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Diagnose Lung Diseases Using Deep Convolutional Neural Network

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Abstract:

X-rays and CT scans are the most commonly used and publicly available radiological modalities. One of the most challenging issues from the last decades is the diagnosis of chest diseases in X-Ray and CT scan images. To solve this problem, a number of machine learning, feature learning, and pattern analysis algorithms are presented. To improve efficiency and diagnosis accuracy, it is necessary to detect anomalies in chest X-ray and CT scan images using advanced technologies like deep learning. Recent developments in deep learning support the classification and diagnosis of lung disorders in medical imaging. As a result, the literature has a large amount of research on the identification of lung illness using deep learning. The abundance of publicly accessible lung radiograph pictures provides the data required for effectively implementing deep learning approaches to lower the rate of thoracic disease misdiagnosis. Deep learning has made recent advancements, and many medical image processing jobs lead to promising results. Chest radiographs, the most common radiological test, are a particularly significant modality for which numerous applications have been studied. As a result, a CNN architecture for automatic detection of chest X-Ray and CT scan diseases is proposed.

Keywords **—**CNN, Chest X-Ray,CT scan, Deep Learning, VGG-16, Transfer Learning

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I. INTRODUCTION

Recently, CXR and CT scan images that have been collected by multiple groups have produced large database of images that are publicly accessible to machine learning researchers. Disease identification and interpretation may be challenging since each image comprises a significant quantity of anatomical and potentially pathological information packed together in each individual projection. Pathology like lung nodules or consolidation may be hidden by superimposed dense tissues (like bones) or by a lack of tissue contrast (i.e., density difference) between neighbouring anatomical structures. The issue of incorrect pathology diagnoses affecting the lungs can be reduced using an automated method. Furthermore, the availability of a fully automated procedure can aid in diagnosis in less developed areas without access to a skilled medical professional.

Artificial intelligence-based computer-aided diagnosis methodologies are getting popular and common these days. A mass population can access this facility for a low cost. Deep learning approaches offer disease prediction accuracy that is which is comparable to and occasionally even higher than that of a typical radiologist. Convolutional neural networks (CNNs), one of the deep learning algorithms, have demonstrated significant promise in image classification and segmentation and are thus widely used in research. Deep learning and computer vision approaches for biomedical image detection have shown to be very beneficial in delivering a rapid and precise disease diagnosis that is on par with a dependable radiologist. With inspiration and insight from various papers, this study aims to perform the task of detecting the disease through radiography images of the human chest.

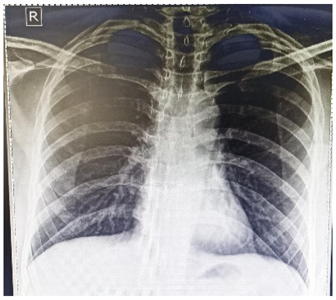

Fig 1. Chest X-ray

Fig 2. CT Scan

II. LITERATURE SURVEY

Mohammad S. Majdi, Khalil N. Salman, Michael F. Morris, Nirav C. Merchant, Jeffrey J. Rodriguez [1] proposed deep learning method for classification of chest X-Rays. The method was applied for the classification of two example pathologies, pulmonary nodules and cardiomegaly, and compared the performance of our method to three existing methods. The results exhibit an improvement in AUC for detection of nodules and cardiomegaly. Dense convolutional network (DenseNet) architecture was used for the main body of the proposed method. From the implementation high (0.92) AUC for cardiomegaly and a moderate (0.73) AUC for pulmonary nodule classification were analysed.

Ali Narin, CerenKaya, ZiynetPamuk [2] proposed Deep Convolutional Neural Network for Automatic Detection of Coronavirus Disease (COVID-19) using X-ray Images. Five pre-trained convolutional neural network based models (ResNet50, ResNet101, ResNet152, InceptionV3 and Inception-ResNetV2) have been proposed for detecting coronavirus pneumonia infected patient using chest X-ray radiographs. In this proposal three different binary classifications with four classes (COVID-19, normal (healthy), viral pneumonia and bacterial pneumonia) have implemented by using 5-fold cross validation. The performance results shows that among other four used models, pre-trained ResNet50 model provides the highest classification performance (96.1% accuracy for Dataset-1, 99.5% accuracy for Dataset-2 and 99.7% accuracy for Dataset-3).

EcemSogancioglu, Erdi C¸ allı , Bram van Ginnekena , Kicky G. van Leeuwena , Keelin Murphy [3] carried out a survey on deep learning for chest X-ray analysis. This study focus on using deep learning on chest radiographs, categorizing works by task: image-level prediction (classification and regression), segmentation, localization, image generation and domain adaptation. The results of this study indicate that although the deep learning community has benefited from the abundance of CXR images that are freely available, the direction of the research has been largely set by the data and labels that are readily available rather than the requirements of the clinician or radiologist. The clinical requirements for AI in CXR interpretation should be a more direct focus of future study in data provision and labelling as well as deep learning. Additional public challenges using adequately labelled data for clinically pertinent tasks would allow for more precise benchmarking and comparison of algorithms.

Edward Verenich, Tobias Martin, Alvaro Velasquez, Nazar Khan, and FarazHussain [4] proposed a technique for Pulmonary Disease Classification Using Globally Correlated Maximum Likelihood. Through the use of GCML, novel attention mechanism, a technique has been created in this work to enhance the classification performance of pulmonary illnesses in chest X-rays. By taking into consideration the global spatial interrelations of variables, demonstrated that supplemental attention mechanism increased the sensitivity of pulmonary disease classifiers. Preliminary findings point to a viable area of study for enhancing existing image classification techniques to aid in the diagnosis of lung illnesses.

TawsifurRahman, Muhammad E. H. Chowdhury, AmithKhandakar, Khandaker R. Islam, Khandaker F. Islam, Zaid B. Mahbub, Muhammad A. Kadir, SaadKashem [5] proposed a Transfer Learning approach with deep CNN for Pneumonia detection from chest X-rays. The work provides a detailed report on the improvements made in the accurate identification of pneumonia before outlining the authors' technique. For transfer learning, four different pre-trained deep convolutional neural networks (CNNs) were used: AlexNet, ResNet18, DenseNet201, and SqueezeNet. Through preprocessing approaches, the altered images were trained for the transfer learning-based classification task using 5247 chest x-ray images, including bacterial, viral, and normal chest x-rays. Three classification schemes—normal pneumonia versus viral pneumonia, bacterial pneumonia versus viral pneumonia, and normal, bacterial, and viral pneumonia—have been reported by the authors in this work. Images of normal and pneumonia,bacterial and viral pneumonia, and normal, bacterial, and viral pneumonia all had classification accuracy of 98, 95, and 93.3 percent, respectively which is the highest accuracies.

Shrinjal Singh, PiyushSapra, AmanGarg, Dinesh Kumar Vishwakarma [6] proposed a model that is CNN based Covid-19 aid. This study aims to focus on the task of detecting the disease through human chest radiography images. CNN model generated a classification accuracy of 87%. In this model they have used the Python programming language, Fast AI, which is built on the PyTorch framework; for the general image pre-processing task. In addition to that, a Windows workstation with GeForce GTX 1050 Ti using CUDA, which is an API model for GPU provided by PyTorch library; for experimental work.

Duaa .F Eljamassi, Ashraf YunisMaghari [7] proposed a Covid-19 detection method using machine learning. Applying advanced artificial intelligence techniques along with radiography were used in detecting disease. In this study, classification model proposes that detect the infected condition through the chest X-ray radiography. A dataset were collected containing chest x-ray images of normal people, people with pneumonia such as SARS, streptococcus and pneumococcus and other patients with COVID- 19. The process of extracting visual features uses a histogram of oriented gradients (HOG).The images are then classified using Support Vector Machines (SVM), random forests and K- nearest neighbours (KNN), with classification rate 98.14%, 96.29% and 88.89% respectively.

ShuaijingXu, hao Wu and RongfangBie [7] proposed an image based deep learning technique for anomaly detection on chest X-rays. A new network CXNet-m1 were introduced to deal with this detection problem. For ChestXray14, created a hierarchical convolutional neural network (CNN) structure, and introduced a novel network called CXNet-m1 that is considerably more compact and effective than fine-tuning. We also provide a unique loss function called sin-loss, which is capable of learning information about discrimination from identical and incorrectly classified images. Additionally, CXNet-convolutional m1's kernels has enhanced to improve the classification's precision. The outcomes of the experiments demonstrate that the model CXNet-m1 with better accuracy, recall, F1-score, and AUC values are obtained with the sin-loss function. Designing CNN architecture is better than customizing deep networks.

RabiaEmhamed Al Mamlook, Shengfeng Chen, HaninFawziBzizi [8] proposed a survey investigating performance of machine learning classifiers for Pneumonia detection in chest X-Rays. This survey proposed a Deep Learning method for the classification, which is trained with altered images, through multiple steps of pre-processing. Experimental results demonstrated that, when compared to the other seven Machine Learning techniques, the Deep Learning technique performs the best for the classification task. With an overall accuracy of 98.46 percent, this model successfully classified chest infection from chest X-ray images using deep learning based on CNN. Identifying Pneumonia cases, it was more accurate.

Arjun ChoudharyAbhishekHazra, Prakash Choudhary [9] proposed chest disease detection method using deep convolutional neural network in chest x-rays. The proposed model have Convolutional layers, ReLU Activations, Pooling layer, andFully connected layer. Last full connected layer is with fifteen output units. Each output part will result in a probability of one of the fifteen diseases. Training is carried out on publicly available dataset called Chest X-Ray 14 which consists of fifteen classes named Atelectasis, Cardiomegaly, Effusion, Infiltration, Mass Nodule, Pneumonia, Pneumothorax, Consolidation, Edema, Emphysema, Fibrosis, Pleural Thickening, Hernia and No Finding images. This model output a good result in multiclass classification. For the classification of various disorders, an average accuracy of 89.77 % is realised.

Daniel A. Moses [10] proposed automatic chest X-Ray disease detection using deep learning. This technique introduces the basic concepts of deep learning as applied to CXR image analysis, the use of transfer learning and the application of data augmentation. Model comprises the DL methods used for the classification of various diseases (multi-class classification). Performance of various methodologies and models is shown, along with a comparison to that of human observers. There is also discussion of some of the difficulties DNN models may encounter, such as their potential implementation and interactions with radiologists. When trained and tested on selected CXR data sets that comprise a single or small number of disease classes, typically with a higher disease incidence than encountered in normal clinical practice, the DL models demonstrated exceptional performance. Although some were trained from scratch, transfer learning was more frequently employed, particularly when significant CXR data sets for a particular disease were unavailable, as was the case during the early COVID-19 pandemic. When there were few training instances of some diseases available, data augmentation was also demonstrated to be advantageous.

III. PROPOSED SYSTEM

CNNs are a class of Deep Neural Networks that can recognize and classify particular features from images and are commonly used for analysing visual images. Their applications includes image and video recognition, image classification, medical image analysis, computer vision and natural language processing.

Transfer learning is a state-of-the-art problem solving method in which a pre-trained model is reused on a new problem. Since the use of convolutional neural networks (CNN) is required for image categorization, it is a prerequisite for learning transfer learning. In transfer learning, a machine uses the information obtained from a previous task to improve prediction about a new task. Pre-trained models are frequently utilised as the foundation for deep learning tasks in computer vision and natural language processing because they save both time and money compared to developing neural network models from scratch and because they perform vastly better on related tasks.

VGG, Visual Geometry Group is a typical deep Convolutional Neural Network (CNN) design with numerous layers. The term "deep" defines the number of layers, with VGG-16 or VGG-19 having 16 or 19 convolutional layers, respectively.

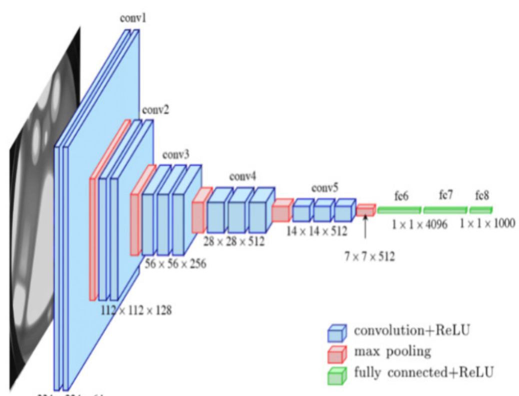

Fig 3. VGG Architecture

VGG-16 contains three different parts: convolution, pooling, and fully connected layers — it begins with two convolution layers followed by pooling, then another two convolutions followed by pooling, and after that repeating three convolutions followed by pooling, and then at last three fully connected layers. In the VGG model, the model weights are available on different platforms and can be used for further analysis that is developing models and applications. The idea of reusing models' weights for new tasks introduces the idea of transfer learning. A brief description of the architecture of VGG is given below.

A. Input

VGGNet accepts an image input size of 224×224. To maintain a consistent input size for theImageNetcompetition, the model's developers chopped out the central 224*224 patch in each image.

B. Convolutional Layers

A minimum receptive field, or 3x3, the smallest size that can still otherwise. In order to maintain the spatial resolution after convolution, the convolution stride is kept at 1 pixel (stride is the number of pixel shifts over record up/down and left/right, is used by the convolutional layers of the VGG.In addition, the input is linearly transformed using 11 convolution filters. A ReLU unit, a substantial improvement over AlexNet that reduces training time, is the following component. The piecewise linear function known as a "rectified linear unit activation function," or "ReLU," outputs the input if the input is positive and zero the input matrix)

C. Hidden Layers

ReLU is utilised by each hidden layer in the VGG network. Since Local response Normalization (LRN) lengthens training time and uses more memory, it is often not utilised with VGG. Furthermore, it doesn't increase overall accuracy.

D. Fully Connected Layers

The VGGNet has three fully connected layers. Among the three layers, the first two have 4096 channels each, and the third has 1000 channels, 1 for each class.

The system architecture is shown in figure 5. The dataset consists of approximately 2000 images in each 6 classes. It has an input size of 80x80.The image is in jpg format. We have split the training and testing data separately. The train dataset undergoes pre-processing and augmentation. That is, RGB images are converted into gray scale images and also rotation angles are also changed. Then, it is gone through our model, Convolutional Neural Network. After that, we will get a trained model. Then test images are taken and pre-processed same as training images, then it is given to the already trained model. Then these images are fed in to the trained model and disease is predicted. Predicted disease will be one among the following disease set: Cancer, Covid-19, Pneumothorax, Fibrosis, Tuberculosis and normal set. Then we have evaluated the performance of that model and the prediction has happened through an unseen image.

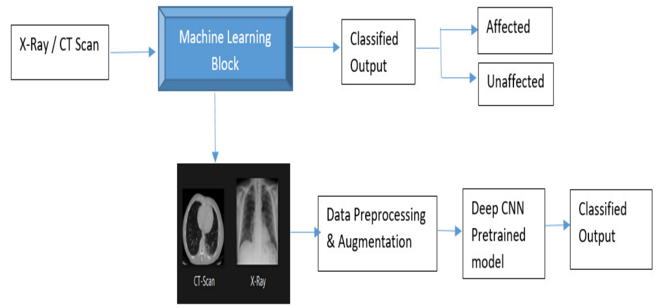

Fig 4. System Architecture

IV. RESULTS

An input image is provided to the system for recognition in order to test it in real time.Image undergoes pre-processing and then predicts the corresponding disease class. The model is trained using the training dataset containing 12000 samples and tested using the testing dataset containing 2500 samples. After training, the final model is saved. The model's accuracy is increased with the number of epochs.

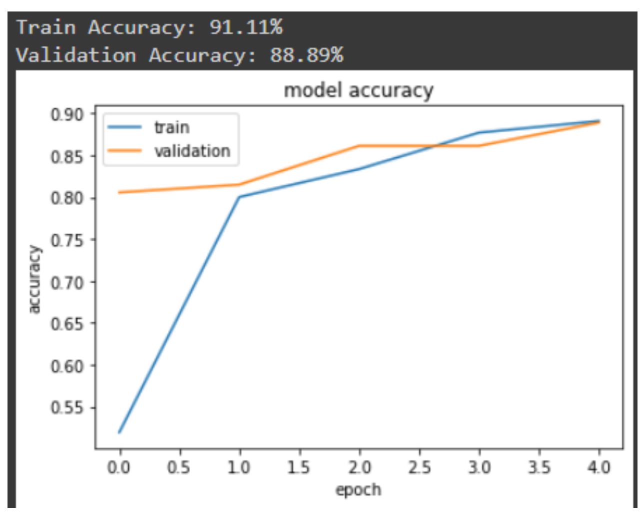

Fig 5. Accuracy Plot

	precision	recall	f1-score	support
cancer	0.97	0.98	0.98	60
covid	1.00	0.98	0.99	60
fibrosis	0.75	0.74	0.74	87
normal	0.74	0.90	0.81	69
pneumothorax	0.88	0.91	0.89	87
tuberculosis	0.99	0.80	0.88	85
accuracy			0.87	448
macro avg	0.89	0.88	0.88	448
weighted avg	0.88	0.87	0.87	448

Fig 6. Classification Report

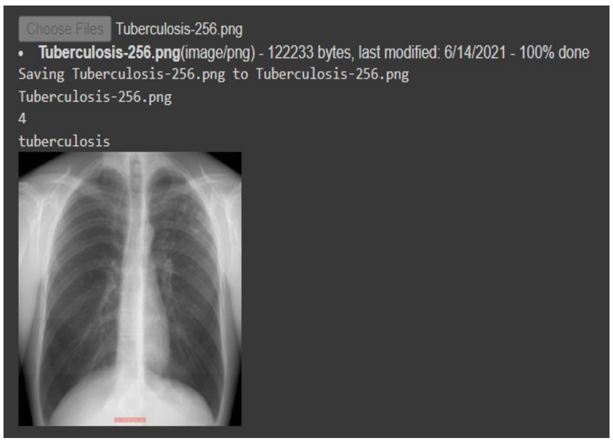

Fig 7. Prediction Output

V. CONCLUSION

A deep learning network for classification of chest x-ray diseases is proposed. A considerable number of lives can be saved by prompt intervention and an effective treatment plan based on an accurate diagnosis of the disease. To make sure that future research will focus on the proper areas, hence boosting the effectiveness of illness detection systems, it is crucial to look into how deep learning was used to detect lung disease. Proposed method exhibits an excellent performance in classifying different X-Ray images by effectively training itself from a comparatively lower collection of complex data such as images, with reduced bias and higher generalization. The best outcome in terms of single-net performance is produced by the VGGNet-16 model.Moreover, the cooperation between a Machine Learning based medical system and the detection of diseases will improve the outcomes and bring benefits to clinicians and their patients. Furthermore, this study can be applied in the diagnosis of more chest related diseases. As future work, it is proposed to build a larger database so we can apply more Deep Learning techniques to train and test the system to predict better results.

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