X-Ray Disease Identifier

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Abstract - Numerous lung diseases are frequently been diagnosed globally and the global pandemic COVID-19 acted in addition to affecting the lifestyle of the people. It is essential to provide a well-timed diagnosis for diseases like Emphysema, Effusion, Pneumonia, Edema, etc., for this various image-processing models are developed. One of the promising research areas in the medicinal field is Medical Image analysis which delivers quick and accurate results along with providing decisions with their appropriate diagnosis.

Inspired by recent research on image analysis that correlates the findings in chest x-ray images, we have developed an approach that uses the existing deep learning model – the VGG19 classification model to process the X-ray images and diagnose them according to the respective disease and provide basic knowledge about them. As the implementation tool, Jupyter notebook is used and this model has the NIH (National Institute of Health) X-ray image dataset. Experiments have shown that the classification method applied in this system is able to detect the findings in the diseases more effectively and with an accuracy of above 60% for most of the diseases.

Key Words: VGG19, Deep Learning, X-Ray images, Classification Methods.

1. INTRODUCTION

Alterations in the environment, lifestyle, and other factors are causing a rapid increase in the effect of diseases on human health. The countries where millions of people are facing poverty and air pollution are especially endangered with the risk of getting several lung diseases. According to the estimation of WHO, over 4 million premature deaths have occurred annually from lung diseases including asthma, pneumonia, and Emphysema. Therefore, it is essential to implement diagnostic systems that will help in detecting lung diseases and providing a respective diagnosis. During the global pandemic, pneumonia i.e. - breathing and lung problem were at their peak. It became crucial for all to early detect the findings in the lungs and for this purpose machine learning and deep learning played a vital role which helped millions of people worldwide.

In general, for the prediction of diseases, we try to use either X-ray, CT, or MRI scan techniques for taking decisions on the appropriate disease but with the help of deep learning methodologies there has been ease for all the doctors, radiologists as well as other researches by giving them a direction for the detection of lung diseases. With this advancement in technology and the use of AI, successful research and viable results help to save countless lives by estimating diseases in remote areas without the use of heavy machinery. Thus, a system capable of predicting lung diseases and diagnosing them with good accuracy will reduce the load on all doctors by helping them to work more effectively and smoothly.

2. LITERATURE REVIEW

2.1 CNN-based Deep Learning Model for Chest X-ray Health Classification Using TensorFlow (2020)[1]

The article discusses the use of machine vision, image processing techniques, and deep learning algorithms as diagnostic tools for respiratory ailments, specifically pneumonia. These tools are more accurate, portable, and cost-effective, making them efficient for physicians to use. Artificial intelligence and machine learning are considered the most accurate methodologies for identifying and classifying health issues, including pneumonia. The study focuses on training a system to distinguish between healthy and diseased lungs based on a set of parameters such as the data set's size and the model and neural network attributes. The MobileNetV2 pre-trained neural network model is used as a backbone for feature extraction, enabling accurate results in object detection and semantic segmentation without prior features. The convolutional neural network was trained and analysed to classify lungs based on the output labels: NORMAL and PNEUMONIA, achieving accurate results of over 90% during testing. The study concludes that the MobileNetV2 convolutional neural network model offers accurate results and several advantages, including high accuracy, even without prior features.

2.2 The use of digital pathology and image analysis in clinical trials. (2019)[2]

The article discusses the potential of digital pathology and image analysis to provide greater accuracy, reproducibility, and standardization of pathology-based trial entry criteria and endpoints. Image analysis can identify, extract, and quantify features in greater detail than pathologist assessment, potentially leading to improved prediction models and tasks beyond manual capability. The article provides an overview of the utility of such technologies in clinical trials, discussing potential applications, current challenges, limitations, and unanswered questions that require addressing before routine adoption in such studies. Machine learning methods can facilitate accurate quantitative assessment of digital images, potentially exceeding human observer performance levels. Central laboratory image analysis should be considered in study design for standardized results, although inter-platform variation between individual centers is a potential source of bias. The article concludes that digital pathology and image analysis technologies can play a role in central review, training, and image analysis, improving the assessment of standard pathological features or extracting novel insights in clinical trials.

2.3 Customized VGG19 Architecture for Pneumonia Detection in Chest X-Rays. (2021)[3]

Pneumonia is a significant illness in both children and aged humans due to lung infections. Early diagnosis is necessary for timely treatment. A Deep-Learning System (DLS) is proposed to diagnose lung abnormalities using chest X-ray images. Traditional diagnosis by a skilled radiologist can be time-consuming and may lead to biased disparities, affecting judgment. Computer Assisted Evaluation (CAE) procedures are proposed to help clinicians identify the disease and its infection rate using chest radiographs. The proposed work employs a customized VGG19 architecture and Ensemble of Features Scheme (EFS) to achieve better classification results. The task is to classify image datasets into normal/pneumonia categories. The performance of VGG19 was better than other DLS, based on Transfer Learning-based classification. EFS is then implemented to improve VGG19's diagnostic ability. The experimental results indicate that the proposed system has the potential to accurately diagnose pneumonia using chest X-ray images, aiding in timely treatment.

2.4 Comparative analysis of lung disease detection using deep learning models. (2020)[4]

The article presents a proposed system for the assistance of radiologists in the detection of lung diseases using deep learning models. The system is designed to classify chest x-ray images and accurately identify any abnormalities present in the lungs. The proposed application uses deep learning CNN models to detect chest or lung diseases from chest x-ray images. The article discusses the use of models like Vgg16 and Vgg19 to predict lung disease from chest x-ray images and determine which model gives the best accuracy and performance. The proposed system aims to benefit rural areas where radiologists are not easily available. The authors gathered several infected lung images and normal lung images to train the deep learning model using a CNN algorithm. They achieved a classification accuracy of 95.0% when applied to the test dataset through various experiments conducted on the proposed model. The proposed system can be used for the prediction of lung cancer from real-world chest x-ray images and assist in the early detection of lung diseases, providing an effective way for expert diagnosis of lung diseases using deep learning models.

3. PROBLEM STATEMENT

With an increasing world population, more people are living with chronic medical conditions that require monitoring to maintain good health and longevity. Autopsies and their related tests and equipment are expensive and require specialized training and education, making it difficult for many people to perform this job. The system will be able to assist radiologists in their diagnoses and provide diagnoses in remote areas with a minimum accuracy of 80%.

The solution aims to reduce the workload of radiologists, who need to undergo 7 years of formal medical education and often work in challenging conditions. Medical professionals use X-ray, CT, or MRI scans to predict diseases, but specialized knowledge is needed to detect abnormalities. Thus, we got the idea to create an X-ray analysis system that provides basic analysis and predictions of diseases based on a known database, even in remote areas with efficient accuracy, making it more accessible for patients and reducing the burden on radiologists.

4. METHODOLOGY

4.1 Dataset

Dataset is collected from [5], which contained chest X-ray images of a normal person and infected person. The database contained 5606 total images of chest X-Ray of 13 lung diseases; namely Cardiomegaly, Emphysema, Effusion, Hernia, Pneumothorax, Atelectasis, Pleural Thickening, Mass, Edema, Consolidation, Infiltration, Fibrosis, Pneumonia; and Normal chest X-Ray images. Images are as follows:

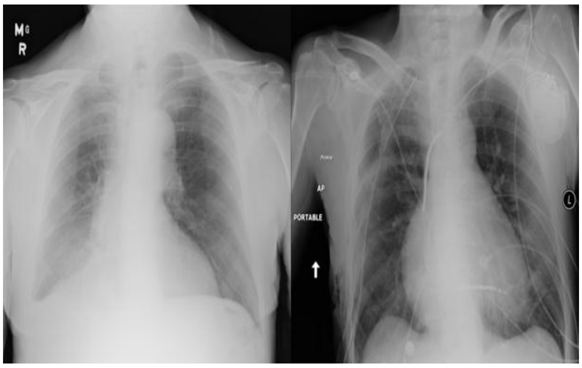

Fig.1 Normal(left), Infected (right)

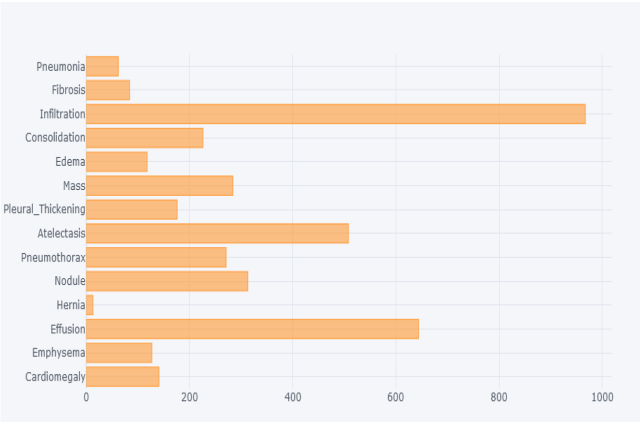

Fig.2 Analysis of Data

The figure.2 depicts a bar graph that shows the analysis of images in our dataset which was collected from the National Institute of Technology. The distribution of images among the 14 diseases is clearly shown in the bar graph.

4.2 Pre-processing

X-ray images may have varying resolutions, which can affect the performance of a machine learning model. Therefore, it is important to resize the images to a consistent size before training the model. We achieved this by using image resizing techniques. Furthermore, X-ray images may have different lighting conditions and contrasts, which can also affect the performance of a machine learning model. So, it is important to normalize the images to reduce the effect of these variations. We achieved this by subtracting the mean and dividing by the standard deviation of the image intensity values. To further improve the performance of the machine learning model, it is often beneficial to augment the data. We did this by applying random transformations to the images, such as rotations, translations, or flips, to increase the diversity of the data.

```
trainset, validset, testset = random_split(trainds, [5000,303,303])

print("Length of trainset : {}".format(len(trainset)))
print("Length of testset : {}".format(len(testset)))
print("Length of validset : {}".format(len(validset)))
```

```
Length of trainset : 5000
Length of testset : 303
Length of validset : 303
```

Fig.3 Splitting the Data set

4.3 Convolutional Neural Network (CNN)

A neural network is called a convolutional neural network, designed to handle multidimensional data such as image and time series data. During the training process, this includes the extraction of features and weight calculation during the training. The identity of such networks is obtained by the use of a convolution operator, which is useful for solving complex tasks [6].

The CNN architecture consists of several convolutional layers, followed by pooling layers and fully connected layers. The convolutional layers extract features from the X-ray images, while the pooling layers reduce the size of the feature maps. The fully connected layers classify the images based on the extracted features.

During training, the CNN learns to recognize patterns in the X-ray images that are associated with normal or abnormal conditions. The model is evaluated using a separate test set of X-ray images that were not used during training.

The results of the project can be evaluated using metrics such as accuracy, precision, recall, and F1 score. Accuracy measures the proportion of correct predictions, while precision measures the proportion of true positives among all positive predictions. Recall measures the proportion of true positives that were correctly identified, while the F1 score is the harmonic mean of precision and recall.

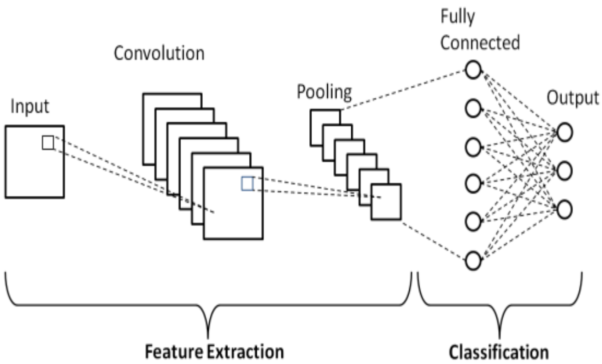

Fig.4 CNN Architecture[7]

4.4 Vgg-19 Pretrained Model

VGG19 is a convolutional neural network model that was proposed by researchers at the Visual Geometry Group (VGG) at the University of Oxford. It is an extension of the VGG16 model, with the addition of three more convolutional layers and one more fully connected layer. The VGG19 model has a total of 19 layers, including 16 convolutional layers and 3 fully connected layers.

The VGG19 model architecture consists of a series of convolutional layers with 3x3 filters, followed by max-pooling layers with 2x2 filters. The number of filters in the convolutional layers increases as we move deeper into the network, from 64 filters in the first layer to 512 filters in the last few layers. The model also uses a rectified linear unit (ReLU) activation function after each convolutional layer. The fully connected layers of the VGG19 model are like those of the VGG16 model. The first two fully connected layers each have 4,096 neurons, while the last fully connected layer has 1,000 neurons, corresponding to the number of classes in the ImageNet dataset for which the model was originally trained. The VGG19 model has been trained on large-scale image classification tasks, such as the ImageNet dataset, and has achieved state-of-the-art performance on these tasks. It has also been used in a variety of other computer vision tasks, such as object detection, segmentation, and style transfer. One of the main advantages of the VGG19 model is its simplicity and ease of use. The architecture of the model is easy to understand and modify, making it a popular choice for researchers and practitioners in the computer vision community. Additionally, the VGG19 model has a relatively small number of parameters compared to more complex models, which makes it easier to train on limited hardware resources. Overall, the VGG19 model is a powerful and versatile convolutional neural network architecture that has been widely used in a variety of computer vision tasks.

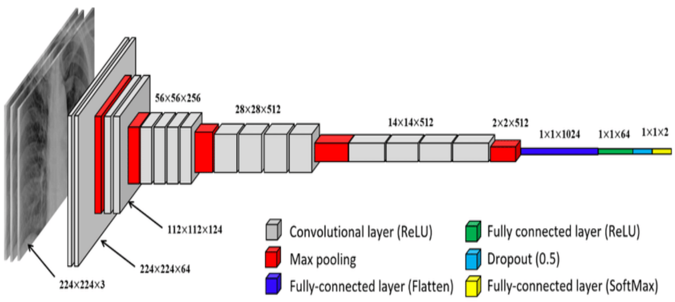

Fig.5 Vgg-19 Model Architecture[8]

4.4 Training Model

Training a machine learning model for X-ray images involves several steps. The first step is to collect a dataset of X-ray images, where each image is labeled as infected or non-infected. Then, the dataset is split into training and testing sets. the training set is used to train the machine learning model. This involves feeding the X-ray images into the model, which will learn to recognize patterns in the images that are associated with infected or non-infected lungs. The model is optimized using a loss function, which measures how well the model is performing at the classification task. The optimization process involves adjusting the weights of the model to minimize the loss function.

VGG-19 is the utilized pre-trained neural network model. It is the backbone of the system. The main blocks are called convolutional blocks; hence, it is a convolutional neural network.

5. DATA AND RESULTS

The model used is trained in 30 epochs of the dataset which yields the following results.

	Labels	Acc		Labels	Acc
0	Cardiomegaly	59.405941	7	Pleural_Thickening	62.376238
1	Emphysema	64.356436	8	Mass	57.095710
2	Effusion	81.188119	9	Edema	81.188119
3	Hernia	60.396040	10	Consolidation	75.577558
4	Nodule	51.155116	11	Infiltration	75.247525
5	Pneumothorax	63.036304	12	Fibrosis	66.996700
6	Atelectasis	76.897690	13	Pneumonia	61.386139

Fig.6 Accuracy results of the 13 diseases tested

These are the validation dataset accuracy that produce the above-mentioned accuracy results for the diseases.

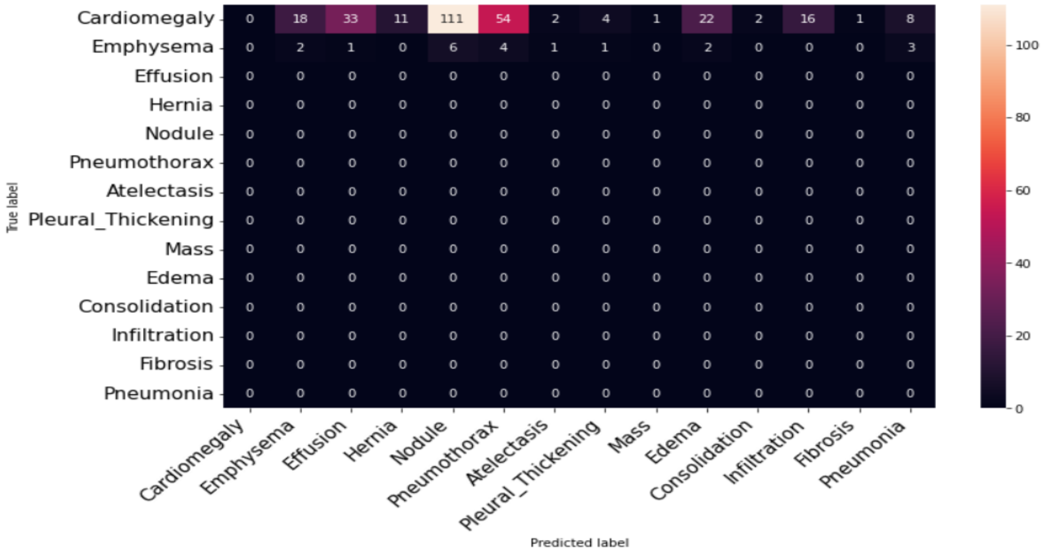

Fig.7 Confusion Matrix

Fig.7 shows the confusion matrix. The confusion matrix shows the summary of the system's capabilities after testing the whole training set. To briefly explain the confusion matrix, the Y-axis shows the fields of diseases that represent true labels and the X-axis shows the fields of diseases that represent predicted labels.

6. SAMPLE OUTPUTS

Upon entering the data in the appropriate fields and uploading the X-ray image as shown in the fig.8 we can click on generate report to get the analysis of the X-ray.

Fig.8 Input Screen

After clicking on generate report the image uploaded by the user is processed and the final report is being displayed on the next screen along with disease predicted, finding and the precautions. It is shown in the fig.9 below.

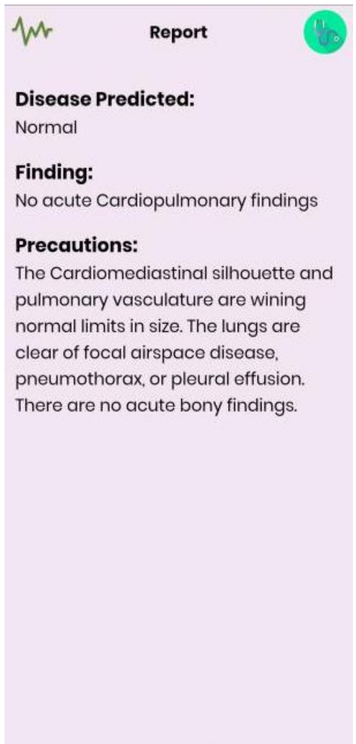

Fig.9 Generated Report

7. CONCLUSION

By using a deep CNN architecture and appropriate data pre-processing, the model could achieve high performance in classifying X-rays into disease categories. The convolution neural network particularly utilizing the VGG-19 offered not only accurate results but also offered advantages as well such as low computing power needed for the processing of data. The main objective of present researches is to classify a certain x-ray image at a fast rate which is achieved. Accurate results are proven in the percentage range during testing which is above 60% for majority of the diseases. A single model used to train and classify multiple diseases will yield results but the training of the model is resource intensive.

8. FUTURE WORK

For Future work, different models can be trained to provide more accurate results and more disease diagnoses. Different CNN models can be implemented to give better and faster results. Patients' medical history can be stored on cloud services so that it is accessible to the hospital or doctor. It can also provide patients with easy and secure access to their medical records. This can help doctors in giving a better diagnosis with consideration to the patient's previous diseases. Our application can provide 80% accuracy for some of the diseases predicted. With tie ups with medical practitioners, we may be able increase the accuracy of other diseases tested. The application can also be used to aid in remote areas, whether a patient should get tested by a more advanced hospital. This project can be further extended to address other radiology related analysis. AI applications for disease prediction/diagnoses holds great promise but further research is needed.

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