Comparative Study of Pneumonia Detection Using Supervised Learning (Feed Forward Back Propagation) and Unsupervised Learning (Radial Basis Function)

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Abstract - *Pneumonia is one of the most life-threatening diseases in the world which affects the lung(s) of humans and is one of the leading causes of death in India. Expert radiotherapists use X-Rays to diagnose for pneumonia. The aim of this project is to create a software that uses Machine Learning and Deep Learning techniques like Radial Basis and Back Propagation Network to detect pneumonia automatically from the medical images like X-Rays which are used for diagnosis by experts and also do a comparative study on which algorithm performs better. Chest X-Rays used to detect pneumonia are to be reviewed by expert radiotherapists. The implementation of an automated pneumonia detection system would therefore be helpful for the treatment of the disease, particularly in remote areas, without any delay. Thanks to the popularity of deep learning algorithms in the processing of medical videos, Convolutional Neural Networks (CNNs) have received a great deal of interest in the classification of diseases. In addition, features learned from pre-trained CNN models on large-scale datasets are very useful for image classification tasks.*

***Key Words*: Pneumonia, CNN, Ensemble**

1. INTRODUCTION

An acute respiratory infection that affects the lungs is pneumonia. It is a deadly disease in which pus and other fluid fill the air sacs. Two forms of pneumonia are primarily present: bacterial and viral. Generally, bacterial pneumonia is found to cause more acute symptoms. The cure is the most substantial distinction between bacterial and viral pneumonia. Bacterial pneumonia treatment is performed using antibiotic therapy, while viral pneumonia typically gets better on its own. All over the world, it is a widespread disorder. A high degree of pollution is their primary cause. In the list of the top 10 causes of death in the United States, pneumonia is ranked eight. Every year, 3.7 lakh children die in India because of pneumonia, which represents a total of fifty percent of the deaths from pneumonia that occur in India. The disease sometimes goes unnoticed and ignored until, especially in the case of old patients, it has reached a fatal stage. It is the single greatest cause of death worldwide in children especially under the age of five. According to the WHO, "Every year, it kills an estimated 1.4 million children under the age of five years, accounting for 18% of all deaths of children under five years old worldwide. Pneumonia affects children and families everywhere but is most prevalent in South Asia and sub-Saharan Africa. Children should be shielded from pneumonia. With simple interventions, it can be avoided and treated with low-cost low-tech medications and treatment. Therefore, there is an important need for computer-aided diagnostic research and development in order to reduce pneumonia-related mortality, especially in children. The goal of this project is to develop software that uses Machine Learning and Deep Learning techniques such as the Radial Basis and Back Propagation Network to automatically diagnose pneumonia from medical images such as X-Rays that are used by experts for diagnosis and also conduct a comparative analysis on whether the algorithm performs better.

1.1 Objective

1. Create a software that takes X-Ray image and user details as input and generates a report for the patient diagnosing from the x-ray whether the patient has pneumonia or not.

2. Use various algorithms like BPN and Radial Basis for studying the accuracy of the algorithms and apply to our dataset to compare the performance on detecting pneumonia when give an X-Ray image of a patient's chest.

1.2 Scope

Increasing medical abnormalities has contributed to growing life insecurities. At an early stage, diagnosis and treatment of such anomalies will help save lives. Deep learning models that can detect such anomalies with high precision must be established with reliability and interpretability. In this research, an automated diagnostic method based on a neural network for the diagnosis of chest X-ray pneumonia is suggested. For this Research, a radial basis and feed forward neural network model is proposed. In terms of precision, recall, and accuracy we compared radial basis with feed forward backpropagation neural network. This analysis is conducted on the generic Chest X-ray dataset gathered from Kaggle

2. LITERATURE SURVEY

2.1 Existing Techniques:

Ergen and Comert used existing techniques for feature extracting. At the time of classification, they didn't use any pre-processing procedure on pneumonia images. The fusion of LDA and mRMR approaches provided the highest results. The mRMR technique enhanced the performance of the classification. There was no application of cross-validation in the planned method. Since the dataset guarantees enough samples for training and test sets, the holdout validation technique was used. To balance the distribution of the samples over the classes, the imaging augmentation was only conducted over the usual class. As a feature extractor, they used existing CNN models such as AlexNet, VGG-16, and VGG-19 [1]. In [2], the researchers used the method of transfer learning and used pre-trained models to derive features. They used 5 different models of ImageNet. The classifiers of the respective models are supplied with derived features, and the output is obtained from individual models. Finally, they used an ensemble model that outperformed all other simulations using all five pre-trained models. In [3], Liang and Zheng introduced an automatic diagnosis method that classifies chest X-ray pictures of children into regular and pneumonic images. In order to minimize the cross-entropy loss function, training is carried out by adding dilated convolutions and using Adam optimizer. The approach suggested is capable of avoiding the loss of feature space information caused by this while preserving the model depth. Moreover, to speed neural network training and resolve the issue of inadequate data, they used transfer learning. This approach demonstrated the performance of classification superior to the prior strategies. They used the residual network as the structural basis, together with the dilated convolution architecture, based on the interpretation of the original input data, to propose an automatic diagnostic algorithm for children with pneumonia. This approach can retain a certain resolution of the picture space and by migration learning and hyper-parameter modification, achieves classification efficiency beyond the legal precedence. In [4], the researchers introduced a pneumonia detection strategy ensemble using the largest data collection marked with a focus failure approach and a classification technique. After a study of the development of neural networks for chest x-ray pneumonia identifiers and meetings with clinicians, multiple avenues were noticed for the potential expansion of the research provided. In [5], the paper includes an electronic diagnosis method that classifies patient X-ray images as normal and pneumonia. Various pre-processing steps have been used to optimize images such as medium filters, histogram equalization, gamma-correction, CLAHE, and JPEG compression so machine learning modules can take advantage of these enhanced image results. In order to construct the model, transfer learning is used along with fine-tuning of hyperparameters. The architecture consists of one dropout layer one batch normalization layer, one global hot tub, and two thick layers. This model is built on top of an InceptionV3 model. Elshennawy and Ibrahim suggested a deep leaning system of four distinct CNN models for the classification of pneumonia. Two of them, ResNet152V2 and MobileNetV2, were pre-trained models, and the others were built from scratch. The output of the proposed deep learning system for the experiment was evaluated on the basis of precision, F1 score, recall, and AUC. They discovered that the best results were obtained by the proposed ReNet152V2 model compared to the others [6]. In [7], the authors introduced two high-performance neural networks for real-time applications. Both models are exceptionally detailed and accurate. They used Model 2 and VGG19. Model 2 and VGG19 models should be used successfully in order to achieve an excellent result against all performance indicators. Through the implementation of larger datasets, overall models efficiency can be increased. In [8], Pant and Prasad noticed that the proposed model provided amazing results for the high precision and decent recall "Efficientnet-B4 based U-Net" model, but for the other variant, "ResNet based U-Net" had a powerful recall but low accuracy. The ensemble model incorporates the best of all worlds since the high quality is taken from the effective network based on EfficientNet-B4 and the high quality of recall is taken from the U-Net based on ResNet-34. The integration of the two models indirectly achieves great results. But first model "Efficientnet-B4 based U-Net" has individually worked more reliably than our assembled model, but the assembly model in the actual case scenario has yielded a respectable outcome. In [9], the authors proposed a methodology that detects frontal X-ray pneumonia at a level that is way beyond practicing radiologists. They showed that our algorithm was expanded to detect more than one in ChestX-ray14, the largest publicly accessible chest X-ray dataset, diseases surpass the previous state of the art. They downscale the images to 224*224 before inputting the images into the network and normalize depending on the mean and standard deviation of images in the ImageNet training collection. With random horizontal tossing, they also increase the training data. To evaluate if the performance of CheXNet is statistically substantially better than the performance of a radiologist, they also calculated the difference between the variations between CheXNet's average F1 score and radiologists' average F1 score on the same bootstrap samples. In [10], the authors introduced the automatic methods of classifying X-ray chest into pneumonia and regular class by nine architectures of deep learning. They implemented a baseline CNN, DenseNet201, Inception_ResNet_V, MobileNet_V2, VGG16, Inception_V3, Xception, VGG19, and Resnet50. The findings obtained indicate that Resnet50, MobileNet V2 and Inception Resnet V2 performed strongly against the other frameworks discussed in this study. Intensity normalization and Contrast Limited Adaptive Histogram Equalization (CLAHE) were employed for data pre-processing. In [11], the researchers presented ICC, ECC, and the two better versions of it, E4CC and E16CC. Using the decoder, these models were resistant to overfitting and pixel attacks. Compared to the other models, all these models achieved better testing and validation performance and lower validation errors. In [12], the authors proposed a scheme for recognizing pneumonia and understanding how the size of the lung picture plays a significant role in model efficiency. They observed that the difference between the presence or absence of pneumonia in photographs was very subtle, and also concluded that a larger image may be more useful for greater understanding. Although the cost of computing is often exponentially burdened when dealing with massive images. The suggested regional architecture, such as Mask-RCNN, offered an extra framework for the generation of reliable data. Also using context thresholds during practicing tuned the network to perform well throughout the task. Through the use of image augmentation, dropout, and L2 regularization, the overfitting was prevented, but some poorer findings were obtained on the training set concerning the test. Due to the labeled dataset, they carried out assembly in Stage 2, while the dataset was strongly imbalanced in Stage 1. The uncertainty in the dataset is due to the ignored reading of high quantities of images per shifting by radiologists. In Stage 2, they trained the suggested framework on the NVIDIA Tesla P100 GPU and Tesla K80 in Stage 1. This also shows that in order to model certain tasks on a deeply imbalanced dataset, one requires powerful computational power. By introducing additional layers, the model could be enhanced, but this would bring even more hyperparameters that could be modified. In [13], the output of six CNN architectures was evaluated by the authors: StridedNet, AlexNet, LeNet, GoogleNet, ResNet-50, and VGGNet-16. As all six models achieved a reasonable accuracy rate during training with the specified input parameters, the output testing results are very satisfactory. GoogleNet and LeNet models have recorded the highest accuracy. The ResNet-50 model achieved the lowest reported pace. In order to capture feature extraction and fine-tuning for its framework, all six CNN models listed were significantly evaluated. The six models progressed well in the diagnosis of pneumonia and consider the great method of diagnosing and detecting pneumonia that helps medical professionals in supplying their patients with a high-quality medical service.

In [14] the authors proposed pneumonia detection system using the 'Densely Connected Convolutional Neural Network' (DenseNet-169) (DenseNet-169). The architecture of the proposed model has been divided into three different stages - the preprocessing stage, the feature extraction stage and the classification stage.

A. The Pre-Processing Stage

The primary aim of using the Convolutional Neural Network for most image recognition tasks is to reduce the computational complexity of the model that is likely to increase if the input is images. The original 3-channel images have been resized from 1024×1024 to 224×224 pixels to minimize heavy computing and speed up processing. All the other methods have been added to these downsized images.

B. The Feature-Extraction Stage

Although the features were extracted with different versions of pre-trained CNN models, the statistical results obtained by DenseNet-169 were proposed as the best model for the extraction process of the features. This stage therefore deals with the definition of DenseNet-169 model architecture and its contribution to the extraction of functionality. 1) DenseNet architecture-169: Deep Convolutionary Networks (DCNNs) have been the most productive architectures for image recognition owing to the existence of unusual forms of convolutionary and pooling layers.

But as the network deepens, the input information or gradient going through several of the layers disappears when the last layer of the network is reached. DenseNets solve this gradient problem by linking all layers of identical featutre-sizes directly to each other. The key justification for using DenseNet architecture as a function extractor is that more common functionality can be achieved more directly in the network. The 169-layer Tightly Connected Convolutional Neural Network (DenseNet-169) has been used for the extraction of functions. The DenseNet-169 architecture consists of one convolution and pooling layer at the beginning, three transfer layers, four thick blocks. The last layer, i.e. the grouping layer, is present after these layers. The first convolutionary layer consists of 7×7 convolutions with step 2 followed by a max pooling of 3×3 used with step 2. Then the network consists of a dense block followed by 3 sets each of which consist a transition layer followed by a dense block. The lth layer in the network receives the feature-maps of all the preceding layers thus ameliorating the flow of gradient throughout the entire network. This involves the concatenation of the features-maps of the previous layers, which cannot be achieved until all the features-maps are of the same size however as the Convolutional Neural Networks are primarily aiming for a lower sampling of the size of the features-maps, the DenseNets architecture is divided into many densely connected blocks described above. The layers under these thick blocks are referred to as the layers of transformation. Each transition layer in the network consists of a batch normalization layer and a 1×1 convolutionary layer followed by a 2×2 average pooling layer using a 2. As mentioned above, there are 4 dense blocks, each of which comprises 2 convolution layers, the first being 1 × 1 followed by 3×3. The scale of all four dense blocks of DenseNet169 architecture preformed to ImageNet is 6, 12, 32 and 32. Next to this is the third step, the grouping layer, which conducts the global average pooling of 7×7 followed by the final totally linked layer, which uses 'softmax' as an activation.2) Extraction of Functions.

C. The Classification Stage

After extraction of the features, various classifiers, such as Random Forest, Support Vector Machine, etc., were used for classification tasks. But the best results were found to be obtained when the Help Vector Machine was used as a classifier for the query. Thus the best proposed model features derived from DenseNet-169 were used with the SVM classifier to obtain better performance. Definition of the parameters and kernel used for SVM is as follows: Suppose a sample of training data as (x1,y1),(x2,y2)......(xn,yn) and the data needs to be divided into two sets of groups where x I 5-007 F d is the vector function and y I 5-007 (0,1) is the mark type. The support vector machine used for binary classification is capable of finding the best hyperplane for the above training data, i.e. the one with the highest margin between classes, and is capable of distinguishing the data points of one class from the other. The efficiency of SVM is strongly dependent on the selection of the kernel and parameters. The RBF kernel gamma and C parameters have a significant influence on the efficiency of SVM. Intuitively, the gamma parameter is used to describe the amount of control that a single training example can have in which the lower value means 'far and the greater value means 'near.' Thus the gamma parameter shows the reciprocal radius of the effect of the samples chosen by the model as supporting vectors. On the other hand, the C parameter compensates for the misclassification of the training samples. A low C provides a flat surface where a high C tends to correctly distinguish all training samples by including a model exception to pick further samples as support vectors.

3. PROBLEM STATEMENT

Pneumonia is one of the most life-threatening diseases in the world which affects the lung(s) of humans and is one of the leading causes of death in India. Expert radiotherapists use X-Rays to diagnose for pneumonia. Our purpose in this project is to decide whether the patient has pneumonia or not, provided the patient's clear X-ray picture. For this reason, we conducted a comparative study between the radial basis and the feed-forward neural network backpropagation and further used the best model in the X-ray picture for classification for pneumonia detection

4. PROPOSED SYSTEM

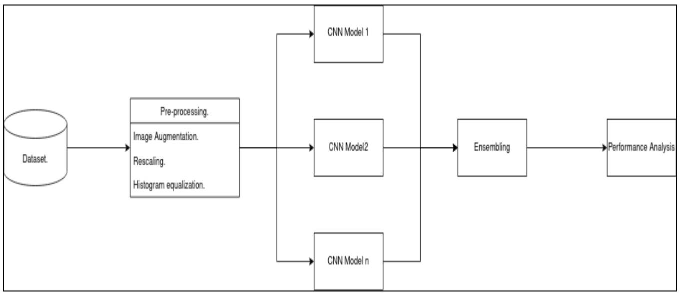

Fig 1: Flowchart

We attempted to develop our architecture to detect pneumonia using X-ray images by analyzing the above research work. The architecture suggested is shown in Fig. 1.

We will conduct preprocessing of the images after downloading the dataset, as shown in the architecture. To increase the efficiency of the model, the preprocessing phase is necessary. Picture augmentation, including cropping, rotating, and increasing the brightness of the images, is included in the preprocessing techniques. This will also mean increasing the dataset size. We will re-scale the images in the next step to make them suitable for Deep Learning models. The equalization of the histogram is then applied to increase image contrast. In addition, we intend to train and compile the outputs of a number of convolutionary neural network models.

4.1 ALGORITHMS

1. Feed Forward Back Propagation:

Neural Network / ANN: ANN stands for Artificial Neural Networks. It is based on the biological neural networks. The ANN structure is affected by the flow of information. Thus, changes in the neural network were based on input and output. Basically, we can view ANN as non-linear statistical data. That means complex relationships define between input and output. Neural networks contain input, output layers, and hidden layers. Data flows in the neural network in two ways.

Feedforward – In these, signals it only goes forward without a loop back i.e towards the output layer. It is used in pattern detection. There is a single input layer and a single output layer and it can have zero or many hidden layers.

Feedback – In this recurring or connected network it can use its internal memory (memory) to process input sequences. Data can go both directions with loops in the network. It is limited to consecutive time / activities. Neural Network Algorithms works on three main layers of its structure namely the input layer, the hidden layer (or there can be many hidden layers), and the output layer.

2. Radial Basis Function:

In the basic neural network i.e single layer perceptron we can separate only linearly separable data because there is no hidden layer to get non-linearity. Without a hidden layer, non-linearity cannot be achieved. RBNN(Radial basis neural network) has only one input, strictly one hidden, and one output layer. The hidden layer in RBNN is called a feature vector. In this function the value depends on the distance from the origin. The RBNN is a great alternative to the multilayer perceptron (MLP), Since the RBF centers and variances are fixed, we only have to evaluate the activations of the RBF units once. So training is faster in RBNN compared to MLP. Every node in the hidden layer of RBNN uses a radial basis function (RBF), denoted by $\phi(r)$, as a nonlinear activation function. The hidden layer is used to perform a nonlinear transformation of the input, and the output layer is a linear combiner mapping the nonlinearity into a new space. The biases of the output layer neurons can be introduced by an additional neuron in the hidden layer.

5. CONCLUSION

We may assume that pneumonia has a global effect and is a deadly disease. A professional radiotherapist is needed to diagnose pneumonia using x-ray images. Therefore, we tried to survey several articles in this paper on the detection of pneumonia using Convolutional neural networks, and we suggested a method for detecting pneumonia using deep learning and assembly techniques.

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