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Detection of Pulmonary Diseases using Transfer Learning methods

Rama Sainadha Reddy Chinta
Dept. of ECE, Aditya Engineering College, (affiliated to JNTUK)
Surampalem, A.P., India
sainadhreddy.1807@gmail.com
Sai Swetha Kapa
Dept. of ECE, Aditya Engineering College, (affiliated to JNTUK)
Surampalem, A.P., India
kapaswetha21@gmail.com
Dr. Sridevi Gamini,
Professor, Dept. of ECE, Aditya Engineering College, (affiliated to JNTUK)
Surampalem, A.P., India
sridevi_gamini@aec.edu.in

Abstract
Respiratory diseases are the third leading cause of death worldwide. Some of these diseases are Pneumonia, COVID-19. The outbreak of these diseases takes a toll on the everyday lives of people globally. According to the estimation of the W.H.O, annually over 4 million fatalities occur due to the household diseases, pollution related diseases like Pneumonia, Tuberculosis, and Asthma etc.To cure them, we need clear identification of such lung infections. It can be intelligently achieved by the multilayer Convolutional Neural Network (CNN), which does feature extraction, and image classification. A CNN (or) ConvNet, is a network architecture for deep learning which learns directly from data, eliminating the need for manual feature extraction. It occurs in three steps: (a) Data Pre-processing, (b) Feature Extraction, and (c) Image Classification. In data pre-processing, the dataset will be pre-processed in different phases using the proposed CNN model to attain its best performance, which includes image resizing and noise removal. The database we used contained approximately 6,900 X-ray images of disease-infected patients and normal individuals. These images are pre-processed and used for extracting the region of interest. The pre-processing can be done by image augmentation methods, such as adjusting the brightness and contrast of an image. Feature Extraction can be achieved by the pre-trained models such asResNet, Inception, and DenseNet… etc. For classifying chest X-ray images into normal, covid, and pneumonia, we need an intensive collection of data and innovative architecture of AI modules.

Keywords: COVID-19,Pneumonia, Transfer Learning, Machine Learning, Deep Learning, Convolutional Neural Network, Neural Networks, Data Pre-Processing,ResNet50V2, DenseNet201, Xception, and InceptionV3.

Introduction

Lung disease is a significant global health burden, affecting millions of people worldwide. According to the World Health Organization (WHO), respiratory diseases such as pneumonia, chronic obstructive pulmonary disease (COPD) and lung cancer are responsible for a large number of deaths worldwide, accounting for 9.4 million deaths in 2019 alone.In addition, the ongoing COVID -19 pandemic has led to a significant increase in respiratory illnesses worldwide. The virus primarily affects the respiratory tract, causing severe respiratory symptoms and complications that lead to hospitalizations and deaths worldwide. By March 2022, the COVID -19 pandemic has resulted in over 450 million confirmed cases and 6.5 million deaths worldwide.

Moreover, lung disease is disproportionately prevalent in low- and middle-income countries, where exposure to risk factors such as tobacco smoke, air pollution, and occupational hazards is more prevalent. These countries often lack access to adequate health resources, including diagnostic tools and treatments, further contributing to the global burden of lung disease.

Efforts to prevent, diagnose, and treat lung disease at the global level are critical to reducing the burden of these diseases and improving health outcomes for people affected by respiratory disease.As pulmonary diseases are a significant public health problem worldwide, and their early detection is critical for effective treatment and control. In recent years, deep learning techniques, especially Convolutional Neural Networks (CNNs), have shown promising results in detecting various medical diseases from medical image data. CNN models can extract features from medical images and make accurate predictions for various diseases, including lung diseases. This has led to increased interest in the use of CNN models for lung disease detection using chest X-rays and CT scans.

In this paper, we will review the use of CNN models to detect pulmonary diseases, including covid-19, and pneumonia discuss the potential benefits of this technology for early detection and diagnosis.Chest imaging, including chest radiographs and computed tomography (CT), are important tools in the diagnosis and treatment of several respiratory diseases, including COVID-19, and pneumonia. The current pandemic situation has highlighted the importance of accurate and rapid diagnosis of respiratory diseases to prevent the spread of infection and to ensure appropriate treatment. In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown promising results in detecting respiratory disease from chest imaging data.

CNNs are a type of neural network that can automatically learn and extract features from images, enabling accurate diagnosis of disease from medical imaging data. Prebuilt CNN models, which have already been trained on large datasets of chest images, are becoming increasingly popular for detecting respiratory diseases such as COVID-19, and pneumonia. These models can detect specific patterns and abnormalities associated with these diseases in chest images and make an accurate and efficient diagnosis.

Several pre-trained CNN models have been developed for the detection of COVID -19, including the COVID-Net model and the ResNet-50 model. These models can accurately detect COVID-19 on chest radiographs and CT with high sensitivity and specificity. In addition, pre-trained CNN models such as the Inception-ResNet-v2 and the MobileNet-v2 have been used to detect and pneumonia, respectively, with promising results.

The use of pre-trained CNN models for the detection of respiratory diseases such as COVID -19, and pneumonia has the potential to significantly improve the diagnosis and treatment of these diseases. These models can provide accurate and efficient diagnosis, allowing early detection and appropriate treatment. However, further research and validation is needed to ensure the reliability and generalizability of these models for clinical practice.

In proposed methodology, the images are preprocessed by resizing them to 224x224 pixels and normalizing the pixel values.As base models, pre-trained such as ResNet50V2, InceptionV3, Xception, and DenseNet201are used. Themodel is fine-tuned by replacing the final fully connected layer consists a flatten layer & 3 dense layer corresponding to the number of disease categories.The model is trained for 20 epochs and regularization techniques were used stopping to prevent overfitting. The performance of the model is evaluated using the area under the receiver operating characteristic curve accuracy and loss.

II. Literature Review

[1] Tulin Ozturk, Muhammed Talo (2020) describes a typical CNN structure has a convolutional layer that extracts the features from the input with the filters it applies a pooling layer to reduce the size for

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computational performance and a connected layer, which is a neural network. it used fewer layers of Darknet architecture. The proposed model is based on heatmaps and the model may be more useful evaluate the efficacy of treatment based on the heatmap. The developed system is able to perform binary and multi-class tasks with an accuracy of 98.08% and 87.02%, respectively.

[2] Karim Hammoudi, Halim Benhabiles (2020) recommended the use of radiography and CT for suspected covid infection. A set of tailored models based on CNN have been designed, the trained models exploit the CNN backbones ResNet34, ResNet50, and DenseNet169 through the fast AI library and a fully connected head, with a single hidden layer as a classifier. Tailored models have shown promising performances since they all exceeded 84% of average accuracy. The Inception ResNetV2 model has detected the minimum of false negatives.

[4] Several studies have reported high accuracy using CNN models in detecting various lung diseases, including pneumonia, tuberculosis, and covid. A study at Iran byMohammad Rahimzadeh , Abolfazl Attar (2020) introduced training techniques for classifying X-ray images into three classes: normal, pneumonia, and COVID-19, comparing the performance of concatenation of Xception and ResNet50V2. The average accuracy of the proposed network for detecting COVID-19 cases is 99.50%, and the overall average accuracy for all classes is 91.4%.

[7] Gonçalo Marques, Deevyankar Agarwal, Isabel de la Torre Díez (2020) propose a medical decision support system using the implementation of a convolutional neural network (CNN). This CNN has been developed using EfficientNet architecture. The main contribution is to present the results of a CNN developed using EfficientNet and 10-fold stratified cross-validation. First, the binary classification results using images from COVID-19 patients and normal patients are shown. Second, the multi-class results using images from COVID-19, pneumonia and normal patients. The experiments were carried out on Google Colab notebook using GPU run time type. The results show average accuracy values for binary and multi-class of 99.62% and 96.70%, respectively.

[13] The authors Naufal Hilmizen, Alhadi Bustamam, Devvi Sarwinda (2020), proposed a concatenation of two different transfer learning models using an open-source dataset of 2500 CT-Scan images and 2500 X-ray images for classifying them into two classes: normal and COVID-19 Pneumonia. They have used DenseNet121, MobileNet, Xception, InceptionV3, ResNet50, and VGG16 models for image recognition in their work. This study achieved results with best classification accuracy of 99.87% of the concatenation of ResNet50 and VGG16 networks. Also achieved the best classification accuracy of 98.00% when using a single modality of CT-Scan ResNet50 networks and classification accuracy of 98.93% for X-Ray VGG16 networks. This multimodal fusion method shows a better classification accuracy compared to the method of using a single modality of biomarkers

[17] Lung disease detection using chest X-rays is a significant medical problem that has been tackled by various deep learning models, including convolutional neural networks (CNNs). In this literature survey, we explore the current state-of-the-art methods in detecting lung diseases using chest X-rays, with a focus on the performance of the four pre-trained models: ResNet50V2, InceptionV3, Xception, and DenseNet201.Regarding thecomparison of different pre-trained models, several studies have evaluated the performance of different models in detecting lung diseases include Covid, and Pneumonia. Latheesh Mangeri and Gnana Prakasi (2021) used a CNN model to classify chest X-rays into 4 different categories. The detection of these diseases is analyzed with the support of three CNN Models such as VGG19, Resnet50V2, and Densenet201, and results are elaborated in the terms of Accuracy and Loss. It trained with F1

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score accuracies of 0.98,0.92,0.97 for pneumonia, covid respectively.

[22] More recently, ATMS labs studies have evaluated the performanceusing the data augmentation algorithm. They conducted a detailed evaluation of two pre-trained deep neural networks: VGGNet-16 and MobileNet. The MobileNet model outperforms the VGGNet-16 model where it achieved 82% accuracy, 83.5% recall, and 82.5% F1 score, while VGGNet-16 version gave the highest precision value which equals 84.5% but accuracy, recall and F1 score were respectively equal to 80%, 76% and 79%. On the other hand, and by calculating the AUC of the two models, MobileNet presents the best score which is 95% while VGGNet-16 has a score of 94%. Overall, these studies demonstrate the potential of CNN models, particularly pre-trained models such as ResNet50V2, InceptionV3, Xception, and DenseNet201, in detecting lung diseases using chest X-rays. While each model has its strengths and weaknesses, the choice of model depends on the specific application and dataset. Further research is necessary to optimize these models and improve their accuracy and interpretability.

III. METHODOLOGY:

Methodology includes image data collection, pre-processing, augmentation, and classification. The next sections provide a full discussion of the proposed method employed in this study for identification of lung disease as well as the data utilized to validate the proposed model.

i. Data Collection

The proposed methodology includes the analysis of dataset consisting three classes: COVID, Pneumonia, and Normal. The collected dataset that used to train the model is gathered from “Kaggle”, an open source website which contains different datasets. The collected dataset contains of chest X-ray images who were infected to COVID-19, Pneumonia, and it also contains the chest x-ray images of Normal patients. The entire dataset is a collection of 6600 and divided into “Train” and “Validation”. The Training group having 5600. Validation group consists of 300 images. And the Testgroup consists of remaining 1300 images. Once the dataset was gathered, they need to be pre-process for making them as suitable input to train the model.

Class	Train	Validation	Test
Covid	1600	100	400
Pneumonia	1300	100	400
Normal	2700	100	500
Total images	**5600**	**300**	**1300**

ii. Data pre-processing

In data pre-processing, the goal is to enhance the quality of images by removing unwanted spatial dimensions, so that theimportant features were boosted and prepare the data in a way that is suitable for feeding into the machine learning model. In X-ray radiography, usually images are in the form of gray scale and not every pixel will exactly detect the same photon to others, some pixels have more X-ray and appears darker, where as some pixels get fewer X-ray photons and appear brighter. So, pre-processing was implementedto jump this wall.

Firstly, The chest x-ray images are loaded from the dataset into memory for further processing. The images are resized to a standard size to ensure that they all have the same dimensions. This is important because neural networks typically require inputs of a fixed size. The pixel values of the images are scaled so that they are in the same range. This helps to ensure that brightness and contrast differences between images do not have a significant impact on the performance of the model. The images may be cropped to remove any parts of the image that are not relevant to the task at hand. In the context of lung disease detection, this may involve cropping out parts of the image that do not contain the lungs. Filters may be applied to the images to enhance certain features or remove noise. In the context of lung disease detection, this may involve applying a filter to enhance the edges of the lung regions.

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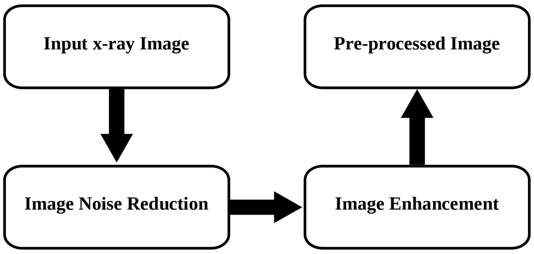

Flow Diagram representing the Pre-processing

iii. Image Augmentation
Limited data is a major challenge in deep learning models for image classification. Often, imbalanced classes can be related difficulty; while there may be sufficient data for some classes, equally important, but under sampled classes will suffer from poor class-specific accuracy. There are many ways to address complications associated with limited data and imbalanced classes.
Data augmentation is a powerful technique that helps to improve the performance and the robustness of deep learning model in various computer vision tasks, such as image classification, object detection, and segmentation, by increasing the size of a dataset artificially through generating additional samples from the existing data. The goal of data augmentation is to overcome the problem of overfitting, which is a common riddle in deep learning models where the model becomes too closely fit to the training data and performs bit poor on new and unseen data. It can be achieved by applying various transformations such as image rotating, flipping, cropping, zooming to the existing data. In proposed methodology, augmentation techniques like: rescaling, rotation range, height and width shift ranges were used.

iv. Image Classification
In this work, multi class classification model has been used to classify X-ray images into three classes (normal, pneumonia, COVID). Collected images werepre-processed by resizing them to 224x224 pixels and normalized to have pixel values between 1 and 255. The pre-trained models were used as the base models. The main intension of transfer learning is to put on previously gained knowledge and applying it to a target task that is still related. The models include ResNet50V2, InceptionV3, Xception, and DenseNet201.In this work,the algorithms were implemented using the applications like keras and tensorflow. To save the computation time and resources and to run the simulation smoothly “Google Colab”was used.

ResNet50V2:Resnet50V2 is a huge architecture, it is taken and modified from Resnet50 in later years for better performance than previous architectures like resnet101. It is a contemporary convolution neural network (CNN) which addresses vanishing gradient problems using residual blocks in the architecture. In a residual network, multiple residual blocks are stacked up one after another. Each residual block is formed of short-cut connections skipping one or more layers. Resnet50V2 uses the pre-activation of weight layers. ResNet50V2 achieves accurate predictions on the datasets.

InceptionV3:The InceptionV3 architecture is composed of a series of convolutional layers, followed by max pooling layers, and then a series of "inception modules" that allow for multi-scale feature extraction. One of the key features of InceptionV3 is the use of "bottleneck" layers, which reduce the number of input channels to the next layer, while preserving the spatial information. This reduces the computational complexity of the network, while still allowing it to learn complex features. InceptionV3 has 48 layers and has been pre-trained on the ImageNet dataset, which contains over a million images in 1,000 different categories.

Xception:The name "Xception" stands for "Extreme Inception", as the architecture is based on the Inception model, but takes the concept of depth-wise separable convolution to an extreme. Xception is a model that uses depth-wise separable convolutions, whichseparate the spatial and channel-wise operations in the convolutional layers. This makes it more efficient than traditional convolutional neural networks while maintaining high accuracy. Xception has 71

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layers and has been pre-trained on the ImageNet dataset.

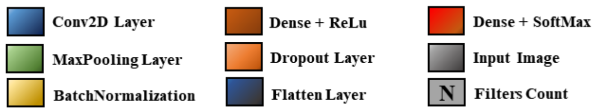
DenseNet201:DenseNet-201 is a convolutional neural network that is 201 layers deep. Recent work has shown that convolutional networks can be substantially deeper, more accurate, and efficient to train if they contain shorter connections between layers close to the input and those close to the output. DenseNet connects each layer to every other layer in a feedforward fashion. Whereas traditional convolutional networks with L layers have L connections - one between each layer and its subsequent layer - the DenseNet network has L(L+1)/2 direct connections. For each layer, the feature maps of all preceding layers are used as inputs, and their feature maps are used as inputs into all subsequent layers[21,22]. DenseNet have several compelling advantages: they alleviate the vanishing gradient problem, strengthen feature propagation, encourage feature reuse, and substantially reduce the number of parameters.

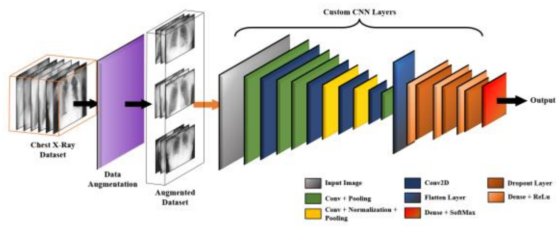
NeuroBlend: Other than these, we built a customised CNNmodel, starts with two convolutional layers with 30 and 120 filters respectively, followed by max pooling layers to downsample the feature maps. Next, you have two more convolutional layers with 500 and 400 filters, respectively, and both followed by max pooling layers. The following two convolutional layers use fewer filters and a 1x1 kernel, which is commonly used to reduce the number of filters and computational cost while keeping the dimensions unchanged. The model also includes batch normalization layers to help with training stability.

The final part of the model is composed of fully connected layers with dropout regularization to avoid overfitting. The model has three dense layers with 500, 350, and 200 neurons, respectively, before the final dense layer with 3 neurons for classification into three classes. Overall, this model has a deep architecture with a considerable number of filters, which allows it to extract more complex features from the input images. Additionally, regularization techniques, such as L2 regularization were applied and the dropouts, which can help avoid overfitting and improve the generalization of the model.

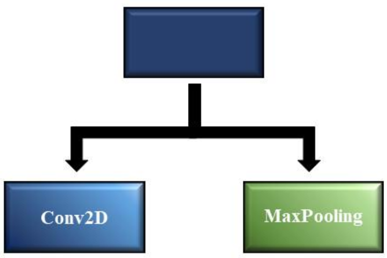
The reason it was named“NeuroBlend”because Neuro suggests the model is a neural network, while Blend implies a combination of different techniques, which is fitting given the various layers and operations in your architecture. The name also has a slightly futuristic feel, which could make it stand out in a research article or paper. Additionally, Blend can refer to mixing or combining different elements, which could be interpreted as a nod to the way your model combines convolutional, pooling, and fully connected layers.

Details on the designed NeuroBlend Architecture





Conceptual representation of NeuroBlend



Micro Structure of Conv + Pooling Layer

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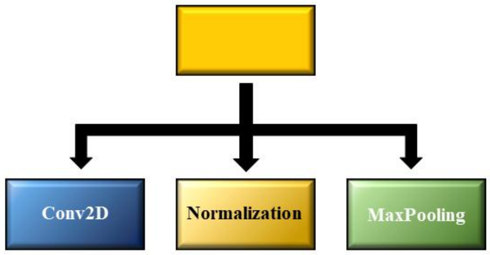

Micro Structure of Conv + Normalization + Pooling Layer

RESULTS

The model we used achieved the following performance for detecting lung diseases using CXR images:

Nets Used	Training		Validation		Test	
	Acc (%ge)	Loss	Acc (%ge)	Loss	Acc (%ge)	Loss
NeuroBlend	94.01	0.2607	81.85	0.5866	88.62	0.4152
ResNet50V2	95.13	0.1707	83.08	0.5015	91.62	0.2743
Xception	94.39	0.1938	88.08	0.4063	91.31	0.2440
DenseNet201	95.27	0.1450	89.46	0.3529	91.31	0.2440
ResNet50 V2 + DenseNet201	95.68	0.1712	90.00	0.3733	94.33.00	0.2341
ResNet50 V2 + Xception + DenseNet 201	98.84	0.0564	89.38	0.3255	99.33	0.1301

The results showed that all the models achieved better performance in detecting lung diseases from chest X-ray images. But Renet50V2 and Xception concatenated model achieved the highest Accuracy of 97.20% and less loss. The Resnet50V2 and DenseNet201 concatenated model stood next to it with theaccuracy 95.68%.

V. DICUSSION / LIMITATIONS

The results demonstrate the potential of using pre-trained CNN models for detecting lung diseases using CXR images. All seven models achieved good performance, butResNet50V2& Xception model achieved the best performance, followed closely byResNet50V2 &DenseNet201 model.Comparing results to the state-of-the-art models, our models performance is competitive or even better, indicating the potential of using these pre-trained models for CAD systems.

However, it is essential to note that our dataset only includes CXR images from one source, which may limit the generalizability of our results to other populations. Future studies should consider using larger datasets from multiple sources to improve the generalizability and robustness of the models.However, there are several limitations to our study. First, our dataset only includes CXRs from one source, which may limit the generalizability of our results to other populations. Second, our model was trained on a relatively small dataset, which may limit its performance. Future studies should consider using larger datasets from multiple sources to improve the generalizability and robustness of the model.

VI. CONCLUSION

In conclusion, we evaluated the performance of the five models: four different pre-trained CNN models (ResNet50V2, InceptionV3, Xception, and DenseNet201) and the fifth one is custom CNN – NeuroBlend for detecting lung diseases using chest X-ray images. All seven models including the concatenated achieved high accuracy in classifying the lung diseases. However, the results suggest that InceptionV3 model outperforms the other six models in terms of accuracy, loss. This is likely due to the model's efficient use of depth-wise separable convolutions, which reduce the number of parameters and computational complexity, while maintaining high accuracy.The concatenated models – “Renet50V2+Xception” and “Renet50V2+DenseNet201” has performed well when compared to other models, but “Renet50V2+Xception” achieved better accuracy with less loss compared others. Through our work it might be a suitable option for real-world applications where computational efficiency is important, such as in low-resource settings or in large-scale screening programs. Nonetheless, the remain models are viable options for detecting lung diseases using chest X-ray images.

Overall, our study highlights the potential of pre-trained CNN models in detecting lung diseases using chest X-ray images and provides insights into the strengths and weaknesses of different models. Future work could focus on fine-tuning these models on more specific datasets and exploring other architectures to improve the accuracy and efficiency of lung disease detection.

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