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AUTOMATIC PNEUMONIA DETECTION USING DEEP LEARNING

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Abstract: Pneumonia is an infection that affects oneor both lungs. It is caused by bacteria called Streptococcus pneumoniae. According to the world health organization one in three deaths in India is caused due to pneumonia. To diagnose pneumonia using chest X-Rays need expert radiotherapists for evaluation. However, it is not an easy task for a radiotherapist to examine chest radio-graph. There are different types of pneumonia such as a normalpneumonia, Bacterial pneumonia, Viral Pneumonia and covid-19 pneumonia. Thus, developing an automatic system for detecting pneumonia would be beneficial for treating the disease without any delay. To detect the exact type of pneumonia we are developing an automatic system for detecting the exact type of pneumonia.

***Index Terms* - Pneumonia, Convolutional Neural Network, Restnet50, Deep Learning**

I. INTRODUCTION

Pneumonia is an infection that occurs in the air sacs of one or both lungs. It is in the form of fluid or pus. Causes of pneumoniacan be a variety of organisms including bacteria, viruses, and fungi. There are different types of pneumonia, such as normal, viral, and covid-19 pneumonia. In viral pneumonia, viruses affect the airway and cause inflammationin the lungs. The Person having fewer or mild symptoms of cold and cough leads to normal pneumonia. Covid-19 pneumonia is different from the other types of pneumonia. Covid-19 is currently one of the most serious respiratory illnesses causedby the virus SARS-CoV-2 and it can lead to trouble breathing, loss of tests, or smell. Covid-19 pneumonia tends to be more serious than other types of pneumonia. Covid-19 infects a large area of the lungs as compared to other types of pneumonia. The range of pneumonia symptoms can be from mild to life-threating. It is most serious for young children, old people above age 65, and people with low immunity, suffering from chronic diseases like diabetes or asthma. Chest X-Rays are used to determine the inflammation and location of the septic region in the lungs. Mostly, chest X- Rays are used to diagnose pneumonia. Manually, it is adifficult task for a radiotherapist to detect the exact type of pneumonia using a chest radiograph. The main aim of this project is the development of a model which will help identifying the type of pneumonia the patient is suffering from using deep learning techniques.

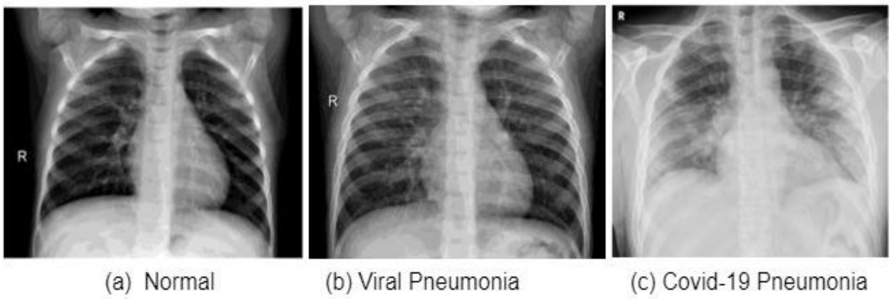

Fig 1: Types of Pneumonia

From above fig 1, we can say that it is no easy task for a doctor to detect the type of pneumonia by looking at the chest X-ray's image.

II. Existing System

The detection of Pneumonia using chest X-rays has been a problem for several years. It can have many reasons such as the X-ray images may have a lower contrast which makes it difficult for manual evaluation. Chest radiography is the most common method to detect Pneumonia. It is fast and cheap. But the major drawback of this methodology is that it requires expert radiologists who have lots of experience and knowledge. In the modern day, there are lots of Machine learning, Deep learning models to determine the presence of Pneumonia through chest X-rays, but there are still some difficulties and complications for these existing models. For example, let's take the VGG16 algorithm, it has too many weight parameters and the models are very heavy which in turn results in a long inference time. Hence, we have chosen a more appropriate method to tackle this problem.

III. Proposed System

Existing systems have problems like long inference time, class imbalance, etc. Those problems were supposed to be tackled. For the VGG16 algorithm, there were lots of weight parameters, as a result of which, models were heavy. Due to this, models were resulting in a long inference time. To tackle this problem, in the proposed system, an appropriate method is used.

To tackle imbalanced data, data augmentation is needed. Data augmentation is artificially expanding the size of X-ray images with pneumonia. In the proposed system, 3 stages are required to classify X-ray images in a specific type of pneumonia. 3 stages are pre-processing stage, data augmentation stage, and classification model stage.

In Pre-processing stage, resizing of the image takes place. It reduces heavy computation and speeds up the processing. A balanced dataset is important for the accurate classification of the image. While dealing with imbalanced data, the data augmentation stage is very essential.

For the data augmentation stage, oversampling will be used to increase the number of viral images. In the classification stage, the CNN algorithm will be used with almost 50 epochs to train the module. New predictions will be done based on the best-saved module.

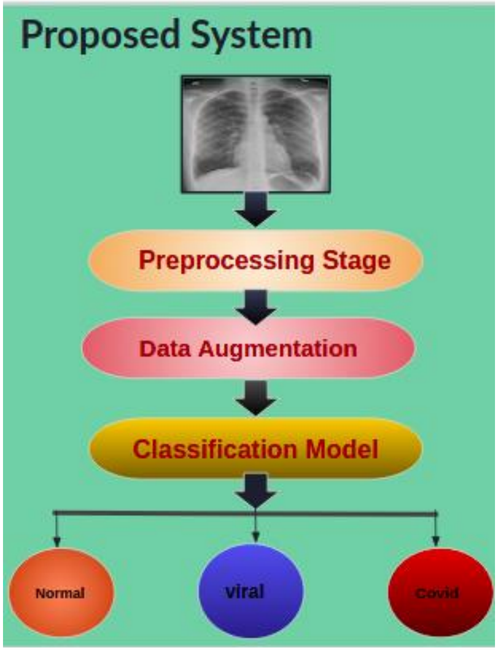

Fig 2: Proposed System

IV. LITERATURE SURVEY:

Several other research papers are related to the detection of Pneumonia and many models and improvised models. These research papers are used as a reference to analyze different models and provide a new and improved solution for this problem.

According to [1], the authors used a method based on DeepConv-DilatedNet to identify pneumonia through chest X-ray images. They used the K-means++ method to improve the accuracy. The data set is from the National Institutes of Health and it can be found on Kaggle, and it has around 53,400 X-ray images in this data set. They used the YOLOV3 algorithm to speed up the process and improve the prediction accuracy.

According to [2], the authors used a CNN (Convolutional Neural Networks) model as the base, DenseNet-169 for the feature extraction purpose, and SVM for the classification stage. The data set they used was released in 2017 and is publicly available on Kaggle which consists of 112,120 Chest X-ray images from 30,085 people. The proposed model in their work gives an AUC of 0.8002. The limitations of this model are, that the model needed very high computational power, the time taken for the results was very large, and only frontal chest X-rays were used.

According to [3], a brief overview of supervised and unsupervised learning is provided. It explains the architecture of the Convolutional Neural Network and gives detailed information about the layers in CNN. This paper helped the authors to understand the working of CNN.

According to [4], the authors give a detailed and thorough explanation of what is Convolutional Neural Networks and how it works. The detailed architecture is explained with the help of various diagrams and a step-by-step procedure is provided for the use of CNN. Two major models are illustrated in this research paper which is gradient descent and Adaptive Moment Estimation Optimization.

V. METHODOLOGY:

A. DATASET ANALYSIS

We have used the data collected from a team of researchers from Qatar University which is freely available on the Kaggle website, as a COVID19 radiography database. This dataset consists of 3616 covid pneumonia x-ray images, 10.2k normal healthy images, and 1345 viral pneumonia images. All these images are RGB, meaning they have three input channels. We have a total of three classes to detect. Each type of image is stored in different folders. The dataset contains a total of 15161 images from three classes. We have used only 5400 images out of 15661 for this project. The dataset is split into 80:20 proportions for training and validation purposes.

B. DATA AUGMENTATION

If there is bias in the training dataset then it may influence the algorithm to ignore minority classes completely leading to the wrong classification. A balanced dataset is very necessary for the accurate classification of the image. In the above dataset viral folder contains only 1345 images but a total of 1800 images are needed for training and validation. Data augmentation is used to generate new images from already available images. The images are required to flip horizontal, zoom, shear, and rescale to generate new images. Fig 3 shows the balanced data in the form of a bar graph.

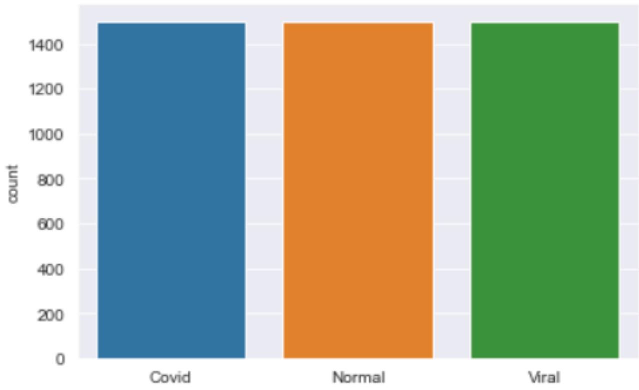

Fig 3: Balance Dataset

C. IMAGE PRE-PROCESSING

The dataset contains the different sizes of images. Image pre-processing is done to resize all images to one common size. Generally, CNN works well on 256 X 256 image sizes, but x-ray images have some thin layers which differentiate the type of pneumonia and if we reduce the size, it may impact the classification. Therefore, the images are resized to one common size 500X500. The images are zoomed, rotated, and rescaled to focus on infiltrates in the alveoli.

D. CONVOLUTIONAL NEURAL NETWORK

CNN is a Deep Learning algorithm. It takes input image and extracts features from it to classify the images. How this CNN algorithm is going to be used in this paper is shown in the fig-4.

Pre-processed images are passed to different convolutional layers to train the dataset. Conv2d is the first layer that gives a pre-processed image as an input to different layers to apply to various feature extraction layers. For maintaining the nonlinearity, the RELU activation function is used. Then pooling layer is applied. Images will be pooled and down sampled to get the feature matrix. Here MaxPooling2D layer is used.it calculates the maximum valued element from the feature map and stores it into a 2X2 matrix. Its output contains a feature map with the most useful features from the previous feature map. Then it will again pass to the number of filters and pooling layers. After flatten function is used to convert the matrix into a one-dimensional array to pass to the dense layer. The dense layer receives input from all the neurons from the last layer here two dense layers are used with filter sizes 64 and 128. Then dropout layer is used to avoid the over fitting with a value of 0.5 after each dense layer. In the end, the SoftMax function is used for multiclass classification as we have a total of 3 classes to classify. Then the model is compiled with the Adam optimizer and the categorical cross entropy function is used for loss.

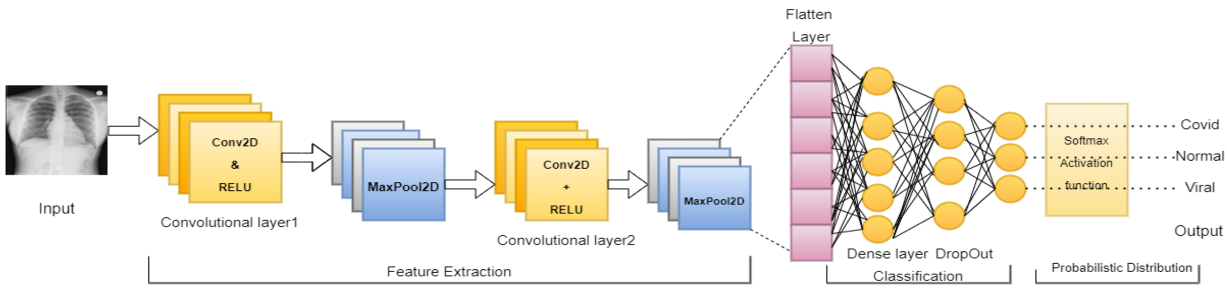

Fig 4: Deep Convolutional Neural Network

The model is trained with 4500 training images on Google Colab by selecting runtime environment as GPU with image size 224X224 and batch size 32 for 40 epochs with the patience of 10. The improved weights are stored in a separate directory. After 40 epochs the model is re-trained by loading the best-saved weights.

E. Residual Network (ResNet50)

Residual Network is the deep learning model. It was introduced in 2015 by researchers at Microsoft Research. It is 50 layers deep convolutional neural network. It has pre-trained models that one can use in their image classification for more accuracy. It is observed that training a model with ResNet50 gives more accuracy than basic CNN. Resnet50 is trained on more than a million images from the Image Net dataset. It is well suited for medical related work. CNN has a problem with vanishing gradients as it become deeper. Restnet50 has skip connection feature which allows gradients to back propagate to previous layers. There are two ResNet50 blocks used in this paper. Identity block in ResNet50 is also called as residual block or building block. It is related to the case where the input activation function has the same dimension as the output activation. Convolution Block is used when input size and output size are different. The task of Convolution block is to make the size of the input volume same as the size of the output volume. We have used ResNet50 model with pre-trained weights. It has over 31,956,739 trainable parameters. The model was trained for 30 epochs to get better accuracy. Fig-5 shows the architecture of ResNet50 used in this paper.

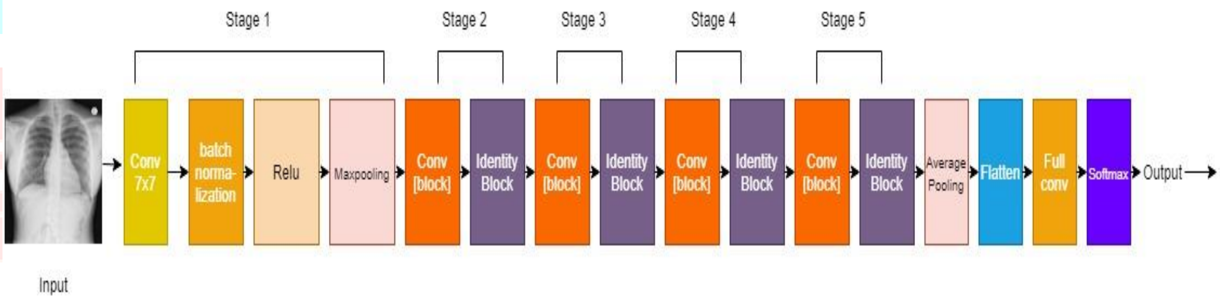

Fig 5: Architecture of ResNet 50

F. Model Training And Validation

The validation dataset has all unique images which were not included in the training dataset. The training and validation accuracy achieved at the end of the training phase is 97.11% and 92% respectively, which is the higher accuracy we get comparing other algorithms. The model with the highest accuracy is saved as result.h5 in the output folder. 300 more images are tested with this model out of which two covid samples were classified as false positive. The module has classified Normal and viral pneumonia images with 100% accuracy.Fig-6 shows the confusion matrix of all classifications. Same dataset is trained with three different alorithms for image classification and each algorithm gave different accuracy. Table-1 shows the training accuracies of different algorithms.

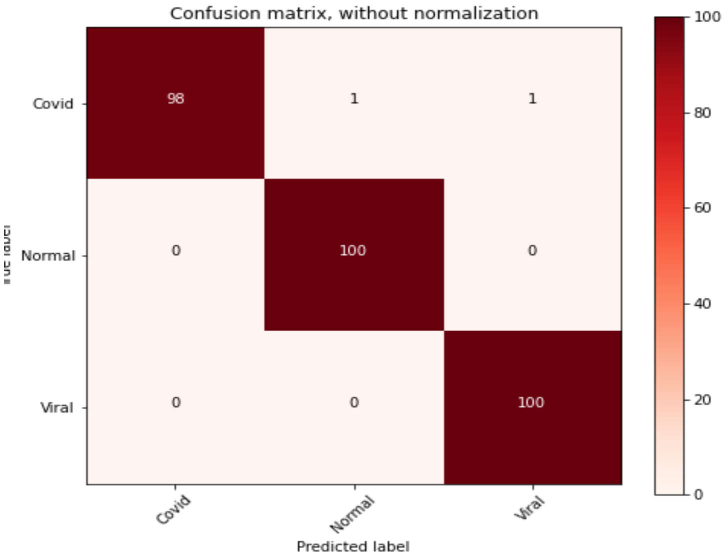

Fig 6: Confusion matrix of ResNet50

Table No-1: Accuracy Table

Sr. No	Algorithm	Accuracy
1	SVM	75%
2	KNN	90.5%
3	Simple CNN	92.18%
4	ResNet50	97.11%

VI. CONCLUSION:

In this paper, we used four algorithms to train the same dataset and the accuracy we achieved is 75% for SVM, 90.5 % for KNN, 92.18% for CNN and 97.11% for ResNet50. ResNet50 proved to be the best amongst other algorithms for the pneumonia classification. Pneumonia is a dangerous, life-threatening disease. Also, the COVID-19 virus and its variants candirectly affect the lungs and can cause diseases like Pneumonia, and can affect respiratory systems too. Types of pneumonia can be differentiated into normal, viral, and covid pneumonia. It is necessary to identify the type of pneumoniaso that patients can get proper treatment. To diagnose pneumonia, most of the time chest X-ray imagesare used, but they need expert radiotherapists for evaluation. It becomes a very time-consuming process and can affect the life of the patient. In rural areas, there can be unavailability of expert radiotherapists. To tackle such situations, the "Automatic pneumonia detection using CNN" model with improved accuracy came into existence. By uploading the thermal X-ray image, categorization of whether the patient isdiseased or not is done. And if the patient is diseased, then the type of pneumonia can be identified. Using this model, there is no need to wait for radiotherapists for diagnosis in remote areas and the system reduces the time for diagnosis and evaluation of pneumonia.This style of detection can assure better healthcare services.

VII. REFERENCE:

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