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CLASSIFICATION OF CHEST X RAY IMAGES BASED ON PNEUMONIA

[1] Dharani .R, [2] Madhumithaa I, [3] Kapilavani.R.K, [4] Reena.R, [5] Dr. Ayyappan,

[1,2] Students, [3,4,5] Faculty,

[1,2,3,4,5] Prince Shri Venkateshwara Padmavathy Engineering College, Ponmar,

ABSTRACT

Pneumonia is a life-threatening infectious disease affecting one or both lungs in humans commonly caused by bacteria called Streptococcus pneumonia. One in three deaths in India is caused due to pneumonia as reported by World Health Organization (WHO). Chest X-Rays which are used to diagnose pneumonia need expert radiotherapists for evaluation. Thus, developing an automatic system for detecting pneumonia would be beneficial for treating the disease without any delay particularly in remote areas.

Due to the success of deep learning algorithms in analyzing medical images, Convolutional Neural Networks (CNNs) have gained much attention for disease classification. In addition, features learned by pre-trained CNN models on large-scale datasets are much useful in image classification tasks. In this work, we appraise the functionality of pre-trained CNN models utilized as feature-extractors followed by different classifiers for the classification of abnormal and normal chest X-Rays. We analytically determine the optimal CNN model for the purpose. Statistical results obtained demonstrates that pretrained CNN models employed along with supervised classifier algorithms can be very beneficial in analyzing chest X-ray images, specifically to detect Pneumonia

Keywords - convolutional neural network, chest x-ray images, detection and classification.

1. INTRODUCTION:

Pneumonia is a life-threatening infectious disease affecting one or both lungs in humans. Pneumonia is a major cause of death amongst children. One of the best medical imaging method available for diagnosis of pneumonia is chest X-ray. The project titled Pneumonia detection is used to detect whether a patient is affected by pneumonia or not. The project aims to train the chest x-ray images of patients on YONO CNN algorithm which will be able to predict whether a patient is affected by pneumonia or not.

2. Related Work

The problem of classifying chest x-ray images into different classes has been significantly explored in the field of medical diagnosis. Many research papers have been published, tackling this problem. Rajpurkar et al. trained a deep learning model to detect pneumonia in chest x-ray images on the dataset ChestX-ray14. Using ChXNet, which is a 121 layer CNN they classified chest x-ray images at a level exceeding practicing radiologists.

Apart from detecting pneumonia, their model also detected 14 other diseases. They compared the performance of their model with practicing academic radiologists. Their model provides a state of the art performance and hopes to improve the delivery of healthcare. Guan Q. et al. developed an AG-CNN model approach to detect thorax disease from chest x-ray images. This research has been conducted on Chest X-ray 14 dataset.

The classification was done using two branch attention guided CNN. The two branches being global and local pick up global and local cues to predict thorax disease. Heat maps are also used to train the CNN model. They compared their model's performance with other models. Their approach outperformed various other models, having an average AUC of 0.871.

Xu Y. et al. trained a CNN model for classification and segmentation of brain tumor images of large dimensions. This model uses data augmentation, feature selection, and feature pooling techniques. The accuracy of segmentation and classification of this model are 84% and 97.5% respectively. They presented their approach in MICCAI 2014 Brain Tumor Digital Pathology Challenge. Rubin et al. presented a dual CNN which performs large scale automatic recognition of front and lateral images of chest x-ray on MIMIC-CXR dataset, which is the largest available dataset of chest X-rays till date. This neural network is used to detect common thorax disease. The dataset was divided into training data, testing data, and validation data. 70% of the data was used for training, 20% was used for testing, and 10% for validation. Their model has an average AUC of 0.721 and 0.668 for PA and AP, respectively. They aim to improve their model's performance by using data augmentation and pixel normalization techniques to provide aid to the workflow of the process to identify common thorax disease.

Lakhani P. et al. trained a deep CNN for automated classification of pulmonary tuberculosis from chest radiographs. AlexNet and GoogLeNet, which are dual CNNs, were used for classification purposes. The dataset was pre-processed before evaluation. Their model had an astounding AUC of 0.99. Their model had a specificity 100% and sensitivity of 97.3%. CNN is used to detect and classify abnormalities in frontal chest radiographs using deep convolutional neural networks was trained by Cicero M. et al. The input images were of the size 256X256 pixels. The AUC of the model is 0.964 with an average specificity and sensitivity of 91% showing that deep convolutional neural networks can be developed with high classification accuracy and can help in the diagnosis procedure. Anthimopoulos M. et al. presented a CNN model to identify interstitial lung disease patterns. Their model consists of 5 convolutional layers, employing leaky ReLU activation function, average pooling layers, and three dense layers. The dataset on which it was trained contains seven classes, and the dataset has 14696 images. Their model had an accuracy of 85.5%. They hope to extend their model to classify 3D images to be a supportive tool for diagnostic purposes.

Glozman T. et al. presented a transfer model, which is an extension to AlexNet to classify Alzheimer's disease on the ADNI database. Data augmentation technique was employed to enhance the performance of the deep neural network. Cho Y. et al. presented an ISC method which is based on incremental learning. They used a dataset which comprised of cortical thickness data. Their model achieved a specificity of 93% on the classification of AD patients from HC subjects. Hemanth D. J. et al. dealt with the problem of the high convergence time period for ANNs. They presented two models, which are MCPN and MKNN, which classified MR images iteration free with high accuracy. They used sensitivity and specificity as performance measures for their models.

Three new deep CNN models were presented by Szegedy C. et al. which are variants of the combination of Inception and ResNet models. Their model showed promising results. They achieved 3.08% top 5 error on the testing dataset of ImageNet classification challenge.

The ability of deep CNN models to achieve groundbreaking results on complex datasets was shown by Krizhevsky A. et al. achieving a top 5 error percent of 17%. The dataset used was the ImageNet dataset. Dropout increased the efficiency of the model considerably. Their network contains 60 million total number of parameters and has five convolutional layers and max-pooling layers. Three fully connected layers were used to provide optimum results. State of the art deep CNN model, which was submitted to ILSVRC 2014 developed by Simonyan K. et al. which was also used in this paper achieved a 92.7% top-5 test accuracy on the ImageNet dataset.

Their model has multiple variants, being widely used for classification purposes in medical research. This model was the first model to introduce small kernel sized filters one after the other instead of using one large kernel sized filter. He K. et al. presented the approach of residual learning for classification purposes. This model introduces shortcut connections to improve performance. The dataset used for training and testing was the ImageNet dataset.

This model was submitted to ILSVRC 2015. Jaiswal, A. et al. presented a Mask-RCNN based identification model for pixel-wise segmentation incorporating global and local features. They introduced critical alterations in the training process merging bounding boxes from multiple models. The performances evaluated on chest radiograph dataset which depict potential pneumonia causes. The quality of images is an imperative factor in diagnosis of disease.

Elhoseny, M. et al proposed an optimal bilateral filter to remove noise from the medical images. A detailed review is presented by Chandra, T et al. analyzing the filters to reduce quantum noise in chest x-ray images.

3. PROBLEM DEFINITION

The project aims to train the machine with the chest x-ray images to classify the pneumonia affected patients using the YOLO and CNN model. By comparing both the models, best accuracy rate is determined. Thus the best model for classifying the chest x-ray images can be found.

3.1. SYSTEM MODEL

3.1.1. DATASET

In this work, the kaggle chest X-ray pneumonia database was used, which is comprised of 5247 chest X-ray images with resolutions varying from 400p to 2000p . Out of 5247 chest X-ray images, 3906 images are from different subjects affected by pneumonia (2561 images for bacterial pneumonia and 1345 images for viral pneumonia) and 1341 images are from normal subjects . Mixed viral and bacterial infection occurs in some cases of pneumonia. However, the dataset used in this study does not include any case of viral and bacterial co-infection. This dataset was segmented into the training and test set.

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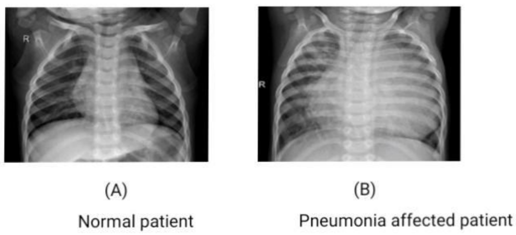

Fig1 : different images

3.1.2 DATA PREPROCESSING

In this work, several preprocessing methods were employed to increase the quality of the image data. The rescale operation was used for image size reduction, since the images were of various dimensions. The input images are generated using ImageDataGenerator class and augmentation techniques are used to rotate, shift and zoom the images. The rotation range of 10 denotes the range in which the images were randomly rotated during training. Width shift is the horizontal translation of the images by 0.1 percent and height shift is the vertical translation of the images by 0.1 percent. The zoom range randomly zooms the images to the ratio of 0.2 percent.

Workflow for development of the model: As illustrated above, the first step is data collection. It is followed by data preprocessing to prepare the data for application of algorithm. Then, YOLO CNN architecture is built to classify images as pneumonia and normal. The testing phase involves predicting the presence of pneumonia in X-ray image using the trained model. Finally, the performance of the model is evaluated using various metrics.

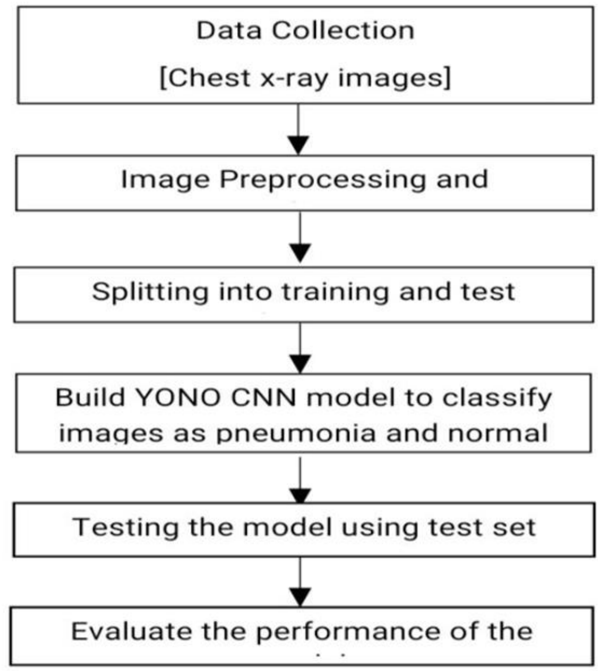

Fig 2: Flowchart

3.1.3. PRE-TRAINED TRANSFER MODELS

We implemented the present contribution for automatic multiclass classification based VGG16, VGG19, Resnet50 models for the classification of Chest X-ray images to normal, bacteria and coronavirus classes. Moreover, these deep learning models require a large amount of training data, which is yet not available in this field of applications Following the context of no availability of medical imaging dataset and motivated by the success of deep learning and medical image processing, the present work is going to apply transfer learning technique that was utilized by using ImageNet data to overcome the training time and insufficient data.

Data augmentation is used for the training process after dataset pre-processing and splitting and has the goal to avoid the risk of over-fitting. Moreover, the strategies we used include geometric transforms such as rescaling, rotations, shifts, shears, zooms, and flips

3.1.4 BUILDING CNN YOLO MODEL

Convolutional Neural Network (CNN) is a deep learning algorithm that can recognize and classify features in images for computer vision. It is a multi-layer neural network designed to analyze visual inputs and perform image classification. It assigns importance to various aspects in the image and differentiate one from the other. This work implemented the YOLO (Visual Geometry Group) model, which is a CNN transfer learning model.

The architecture consists of 16 layers. There are 2 contiguous blocks of 2 convolution layers, each block followed by max-pooling. Then, there are 3 contiguous blocks of 3 convolution layers, each block followed by max-pooling. At last, there are 3 dense layers. After developing the model, it is trained in batches of 32 images. The evaluation metric used for model is accuracy. The loss function used is sparse categorical crossentropy because the classes are mutually exclusive (i.e) each image belongs exactly to one class. The optimizer function used in the model is Adam optimizer.

3.1.5 PERFORMANCE MATRIX FOR CLASSIFICATION

CNNs were trained and evaluated using five-fold cross-validation in this study. The performance of different networks for the testing dataset is evaluated after the completion of the training phase and was compared using the following six performances metrics: accuracy, sensitivity or recall, specificity, precision (PPV), the area under curve (AUC), and F1 score. Table 3 shows six performance metrics for different deep CNNs:

Accuracy=(TP+TN)(TP+FN)+(FP+TN)(1)

Sensitivity=(TP)/(TP+FN)(2)

Specificity=(TN)/(FP+TN)(3)

Precision=(TP)/(TN+FP) (4)

F1 Score=(2*TP)/(2*TP+FN+FP) (5)

In the above equations, while classifying normal and pneumonia patients, true positive (TP), true negative (TN), false positive (FP), and

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false negative (FN) were used to denote the number of pneumonia images identified as pneumonia, the number of normal images identified as normal, the number normal images incorrectly identified as pneumonia images, and the number of pneumonia images incorrectly identified as normal, respectively. On the other hand, while classifying viral and bacterial pneumonia, TP, TN, FP, and FN were used to denote the number of viral pneumonia images identified as viral pneumonia, the number of bacterial pneumonia images identified as bacterial pneumonia, the number bacterial pneumonia images incorrectly identified as viral pneumonia images, and the number of viral pneumonia images incorrectly identified as bacterial pneumonia, respectively.

4. RESULT AND DISCUSSION

propose a deep learning-based approach to classify pneumonia . In this article, our goal is to propose a deep learning-based approach to classify pneumonia from chest X-ray images using transfer learning. In this framework, we adopted the transfer learning approach and used the pretrained architectures, YONO trained on the ImageNet dataset, to extract features. These features were passed to the classifiers of respective models, and the output was collected from individual architectures. Finally, we employed an ensemble model that used pretrained models and outperformed all other models.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808

block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0

Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0

```
/usr/local/lib/python3.6/dist-packages/tensorflow/python/keras/engine/training.py:1844: UserWarning: `Model.fit_generator` is deprecated
  warnings.warn('`Model.fit_generator` is deprecated and '
Epoch 1/5
10/10 [==============================] - 13s 1s/step - loss: 0.0521 - accuracy: 0.9688 - val_loss: 0.4446 - val_accuracy: 0.8814
Epoch 2/5
10/10 [==============================] - 13s 1s/step - loss: 0.1047 - accuracy: 0.9625 - val_loss: 0.3380 - val_accuracy: 0.9087
Epoch 3/5
```

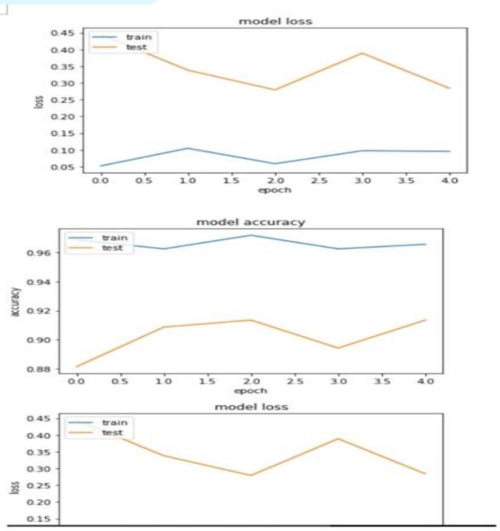

Fig 3: Output

5 . CONCLUSION

We observed that performance could be improved further, by increasing dataset size, using a data augmentation approach, and by using hand-crafted features, in future. Our findings support the notion that deep learning methods can be used to simplify the diagnostic process and improve disease management. While pneumonia diagnoses are commonly confirmed by a single doctor, allowing for the possibility of error, deep learning methods can be regarded as a two-way confirmation system. In this case, the decision support system provides a diagnosis based on chest X-ray images, which can then be confirmed by the attending physician, drastically minimizing both human and computer error. Our results suggest that deep learning methods can be used to improve diagnosis relative to traditional methods, which may improve the quality of treatment. When compared with the previous state-of-the-art methods, our approach can effectively detect the inflammatory region in chest X-ray images.

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