CONCLUSIONS

Pneumonia constitutes a significant cause of morbidity and mortality. It causes a considerable number of adult hospital admissions, and a significant number of those patients ultimately die. According to the WHO, pneumonia can be prevented with a simple intervention and early diagnosis and treatment.

The main purpose of this paper was to perform a comparative study between different algorithms such as Basic CNN, AlexNet, VGG16 and VGG19. The comparison was performed based on the parameters: Accuracy, Precision, Recall, F1 Score and Specificity. The algorithms were implemented with different combinations of Image Augmentation Techniques to find of the best working combination. After comparison of the algorithms, the best working algorithm was used to build the user interface. In the user interface, after giving age and chest x-ray of the patient as an input, the application will suggest the further course of action to be taken.

IX. FUTURE SCOPE

There are other types of lung's diseases which has many different causes. As pneumonia, the diseases such as Asthma, Lung Cancer are having higher fatality rate. In the future, if dataset is made available, the scope of this project can be extended to detected and classifying different types of lung diseases which can be diagnosed using Radiology.

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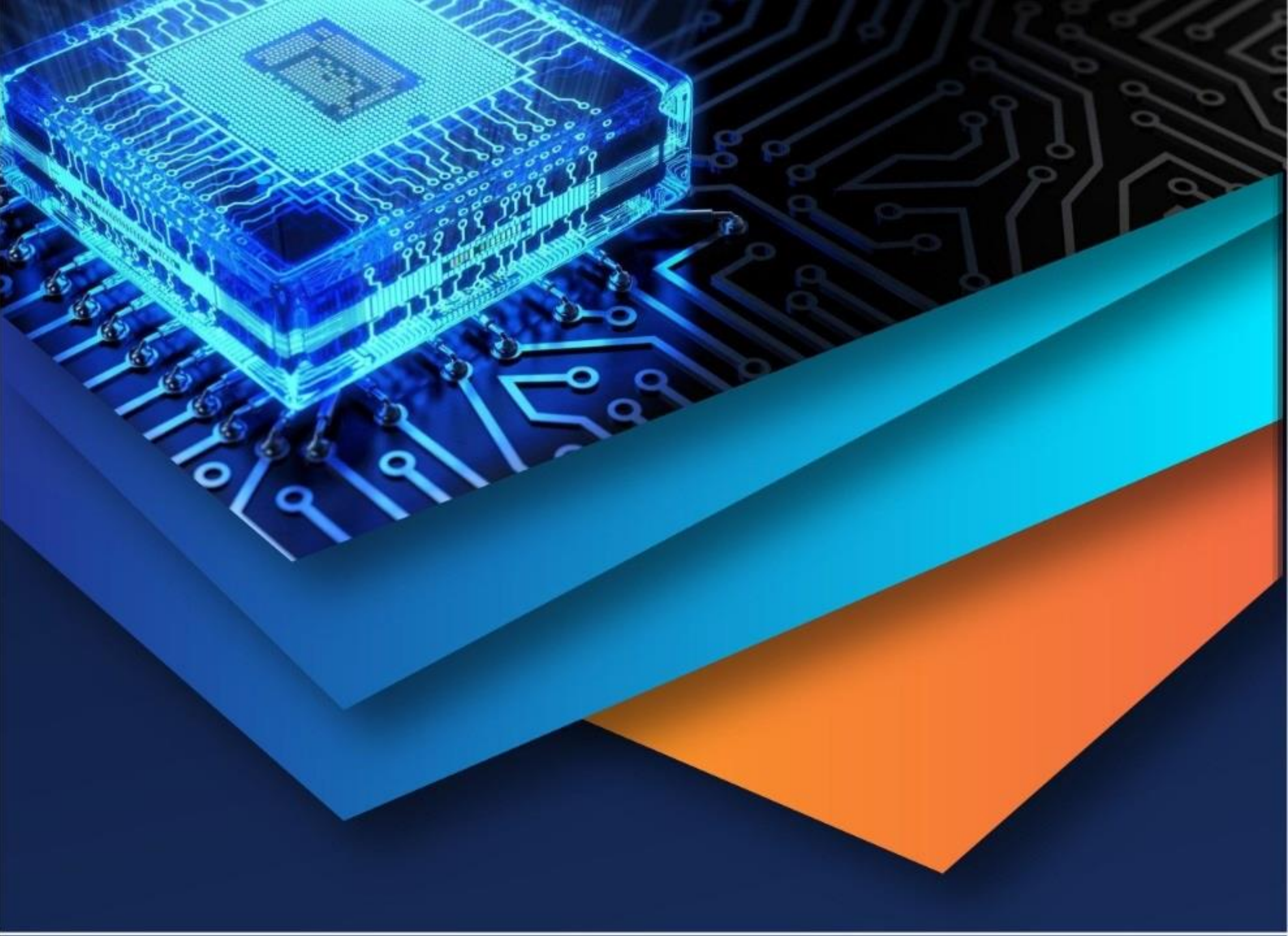

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