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# PREDICTION OF BACTERIAL LUNG INFECTION USING MODIFIED CONVOLUTIONAL NEURAL NETWORKS

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**Abstract**
Detection of the chest bacterial infection in the critical point of diagnosis can be very dangerous and fatal .Deep learning and neural network techniques simplify the method of infection detection method. Radiologists feel that it is better to discretely classify chest X Ray photo sover the existence or inexistence of chest bacterial infection,using deep learning model which further uses convolutional neural networks to distinguish the chest x-rays. Here basically modification of the usually used CNN method by adding pre-trained model, vgg-16 is done.The stated prediction project module provides greater accuracy based on the results in accordance to the X Ray image datasets which show possible chest infection reasons**.**

**Keywords---** dataset, Machine learning-Classification method, Prediction of Accuracy result


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## INTRODUCTION

Chest X Ray is a monetarily economic and easy procedure for imaging and diagnosis. The procedure is a widely used diagnosisway among medical practitioners and is of upmost importance in lung disease identification. Specialist radiologists make use of chest X Rays for diagnosing conditions such as tuberculosis, pneumonia, and priorstage of lung cancer, all of which can be diagnosed just through the x-ray image.

Great benefits of chest X Rays comprise of their low costs and ease of operations and handling. Under even underdeveloped areas, there are very inexpensive modern digital radiography (DR) machines. Hence, chest X-rays are used at widespread in the identification, and prediction of the lung infections and diseases, like tuberculosis, and other such diseases indulging lung disorders.

Chest X-ray imaging comprises of a huge quantity of data and information about a patient's health .Though, accurately depicting information is surely a major difficulty and responsibility for a practitioner. The overlapping of tissuesregions in chest X-rays increase the difficulty of identification and analysis. Even for a specialized practitioner, it is sometimes very difficult to differentiate between similar lesions or to find very obscure bodies.

Hence, a proper diagnostic of lung based disease in chest X-rays can reveal some level of omission. Widespread usage of X rays and the difficulty in understanding them makes Computer Aided Detection (CAD) a very important anddesirable topic because the system can be a helping hand to the doctors in easily detecting suspicious lesions that are missing, thus identifying them effectively. Hence, the prediction accuracy is improved.

## LITERATURE SURVEY

[1] It presented a pneumonia detection ensemble approach making use of the greatest dataset which is classified as labels and highlighted the importance of the loss of focus and object-identificationmethod in terms according to theclassification and differentiation metrics. Upon evaluating the success of neural schema on the detection of lung diseases from chestradiograph images and the practitioner's consultancy, it was recognized that many scopes for the upcoming expansion of the research could beintroduced. Second, while medical-diagnosis is the most importantre source of information for detecting pneumonia, the thorough identification must bein complete accordance to thepathologicaltests, pulse monitoring, lung examination, and so on.

[2] Proposed a powerful method of 2D-3D registration from dynamic radiography for 3D rib-motion recovery. Precisely, the outputs of thereport are introductions of single-axial, rib, motion model along,with rotation axis optimization for improvement ofstrength in optimized solution, also retaining a superior level ofprecision and accuracy. The defined approach was tested using severalpractical experiments with2-phase CT (that is, inhalation-exhalation) along with real time images usingx-ray media obtained usingtechnique of any standard laboratory procedure.

[3] Presented an approach to pneumonia detection and understanding how the size of the lung picture plays an important role in model efficiency. They find that for photos the distinction between presence or absence of pneumonia is quite subtle, broad picture may be more useful for deeper data. However, when dealing with large image, the computation also exponentially burdens. The proposed local architecture, such as Mask-RCNN, provided additional background to deliver accurate results. In addition, using background thresholds while training, the network has been tuned to perform well in this task.

[4] Once there are enough maths, computer based and technology-based high-impact software systems entering the clinic's everyday workflow, theapprovalof such new systems also increases. Accessing with the biological sensors with computation over wearable gadgets for monitoring disease or lifestyle, facilitates the transition to a new predictive, preventive, personalized, and participatory medical paradigm.

[5] Proposed a proposed segmentation focused on deep learning and crowd sourcing. Next, improved and more specific data segmentwas developed with the inferences of the integration processes tested in ISIC2017. Instead, with the VGG16 model along with the ResNet50 models which are already trained over the pre-fed Image Net dataset, they carried out transfer training.

The extraction, of features, from the convolutionregionwith training of one top classifier to classify Dermoscopic image test dataset into five groups that demonstrate the most important methods of segmentation was carried out. Accuracy was best reported by the proposed recommender.

[6] S,D,Lwas proposed for addressing the difficulties of clinical imaging due to the differences within the class and similarities among the classes. Several DCNN layers are used in this model with synergistic networks simultaneously allowing these DCNN layersgain information from one another. The findings over datasets of Image CLEF with years of 2015,16 and 2017 indicate that the defined SDL model deliversbest-in-class quality in the of differentiation of medical photos. For upcoming time, importance should be given over the strengthening of training algorithms which canautomate the checking of number of layers for DCNNs, design simultaneous computation, along with theframework enhancement to expand scope of the SDL model.

[7] To predict the severity of Parkinson's disease, implement a deep learningNN. Compared to other existing techniques, the proposed DNN model has achieved greater accuracy. It was highlighted that differentiation based on UPDRS motor value is of more help than differentiationin accordance with the total UPDRS value, hence, be inferred as more efficient Severity Prediction measure. Even when a dataset of 5800+ instances had been used, precision of this methodology can be further improvised by applying it over a still more big dataset with more instances of each gravity group and a consolidated voice database of patients and theircharacteristics.

[8] This showed that deep learning is a strong approach to estimating chest radiographic pulmonary edema. In addition, making use of semi-supervised learning by self-training in accordance to pseudo-labeling, large-scale unlabeled objects can be used to improve the performance of classification.

[9] The identification of the lung region at this stage of the project was carried out by identifying the rib cage boundary and computing this region's area. Otsu thresholding is used to separate the disease cloudy form from the normal lung in the image of lung area, but it requires work over other procedures that can be used to threshold the X Ray photos, which produces better results. It must be considered that measuring the proportion of the defined 2 areas after Otsu thresholding to the total lung area. Since pneumonia clouds after Otsu threshold are not visible in the lung image, the ratiomust be much lesser than the time when calculated without clouds for normal lung region.

[10] This paper proposed an object identification simple Convolutionary neural network. A basic neural convolution network imposes less computing costs. It is also evaluated different learning rate set approaches and several enhancing algorithms to solve the requiredcharacteristics parameters over effect on object differentiation based on the CNN. It also tested that there is also a relatively good recognition effect for the shallow network.

[11] Using CNN, CADx based on images can discern different types of lung based disorders like lung-nodules etc. In addition, CAD based on image analysis can also detect such lung abnormalities using R-CNN. Inpopular CAD methodologieswhich use image vectors, it is needed to extract image features using several types of algorithms for image analytics. Nevertheless, it's hard accurately describing different types of lung disorders. CAD methods using CNN or R-CNN don't necessitate extractors of the image function.

[12] It proposes a model of Multi-CNNs and a result synthesizing method of the model components that is called the rules of fusion. The proposed method comprises 3 major CNN techniques. CNN-based development of these components. To integrate the results, the proposed model uses association fusion principle. The process of fusion rules for integrating the outputs in 8 situations to conclude the classification model of the CNNs. It tests three combined approaches for cases with uncertain results in 8 cases of this law.

**SYSTEM MODULES**

**Dataset**

In the proposed work, publicly available Kaggle chest x-ray image dataset is used which consists of unique 5863 Chest X-Rays images. There are two classes of labeled data normal and bacterial infected lung chest x-ray images. The images were separated into training set which have total 4190 images(3875 bacterial infected and 234 normal) and test set have 624 images(390 bacterial infected and 234 normal) and validation set consisted of 242 images(234 bacterial infected and 8 normal).

**Data preprocessor**

In the data preprocessor the chest x ray image dataset is pre-processed. Here chest x-ray image dataset is converted to greyscale image. Further the fixingof pixel sizes of all the images to 256*256 is carried out, so that all images have same pixel size which further would make training of dataset more feasible, as the model required all images to be in a same format and size specification.

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**VGG16 model**

As a weight initialization technique, transfer training from the m odels conditioned on a Microsoft COCO task was used.

Transfer learning technique of ML makes the use of a template which is trained over a single task. e.g. Recognizing object modules from the raw photos for another same job, where there are very few training compatible samples.CAD methods using CNN and R-CNN don't necessitate extractors of the image function.

Transfer learning should improve the detection of bacterial infection, here the VGG16 model is used.

VGG16 is a convolutionary neural network trained on over a milli on ImageNet objects. The VGG16 further is trained on 4190 chest x-ray image dataset through which it extract the features from the chest x ray which have Pneumonia and the one which doesn't have it.

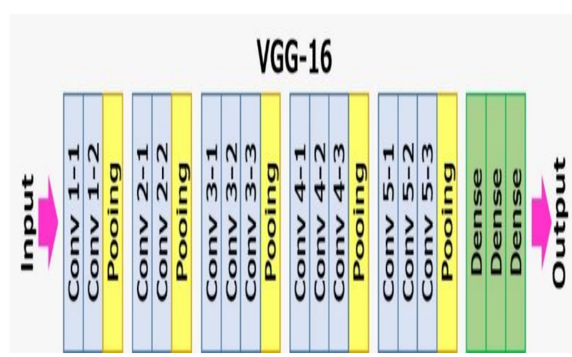


**Figure 1 .** VGG – 16 Work Flow

**Validation**
After the CNN is trained and tested on 5863 chest x-ray image dataset, it is finally saved and the predictor model is now ready. Further now the model will be used for the diagnosis of lung bacterial infection.

**Equation**

$$CrossEntropy(p_t) = -log(p_t)$$

$$FocalLoss(p_t) = -(1-p_t)^{\gamma} log(p_t)$$

**Input parser**
The input parser consist of the path through which the image will be given as a input for determining whether a person is having bacterial lung diseases or not. The input will be directed to the predictor model and it will finally categorize that a person is infected or not.

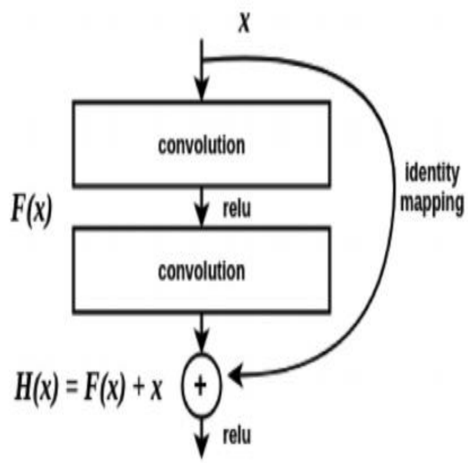


**Figure 2**. Input Parser-Image Processing

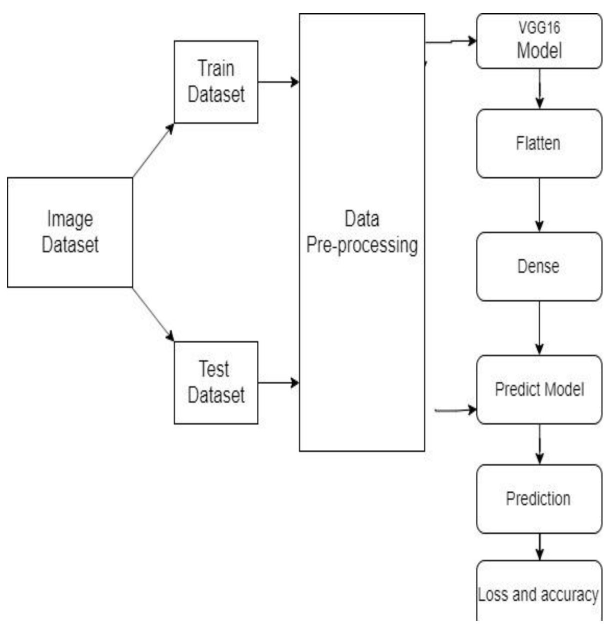


**Figure 3.** Project Model Work Flow

**IMPLEMENTATION**
As this is a classification problem, the project makes use of images as data input all for training, testing and validation. The images are then classified into the following two categories as :-
1) The person with corresponding chest X Ray is not infected with bacterial infection.
2) The person with corresponding chest X Ray is infected with bacterial infection.
For the implementation of this project, python programming has been used.

Various python libraries like numpy, pandas, keras and tensorflow are taken into account, but the most important part is making use of VGG16 convolutional NN application.

**RESULT**
The final result of this project would be in binary format for now. Here there are two indices:-

- First index (column 0) represents a class denoting the absence of any chest bacterial infection within the chest radiograph.
- Second index (column 1) represents a class denoting the presence of any chest bacterial infection within the chest radiograph.

Now considering the row-wise values, the main result values will be presented in the row-wise output. The output will be defined in binary language, i.e. in Zeros and Ones. As in binary representation, **0** denotes **LOW**, hence considering it as an output **"NO"**, and the value **1** denotes **HIGH**, hence considering it as an output **"YES"**the model achievesa clearer vision of the lung area bypresenting an accurate identification in the stages of confusion.

For reference purpose, the model output for an infected person's chest radiograph input, giving a HIGH(1) value in DISEASE class, and a LOW($1.04 \times 10^{-28} \approx 0$) value in NORMAL class is displayed as follows :-

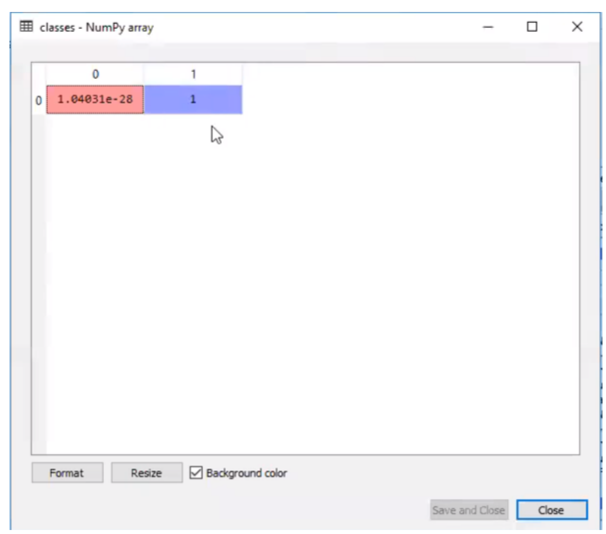


**Figure 4**. Result Class Output

**CONCLUSION**
Introduction to a bacterial infection identification ensemble method is carried out in the given study using the largest labelled dataset. Upon evaluating the success of NN over the detection of lung diseases from chest X rays also communicating with the medical practitioners, it wasdiscovered that many avenues are openregarding the future expansion over the research given.

Formerly, while clinical image diagnostic stays the most important source of information in identifying lung diseases, the immediate primaryidentificationmust be in accordance to theprecisepathologicalreadings, tests, etc. Latter, to provide a clearer picture, also, to insure precise diagnostics for situationsof irregularities, a front part chest X Ray must be attached with the rear part of chest X Ray. Third, the front X Ray must be supplemented with longitudinal X Ray image of chest in order to achieve a clearer vision of lung area to allow accurate identification in stages of confusion.

**Table 1**. Literature Survey Documentation

| REF. No. | OBJECTIVE | ALGORITHM /STRATEGIES USED | DATASETS OR INPUT PARAMETERS | RELEVANCE |
|---|---|---|---|---|
| [1] | Deep NN ensemble for pneumonia localization. | CNN | Chest x-ray images | Object-detection |
| [2] | 3D Rib motion Recovery | Pre-processing of radiography | Functional imaging | Getting proper 3D image of lungs. |
| [3] | Identification of pneumonia in chest Xrays | Convolutional Neural Networks | Pathological bacteria from cancer patients. | Importance of lung image size for model performance. |
| [4] | Deep learning in MRI. | Deep artificial neural networks | MRI Images from various | Molecular marker identification, early detection and predict survival time. |
| [5] | An image-based segmentation recommender. | Deep Learning Techniques(VGG16) | 64 × 64 pixels images | Better Jacard index score. |
| [6] | Synergic classification on Images | Deep convolutional neural networks (DCNNs) | ImageCLEF 2015 and ImageCLEF | S D L Model |
| [7] | Deep Learning Applications in Medical Image Analysis | Arificial neural networks | CT and MRI mage segmentation dataset | How machine learning and deep learning play major role in health care.a |
| [8] | Pneumonia clouds using XRay image analysis. | Deep learning approch | Analog CXR images | Rib cage boundary identification. |
| [9] | CNN over Image classification. | CNN | Grayscale images of digit from 0-9. | Shallow networks has as good recognition. |
| [10] | Detection and Classification of Lung Abnormalities | CNN and RCNN | CT Scan images | Image feature extraction |
| [11] | Detecting abnormal problems on chest. | CNN | X-ray images | Detection of chest problem |
| [12] | Training data independent image registration. | Transfer learnig techniques and segmentation and information | CT lungs images | Results in similar imaging over train and test data. |

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