



## PNEUMONIA DETECTION USING DEEP LEARNING

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### Abstract :

Artificial intelligence has found its use in various fields during the course of its development, especially in recent years with the enormous increase in available data. Its main task is to assist making better, faster and more reliable decisions. Artificial intelligence and machine learning are increasingly finding their application in medicine. This is especially true for medical fields that utilize various types of biomedical images and where diagnostic procedures rely on collecting and processing a large number of digital images. The application of machine learning in processing of medical images helps with consistency and boosts accuracy in reporting. This paper describes the use of machine learning algorithms to process chest X-ray images in order to support the decision making process in determining the correct diagnosis. Specifically, the research is focused on the use of deep learning algorithm based on convolutional neural network in order to build a processing model. This model has the task to help with a classification problem that is detecting whether a chest X-ray shows changes consistent with pneumonia or not, and classifying the X-ray images in two groups depending on the detection results

### INTRODUCTION:

Over the recent years, Computer Aided Designs (CAD) have become the major research domain in machine learning. The subsisting CAD systems have already been proved to facilitate the medical area primarily in detection of breast cancer, mammograms, lung nodules etc. In the procedure of employing Machine Learning (ML) techniques to medical images,

significant features are of uppermost importance. For this reason, most of the previous algorithms used hand crafted features for developing CAD systems based on examining images. However, the hand crafted features with limitations varying according to tasks were not capable of supplying much meaningful features. Employment of Deep Learning (DL) models particularly Convolutional



Neural Networks (CNNs) revealed their self-potential of extracting useful features in image classification tasks. This process of feature-extraction demands transfer learning methods where pre-trained CNN models learn the generic features on large scale datasets like ImageNet which are later on transferred to the required task. Availableness of pre-trained CNN models like AlexNet, VGGNet, Xception, ResNet and DenseNet highly aid in procedure of significant feature extraction. In addition, the classification used with high-rich extracted features exhibit improved performance in classifying images. To obtain the best results, a certain number of combinations of convolution layers, dense layers, dropouts and learning rates have to be trained by evaluating the models after each execution. Initially, simple models with one convolution layer were trained on the dataset, and thereafter, the complexities were increased to get the model that not only achieved desired accuracies but also outperformed other models in terms of recall and F1 scores. The objective of the paper is to develop CNN models from scratch which can classify and thus detect pneumonic patients from their chest X-rays with high validation accuracy, recall and F1 scores. Recall is often favored in medical imaging cases over other performance evaluating parameters, as it

gives a measure of false negatives in the results. The number of false negatives in the result is very crucial in determining the real-world performance of models. If a model achieves high accuracy but low recall values, it is termed as underperforming, inefficacious and even unsafe as higher false-negative values imply higher number of instances where the model is predicting a patient as normal, but in reality, the person is diseased. Hence, it would risk the patient's life. To prevent this, the focus would be only models with great recall values, decent accuracies and F1 scores. The paper is organized into introduces the subject of this research paper, addresses its importance and relevance, the purpose and motive to undertake this research work and the objective of the paper. explores the work related to this field that has been accomplished till now. Explains the methodology of the paper, explaining the architecture of the models, flowchart and the dataset used to train and test the four models. presents the results achieved by the various CNN models and compares the performance of each mode using accuracy and loss graphs and confusion matrices. provides a brief conclusion to the paper and delivers the best-suited model. Furthermore, the future scope of this research work has also been discussed. All

the references which are cited in the paper have been listed in the end

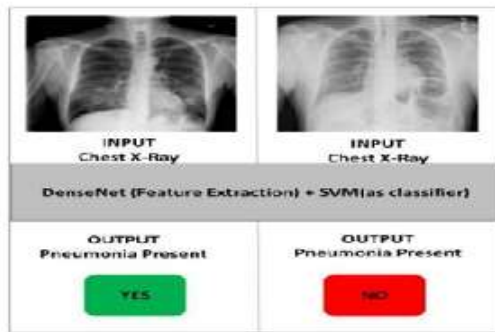


FIG.1

## OBJECTIVE:

In chest X-ray images, appearance of pneumonia can be hazy and can be misapprehended with other diagnoses. The evaluation of chest X-Ray specifically in case of Pneumonia can be misleading because many other problems like congestive heart failure, lung scarring etc. can mimic a Pneumonia. This is the main reason behind the misclassification of the X-ray images in the dataset. Thus, the task is challenging and the development of an algorithm for detecting thoracic diseases like Pneumonia would increase the accessibility of clinical settings in remote areas as well. In this study, we evaluated the performance of different variants of pre-trained CNN models followed by different classifiers for classifying abnormal and normal chest X-Rays. In recent time, exploration of Machine learning (ML) algorithms in detecting thoracic diseases has gained attention in

research area of medical image classification. Lakhani and Sundaram proposed a method of detecting pulmonary tuberculosis following the architecture of two different DCNNs AlexNet and GoogleNet. Lung nodule classification mainly for diagnosing lung cancer proposed by Huang et al. Also adopted deep learning techniques. Performance of different variants of Convolutional Neural Networks (CNNs) for abnormality detection in chest X-Rays was proposed by Islam et al. using the publicly available Open dataset. For the better exploration of machine learning in chest screening, Wang et al. Released a larger dataset of frontal chest X-Rays. Recently, Pranav Rajpurkar, Jeremy Irvin, et al. Explored this dataset for detecting pneumonia at a level better than radiologists, they referred their model as ChexNet which uses DenseNet-121 layer architecture for detecting all the 14 diseases from a lot of 112,200 images available in the dataset. After the CheXNet model, Benjamin Antin et al. Worked on the same dataset and proposed a logistic regression model for detecting pneumonia. Pulkit Kumar, Monika Grewal using the cascading convolutional networks contributed their research for multilabel classification of thoracic diseases. Zhe Li recently proposed a convolutional network

model for disease identification and localization.

## IMPLEMENTATION:

- Faster R-CNN and YOLO are good at detecting the objects in the input image. They also have very low detection time and can be used in real-time systems.

- However, there is a challenge that can't be dealt with object detection, the bounding box generated by YOLO and Faster R-CNN does not give any indication about the shape of the object.

- Instance segmentation identifies each instance (occurrence of each object present in the image and colour them with different pixel).

- It basically works to classify each pixel location and generate the segmentation mask for each of the objects in the image. This approach gives more idea about the objects in the image because it preserves the safety of those objects while recognizing it.

- The stage of region proposal generation is same in both the architecture the second stage which works in parallel predict class, generate bounding box as well as outputs a binary mask for each RoI.

- It comprises of –

- 1.Backbone Network
- 2.Region Proposal
- 3.Network Mask

4.Representation

5.RoI Align

## Mask R-CNN

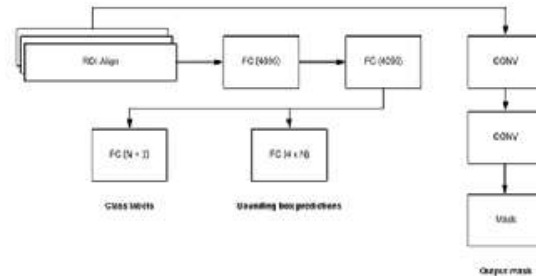


Fig 2. Mask R-CNN Implementation

## PROPOSED MODEL

In this project, we have focused on pneumonia and the use of CNN based algorithm to process chest X-ray images. AI and ML are usually used in the fields that have the ability to build a large database of medical data, typically in a form of digital images, that can be used later for training models. The use of AI in support tools for processing medical images has been suggested in order to improve accuracy and consistency, and time efficiency in reporting. The dataset used for this research is provided by Guangzhou Women and Children's Medical Center, Guangzhou and is openly available on Kaggle . Before the analysis all the bad quality X-rays have been removed by the experts at the Medical Center. The dataset contains images of chest X-rays (JPEG). It is divided into three folders, named train, val and test, that are used as training, validation and testing

data. The original dataset has only 16 images in the validation folder. For the purpose of experiments in this research, an 80/10/10 split has been performed. That means that 80% of the images is used as training data, 10% as validation data and 10% as test data. In this project we are using Convolutional Neural Network. The image classification was done with the use of a CNN based machine learning algorithm. The CNN is a class of deep learning neural networks.

### Advantages of Proposed System

1. Image-based medical diagnosis is possible the user has to give the X-ray image to the model, then our model will predict where the person viral infected or not.

2. CNN is an efficient recognition algorithm which is widely used in pattern recognition and image processing. It has many features such as simple structure, less training parameters and adaptability.

Algorithm Used for Proposed System A Convolutional Neural Network (CNN) is a type of Deep Learning neural network architecture commonly used in Computer Vision. Computer vision is a field of Artificial Intelligence that enables a computer to understand and interpret the image or visual data. When it comes to Machine Learning, Artificial Neural Networks perform really well. Neural

Networks are used in various datasets like images, audio, and text. Different types of Neural Networks are used for different purposes, for example for predicting the sequence of words we use Recurrent Neural Networks more precisely an LSTM, similarly for image classification we use Convolution Neural networks. In this blog, we are going to build a basic building block for CNN.

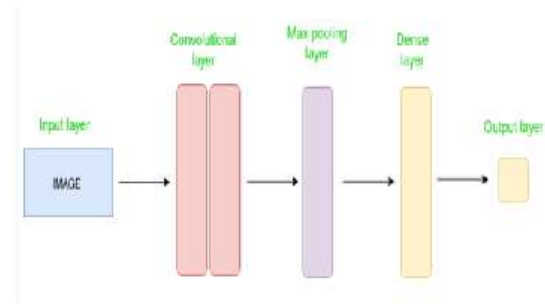


Fig 3. CNN Architecture

### Advantages of Using CNN

1. Efficient image processing – One of the key advantages of CNNs is their ability to process images efficiently. This is because they use a technique called convolution, which involves applying a filter to an image to extract features that are relevant to the task at hand. By doing this, CNNs can reduce the amount of information that needs to be processed, which makes them faster and more efficient than other types of algorithms.

2. High accuracy rates – Another advantage of CNNs is their ability to

achieve high accuracy rates. This is because they can learn to recognize complex patterns in images by analyzing large datasets. This means that they can be trained to recognize specific objects or features with a high degree of accuracy, which makes them ideal for tasks like facial recognition or object detection.

3. Robust to noise – CNNs are also robust to noise, which means that they can still recognize patterns in images even if they are distorted or corrupted. This is because they use multiple layers of filters to extract features from images, which makes them more resilient to noise than other types of algorithms.

4. Transfer learning – CNNs also support transfer learning, which means that they can be trained on one task and then used to perform another task with little or no additional training. This is because the features that are extracted by CNNs are often generic enough to be used for a wide range of tasks, which makes them a versatile tool for many different applications.

5. Automated feature extraction – Finally, CNNs automate the feature extraction process, which means that they can learn to recognize patterns in images without the need for manual feature engineering. This makes them ideal for tasks where the features that are relevant to the task are not

known in advance, as the CNN can learn to identify the relevant features through training

### Use Case Diagram:

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted

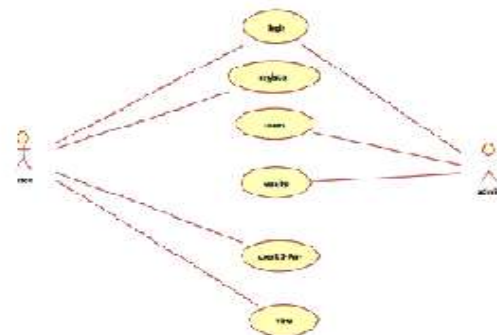


Fig 4 Use Case Diagram

### RESULTS:

Performance Metrics The customized model i.e a combination of CNN based feature-extraction and supervised classifier algorithm resulted in optimal solution for classifying abnormal (Pneumonia labeled) and normal Chest X-Ray images primarily



due to the substantive features provided by DenseNets followed by optimal hyperparameter values of SVM classifier. Literature studies reveal the contribution of transfer learning methods including feature-extractions toward visual recognition tasks. For this reason, we extracted features from various variants of pre-trained CNN models available such as VGGNets, Xception, ResNet-50 and DenseNets. Studies from the literature also reveal the use of classifiers in combination with CNN-based feature extraction majorly in medical image analysis to meliorate the performance of models. Following the mentioned past approaches, we evaluated each of the pre-trained models with distinct classifiers to determine the ideal model for the purpose. We observed from the comparative experimental results presented in that ResNet50 outperformed the results of all the other pre-trained CNN models when employed with default parameter values of SVM classifier. In addition, DenseNets were also observed to achieve results close to ResNet50. Literature studies reveal that DenseNets outperformed all the pre-trained CNNs in the ImageNet dataset. For this reason, we chose ResNet50, DenseNet-121 and DenseNet169 as the optimal CNN models for the featureextraction stage and SVM as the

optimal classifier for the classification stage for further experiments in the study. The selection of SVM classifier with rbf kernel based on the statistical results presented in Figure 3 further led to hunt of optimal hyperparameter values (C and gamma). In the process of tuning hyperparameters, we performed close to 350 combinations of C and gamma, the crucial combinations among these are presented in. We observed in this process that DenseNet-169 outperformed all the other customized models and hence chosen as the best feature extractor for the final customized model followed by optimal hyper-parameter values of SVM rbf kernel. The best results achieved with DenseNet169 architecture as feature extractors can be explained due to its capability of accessing feature maps from all of its preceding layers. Literature studies of DenseNets mentions the information flow from the beginning layer to the end layers and removal of redundant features by transition layers as the primary reasons for the high-features representations.

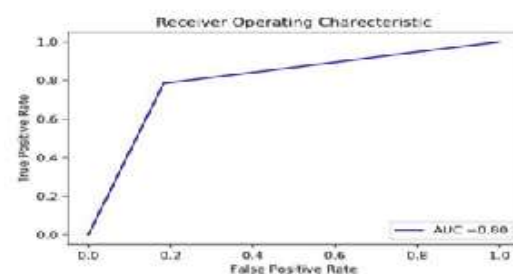




Fig 5. Represents the test ROC curve for DenseNet-169

### **CONCLUSION:**

This paper describes the use of deep learning in order to classify digital images of chest X-rays according to presence or absence of changes consistent with pneumonia. The implementation was based on CNN model using Python programming and scientific tools. Initial experiments show promising results, but more research is needed. Even though the model accuracy is relatively high, nearly 90%, there is a possibility of over fitting due to the size of the dataset. Also, the 90% accuracy means that the prediction model could potentially be used as a decision support tool, but there is still much work to be done. The proper diagnosis of any kind of disease still requires the involvement and presence of medical specialists.

### **FUTURE ENHANCEMENT:**

In order to build a good and reliable disease classification model, it is very important to gather as much data as possible. Further research steps will include experimenting with various preprocessing and CNN configurations, data augmentation techniques, as well as using additional X-ray datasets with additional data labels showing other pathologies.

### **REFERENCES:**

- [1] M. Haenlein, A. Kaplan, "A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence", California Management Review, 61(4), 2019, pp 5-14
- [2] V. Kaul, S. Enslin, S.A. Gross, "The history of artificial intelligence in medicine", Gastrointestinal Endoscopy, In Press, 2020.
- [3] M. Minsky, S.A. Papert, "Perceptrons: An Introduction to Computational Geometry", MIT Press, Cambridge, MA, 1969.
- [4] A. Esteva et al., "A guide to deep learning in healthcare", Nature Medicine, 25(1), 2019, pp 24-29.
- [5] D. Ravi et al., "Deep Learning for Health Informatics," IEEE Journal of Biomedical and Health Informatics, 21(1), 2017, pp. 4-21.
- [6] Y.J. Yang, C.S. Bang, "Application of artificial intelligence in gastroenterology", World Journal of Gastroenterology, 2019(25), 2019, pp 1666-1683.
- [7] A. Hosny, C. Parmar, J. Quackenbush, L.H. Schwartz, H.J.W.L. Aerts, "Artificial intelligence in radiology", Nature Reviews. Cancer, 18(8), 2018, pp 500-510.
- [8] K.W. Johnson, et al., "Artificial Intelligence in Cardiology", Journal of the American College of Cardiology, 71(23), 2018, pp 2668-2679.





[9] V.N. Perisic, B. Jankovic, “Pedrijatrija za studente medicine”, Medicinski fakultet, Univerzitet u Beogradu, Beograd, 2010.

[10] N. Chen et al., “Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study”, *The Lancet*, 395(10223), 2020, pp 507-513.

[11] Dr. S.Balamurugan, & Aurchana, Aurchana & Gurumoorthi Elangovan, Dr & Govindharaj, I. (2022). Augmentation of Decision Tree Characteristics for Agri-Food Supply Chain using Internet of Things.

[12] Vinay, R., Soujanya, K. L. S., & Singh, P. (2019). Disease prediction by using deep learning based on patient treatment history. *Int. J. Recent Technol. Eng*, 7(6), 745-754.

[13] Madhavi, K. R., Kora, P., Reddy, L. V., Avanija, J., Soujanya, K. L. S., & Telagarapu, P. (2022). Cardiac arrhythmia detection using dual-tree wavelet transform and convolutional neural network. *Soft Computing*, 26(7), 3561-3571.