JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Hybrid Deep Learning Algorithm for Detecting Pneumonia Diseases

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Abstract:-Pneumonia is an infection in the lung tissue caused by a variety of different pathogens, including viruses, bacteria, and fungi, and the result is inflammation. The inflammation brings water into the lung tissue, and that extra water can make it harder to breathe. To know if the patient has Pneumonia [1], experts will start by asking about the patient's medical history and doing a physical exam, including listening to your lungs with a stethoscope to check for abnormal bubbling or crackling sounds that suggest pneumonia. If pneumonia is suspected, the doctor may recommend the following tests Blood tests, **Chest X-ray, CT scan, MRI, etc.** Early detection and treatment of pneumonia can reduce mortality rates among children significantly in countries having a high prevalence. The progression of Deep Learning contributes to helping in the decision-making process of the experts to diagnose patients with pneumonia or not. The main motivation behind this research was to identify Pneumonia just by using the X-Ray images of the patients to facilitate the diagnosis decision process. Therefore, a convolutional neural network (CNN) and Machin learning algorithm (Random Forest and XGBoost) ware proposed for diagnosis of pneumonia. To solve the cumbersome problem, six different CNN models will develop, to make the work of the radiologist simpler. CNN model(MobileNet, VGG-16, AlexNet, Inception-v3, ResNet-50, and LeNet models) pre-trained on the ImageNet dataset and other machine learning (Random Forest and XGBoost) classifiers were trained with the appropriate transfer learning with a dataset of 5856 images and using a 224x224 resolution with 32 batch sizes are applied to verify the performance of each models being trained. After the classification of the RF and XGBoosting classifiers differently using CNN model trained features, the accuracy obtained respectively were 97.70%, and 97.50%. This proposed CNN-RF hybrid method is comparable with other existing conventional methods having an accuracy of 97.70% and an AUC score of 98%.

Keywords:-Pneumonia Detection, Deep Learning, CNN, VGG16, XGBoost, Random Forest, Hybrid Algorithm.

Introduction

Pneumonia affects all old and young people worldwide, although it is more common in Sub-Saharan Africa and South Asia. Pneumonia is generally caused by a bacteria, fungus, or virus infecting the alveoli of the lungs. Radiography, CT-scan, and MRI can be used to learn about the disease [1]. Experts (radiologists) use a chest X-ray or radiograph to create a picture of the patient's chest. Raising a skilled radiologist is an expensive and time-consuming process. There aren't enough radiologists in low-income nations' rural areas. Pneumonia diagnosis is challenging, even for well-trained radiologists, because of the similarities between pneumonia and other illnesses. Deep learning-based CAD techniques are becoming increasingly popular for tackling medical challenges. The ability to make rapid decisions and perform complex cognitive tasks is the primary advantage of modern CAD approaches [2]. Convolutional neural networks, which are inspired by the human visual cortex, can assess and learn a wide range of attributes on their own [3]. CNN have been used successfully in a range of medical imaging applications, including skin lesion segmentation [4] and cancer identification from image data [5,] retinopathy identification from retinal images [6,] and lung cancer detection in CT images [7]. Rather than training or constructing a CNN model from the ground up, the suggested approach in this work is based on the notion of training well-known and successful CNN architectures using appropriate transfer learning. LeNet, MobileNet, VGGNet-16, AlexNet, Inception-V3, and ResNet-50 CNN models were trained for this purpose, and the training features were retrieved and categorized using the Random Forest Classifier and XGBoost methods. The suggested technique benefits from the twofold categorization of hybrid models in terms of accuracy and uniqueness. According to this result, the two most effective CNN models, Vgg16 and MobileNet, were chosen for use in conjunction with the Random forest and XGBoosting models. To produce the optimum classification output, the classification results from the selected CNN models were pooled and employed a Majority Vote-based, Vgg16, and Random forest technique. This Hybrid (Vgg16 and Random forest) Algorithm technique produced satisfactory classification results. The major purpose of this work is to choose the best two CNN models from among the six detected CNN models and to deploy a hybrid approach for pneumonia diagnosis utilizing deep learning CNN models. In pneumonia detection, evaluate each model in terms of the performance Matrix utilizing hyper parameters and optimization. While categorizing chest X-ray pictures, I noticed the class distribution effect on the classifiers. The rest of the paper is organized as follows: The second section is a survey of related works. Section 3 goes through the recommended approach and the dataset used in the study. Section 4 discusses the experimental design and evaluation metrics. Section 5 provides the findings and discussion. Sect. 6 concludes with an overview of the study's findings and planned work.

2. Related work

Many important study articles have been published to categorize chest x-ray pictures into distinct classifications, such as normal and pneumonia. R. Jain et al. [8] did research. Using a dataset of 5840 pictures, Convolutional Neural Network models were trained to classify x-ray images into two classes: pneumonia and non-pneumonia, by adjusting different parameters, hyperparameters, and the number of convolutional layers. The accuracy of CNN models VGG16, VGG19, ResNet50, and Inception-v3 is 87.28 %, 88.46 %, 77.56 %, and 70.99 %, respectively. A new deep neural network (CNN) has been developed by Szegedy et al. [9] which are variants of the combination of Inception and ResNet models. Their model achieved 3.08% top 5 error on the testing dataset of the ImageNet classification challenge. Another author, Jelena Bozickovic[10], and her colleagues compare four different neural network topologies and use transfer learning to identify and categorise pneumonia in patient photos. The ResNet50 model produced the greatest results, with an average cross-validation accuracy of 89.97 percent and data augmentation on the outnumbered COVID-19 class. Ibrahim, the author [11] A multi-classification deep learning model for identifying COVID-19, pneumonia, and lung cancer from chest x-ray and CT images is proposed in this study. The performance of four architectures is examined. Based on X-ray/CT images, the VGG19+CNN model obtained 98.05 % (ACC), 98.43 % precision, and 99.5 %.

Krizhevsky et al. [12] achieved 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 parameters and has five convolutional layers and max-pooling layers. Three fully connected layers were used to provide optimum results. Rohit Kundu (13). Researchers created a computer-aided diagnosis system for automated pneumonia identification utilizing chest X-ray pictures and used deep transfer learning to deal with data shortage. They created a convolutional neural network ensemble consisting of three models: GoogLeNet, ResNet-18, and DenseNet-121. On the Kermany and RSNA datasets, the technique attained accuracy rates of 98.81% and 86.85 %, as well as sensitivity rates of 87.02 %. Sammy V. Militante.[14], created a Pneumonia Detection through Adaptive Deep Learning Models of Convolutional Neural Networks. With a dataset of 28,000 pictures, this model uses pre-trained models such as GoogLeNet, LeNet, VGG-16, AlexNet, StridedNet, and ResNet-50.

3. PROPOSED METHODOLOGY

Pneumonia acquired pictures, preprocessed photos, and several CNN models were used in the suggested study. The next subsections go into the specifics of the strategy utilized in each phase of the research framework, as indicated in figure 1.

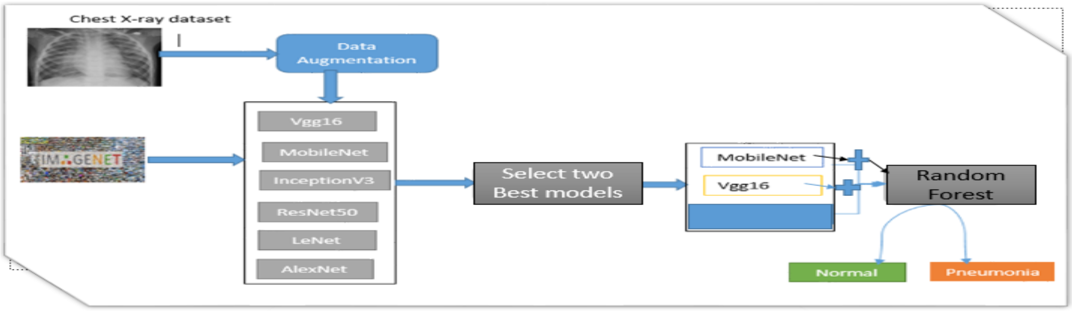

Fig1. Summary of the proposed method

3.1 DATA SET

The suggested technique was evaluated using a publicly available dataset [15]. A Kaggle dataset was utilized. It had 5863 Chest X-Ray Images of size 224 224, and The numerical distribution of normal and Pneumonia samples in the dataset was shown in Table 1. And the photographs were divided into three categories: a) train, b) test, and c) validate. These were further classified as Pneumonia and scaled to 224x224 square pixels. Also, use Data Augmentation.

Table 1: Chest X-ray dataset overview

	Normal	Pneumonia
Train	1341	3875
Test	234	390
Val	8	8
		Total= 5856

3.2 Pneumonia Image Preprocessing

To achieve a consistent measurement, all chest X-Ray pictures are individually cropped. All cropped photos are used to meet the input requirements for Deep learning models.

3.3 CNN Models

This section shows how CNN architectures are used to mimic pneumonia illness detection.

1. Mobile Net.

In 2017, Andrew G. Howard and colleagues presented MobileNet, a lightweight yet effective model that may be used in mobile or embedded systems. After each depthwise separable convolution, MobileNet employs batch normalisation and ReLU layers. It is now available on mobile and embedded devices with minimal hardware requirements.

2. LeNet model

Two convolutional layers, two fully-connected layers, and a sigmoid classifier comprise LeNet. Even if your system does not have graphics processing units, it can nevertheless run on the central processor unit (CPU) (GPU). The LeNet parameter is made up of just 60 thousand parameters.

3. ResNet-50 model

ResNet is 75 layers deep, with three convolutions in each convolution block, and combines different sizes of convolution kernels with residual blocks during training to minimise training time. It has 61 million variables.

4. VGGNet-16 model

Simonyan and Zisserman first proposed the VGG network concept in 2014. The VGG-16 architecture consists of 16 convolutional layers and two fully-connected layers with 4,096 nodes each. It has 138 million parameters and is one of the most widely used image-detection systems.

5. *AlexNet model*

In 2012, AlexNet won an ImageNet Challenge for visual object recognition created by A. Krizhevesky [10]. It is the most researched CNN architecture [18] for image classification problems [18]. AlexNet has five convolutional layers, two fully-connected layers with maximum pooling, and an activation layer that connects to 1000 classes. It has 61 million parameters.

3.4 Random Forest Classifier

This is a supervised learning algorithm and a robust approach for classification and regression. The categorization choice is based on the average potential of all classification trees Random variables are chosen at each node, and the optimal branch is identified. The branch then separates into two other branches, and so on until the Gini index reaches zero.

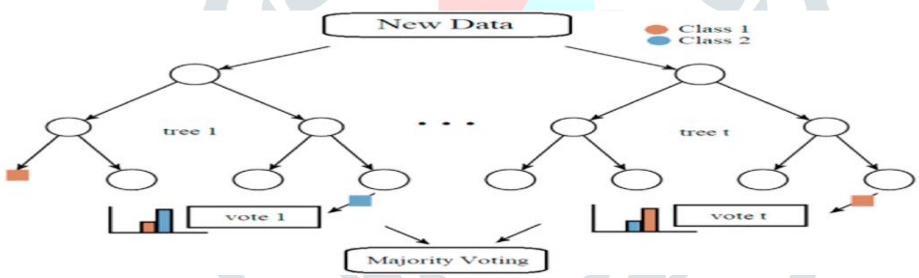

Fig. 2 Random forest classifier

4. Experimental setup

I wrote and ran the code in Colab. All of the tests were performed on a laptop computer with a clock speed of up to 2.8 GHz, seven logical cores, and eight gigabytes of memory. To enrich the dataset, data augmentation techniques are also used. Some of the techniques employed include image rotation, flipping, zooming, and shifting.

5 RESULTS AND DISCUSSION

The primary goal of this project is to provide a mechanism for appropriately identifying pneumonia in chest X-ray pictures. Six distinct CNN models were trained and evaluated. Accuracy, precision, recall, and F1-score are performance metrics used to examine and select the top performing models. For all six models, the same data pre-processing approach was applied.

According to the training results, VGG-16 and MobileNet obtained Accuracy of 97.7 percent and 98.6 percent, respectively, on the dataset. The suggested hybrid technique, on the other hand, attained Accuracy of 97.7 percent for VGG16-RF and 95.97 percent for Mobile-RF. Mobile Net was the first CNN model that was trained. Figure 4 shows the aggregated result, which offers a sense of how the model is working.

According to Figure 3, an Accuracy of 98.8 is obtained, with a Recall value of 96.4 indicating that there are low false negative values, i.e. the model had very few incorrect predictions for the negative class values (negative class here is Pneumonia X-Ray images), precision of 78.9, and f1 score of 86.8. As a result, it is evident that this model is biased toward Pneumonia X-Ray pictures. The F1 score of 88.7 percent and Precision of 83.4 percent for Model 2 (Vgg16) are not good results, but the False Positives and False Negatives are lower following prediction. As a result, this model is not effective on its own. Figure 4 depicts the findings for VGG16. The confusion matrix reflects the accuracy and performance characteristics of the model or classifier in the deep learning classification process. Tables 4 and Figure 5-6 show the CNN architecture's and Random Forest Classifier's confusion matrix: According to the results from Mobile Net-RF in Figure 6, an Accuracy of 95.97 percent is obtained, with an F1-score value of 91.28 percent, recall 94.82 percent, the precision value of 88.9 percent, and VGG-RF Figure 5, an Accuracy of 97.7 percent is obtained, with a Recall value of 95.93 percent, indicating that there are very low false negative values, i.e. the model had very low incorrect predictions for As a result, it is obvious that the hybrid model is not biased on any classes and that the VGG16-RF hybrid model is reliable for this issue.

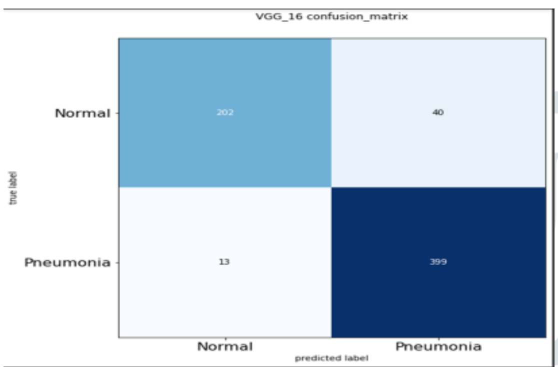

Fig-4 VGG16 Confusion Matrix

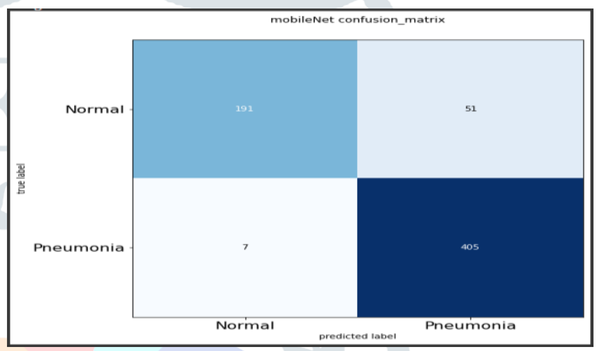

Figure 3: confusion matrix: Model 1

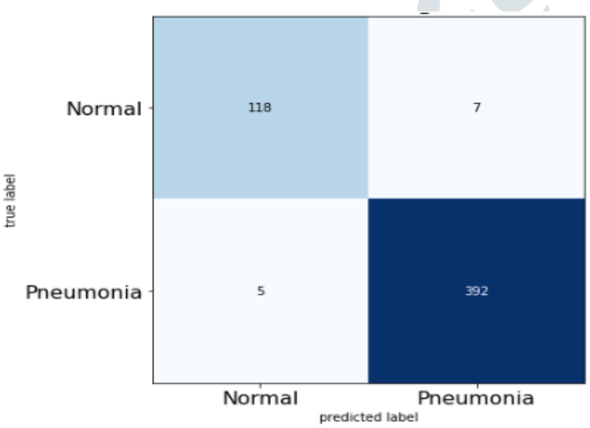

Fig-5 VGG16-Random Forest Confusion Matrix

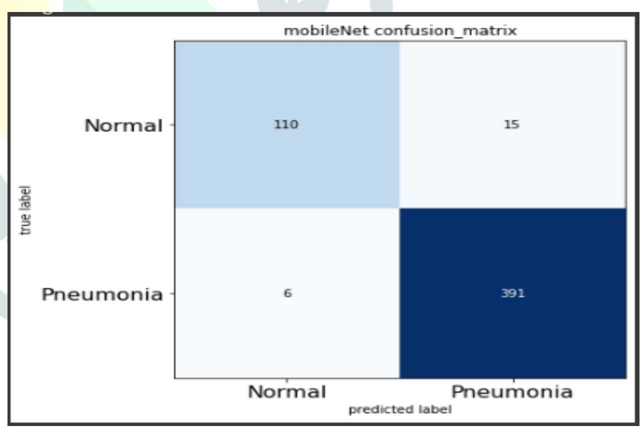

Fig-6 Mobile Net-Random Forest Confusion Matrix

Table 2. Assessment of model performance for CNN models

	Accuracy (%)	Classes	Precision (%)	Recall (%)	F1-Score (%)
AlexNet	94.7		**78.2**	**99.5**	**87.6**
		Normal	0.98	0.53	0.69
		Pneumonia	0.78	1.00	0.88
Vgg16	**97.7**		**83.4**	**0.78**	**88.3**
		Normal	0.94	0.83	0.88
		Pneumonia	0.91	0.97	0.94
Mobile Net	**98.6**		**78.9**	**96.4**	**86.8**
		Normal	0.96	0.79	0.87
		Pneumonia	0.89	0.98	0.97
InceptionV3	95.6		**76**	**98**	**86**
		Normal	0.96	0.50	065
		Pneumonia	0.77	0.99	0.87
resnet50	90.1		**74.4**	**99.2**	**85.1**
		Normal	0.97	0.42	0.59
		Pneumonia	0.74	0.99	0.85
LeNet	92.5		**61.9**	**97.4**	**75.7**
		Normal	0.97	0.62	0.76
		Pneumonia	0.82	0.99	0.89

Table 3. Assessment of model performance for hybrid (CNN and XGBoost) models

	Accuracy %)	Classes	Precision (%)	Recall (%)	F1-Score (%)
XGboost_MobileNet	**97.50**		**93.60**	**95.90**	**94.73**
		Normal	0.96	0.94	0.95
		Pneumonia	0.98	0.99	0.98
XGboost _Vgg16	**96.97**		**93.33**	**95.89**	**94.55**
		Normal	0.96	0.93	0.95
		Pneumonia	0.97	0.98	0.98

Table 4. Model performance evaluation for hybrid (CNN and RF) models

	Accuracy %)	Classes	Precision (%)	Recall (%)	F1-Score (%)
RF_MobileNet	**95.97**		**88.9**	**94.82**	**91.28**
		Normal	0.95	0.88	0.91
		Pneumonia	0.96	0.98	0.97
RF_Vgg16	**97.70**		**94.39**	**95.93**	**95.16**
		Normal	0.96	0.94	0.95
		Pneumonia	0.98	0.99	0.98

The proposed method is distinct in that it utilizes CNN-RF and CNN-XGBoost hybrid models. I demonstrated CNN accuracy using CNN-RF and CNN–XGBoost Classifiers, and it is evident that the CNN-RF Classifier is more accurate. In all hybrid classifier techniques, CNN architecture is used as a feature classifier, while Random-Forest Classifier and XGBoost classify the recovered features from the CNN model. This distinguishes this method, and the final accuracy demonstrates the highest efficiency of the suggested model

.6. Conclusion & future work

The proposed hybrid CNN-RF and CNN-XGBoost classifier algorithms categorized 5856 Chest X-Ray images. This study has the greatest accuracy of 97.70%, Precision of 94.39%, Recall of 95.93%, and a 95.16% F1 score for VGG-RF. This model can also be applied to additional datasets in the future. Some ensemble classifiers can be utilized in the future to improve this method, and a comparison between them can be given, as well as some better ways. This proposed CNN model can also be tested using additional lung disease Chest X-ray datasets.

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