Chest diseases classification using DenseNet121

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***Abstract*—This study explores the application of DenseNet121, a deep learning model, for the accurate classification of various chest diseases such as Atelectasis, Consolidation, Infiltration, Pneumothorax, and Edema. Timely and accurate diagnosis of these diseases is critical to ensure effective treatment and improve patient outcomes. The study utilized a publicly available ChestXray8 dataset to train and evaluate the performance of DenseNet121. The results showed that the model achieved high accuracy in terms of classification performance, demonstrating its potential as a useful tool for chest disease classification. The findings of this study suggest that deep learning models, such as DenseNet121, can aid in the timely diagnosis and treatment of chest diseases, thereby improving patient care and outcomes.**

***Index Terms*—CNN, ChestXray8, Deep Learning**

I. Introduction

Medical imaging has transformed the field of healthcare by providing valuable diagnostic information for a variety of diseases, including those affecting the chest. Chest X-rays are one of the most commonly used medical imaging techniques for the detection and diagnosis of chest diseases. Interpreting chest X-rays is a crucial task for radiologists in diagnosing and treating chest diseases, but it can also be a time-consuming and challenging process. Radiologists are often under pressure to make quick and accurate decisions about patient care, but interpreting X-rays requires extensive training and expertise. In recent years, deep learning techniques have emerged as a promising approach to assist radiologists in medical image analysis. Neural networks, in particular, have shown great potential in automating the analysis of medical images, including chest X-rays, and aiding in the early detection and diagnosis of diseases. In this report, we explore the ChestXray8 dataset and the role of deep learning, especially neural networks, in healthcare. We focus specifically on the application of DenseNet121, a deep neural network architecture, for the accurate classification of chest diseases. The results of this study demonstrate the potential of deep learning models to improve the accuracy and efficiency of chest disease diagnosis, which could ultimately lead to better patient outcomes.

II. Literature Survey

In 2021, Pillai et al. proposed a report achieving an overall accuracy of 87 % and an AUROC of 0.78 in predicting various diseases using deep learning models, with the Dense121 pre-trained model demonstrating the best performance. However, the models were found to be particularly poor in accurately predicting positive cases of certain diseases, which was due to a lack of balanced training data. The number of positive cases in the training data was significantly lower than the negative cases, which may have led to overfitting and bias in the models. Despite these limitations, the models were successful in predicting several other labels with high accuracy rates, including Fracture, Lung Lesion, Pleural Other, Pneumonia, and Pneumothorax, with a success rate of over 95 %. Overall, deep learning models have a lot of potential for medical image analysis, but it's important to stress the value of carefully considering and managing training data to enhance model performance.

III. Implementation

DenseNet is a deep learning architecture that was introduced in 2017, offering several advantages over previous CNN architectures. One of its key benefits is improved parameter efficiency by reusing features learned in earlier layers throughout the network. This is achieved by concatenating the output of previous layers and feeding it as input to the current layer, reducing the number of parameters required. Additionally, DenseNet mitigates the problem of vanishing or exploding gradient signals during backpropagation, improving gradient flow. It also reduces overfitting by encouraging feature reuse and reducing the number of parameters required. DenseNet has been shown to outperform previous CNN architectures on benchmark datasets.

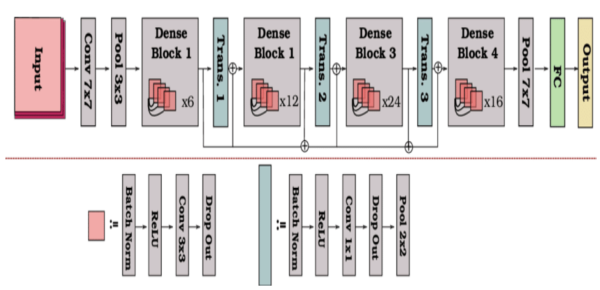

Fig. 1. DenseNet121 architecture

We used PyTorch, a prominent deep learning library, to develop the DenseNet121 architecture on the ChestXray8 dataset. This solution has the potential to improve the accuracy of classifying chest x-ray images. We divided the problem in 2 steps. The first step required a binary classification, which determined whether or not the person's X-ray showed the diseases. If the disease is present, our second goal is to categorize the disease among 14 different lungs diseases.

IV. Results

The receiver operating characteristic (ROC) curve is a graph used to evaluate the performance of classification models by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. The area under the

ROC curve (AUCROC) is a widely used metric that ranges from 0 to 1, with higher values indicating better performance. AUCROC of 0.5 indicates a model with no discrimination ability, while AUCROC of 1 indicates perfect discrimination.

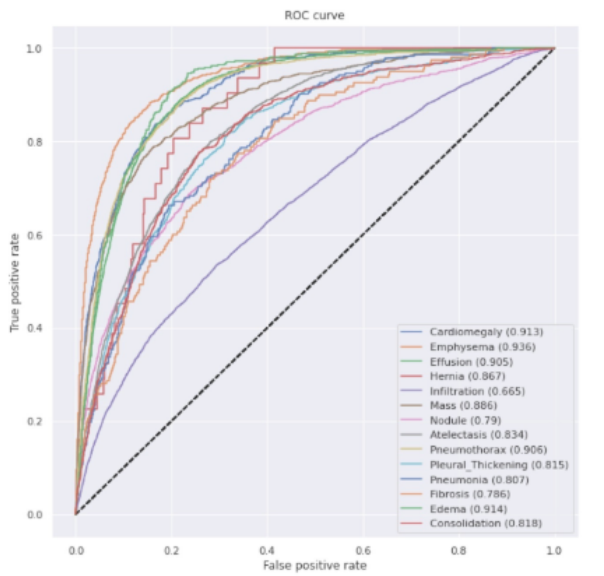

Fig. 2. AUCROC graph for different diseases

The below table displays the various performance measures such as AUC, , Accuracy, Precision, Recall etc. for each class present in the ChestXray8 dataset.

Pathology	AUC	Threshold Value	Sensitivity	Specificity	Accuracy	Precision	Recall	F1 Score
Cardiomegaly	0.912609	0.519135	0.837	0.83309	0.83314	0.101132	0.835366	0.180421
Emphysema	0.936044	0.540763	0.851	0.877387	0.876709	0.145501	0.849162	0.248434
Effusion	0.904604	0.478758	0.891	0.779952	0.793547	0.36228	0.890381	0.515012
Hernia	0.867492	0.465557	0.871	0.734148	0.734293	0.0043573	0.83871	0.00866956
Infiltration	0.665459	0.529498	0.535	0.704771	0.670837	0.312150	0.535268	0.394343
Mass	0.886117	0.474119	0.789	0.837563	0.835285	0.188348	0.787671	0.304003
Nodule	0.789923	0.481894	0.692	0.758957	0.755072	0.147931	0.690923	0.243687
Atelectasis	0.833814	0.509495	0.777	0.74139	0.744705	0.240789	0.776064	0.367541
Pneumothorax	0.906098	0.408846	0.892	0.772429	0.779516	0.198896	0.891304	0.325219
Pleural_Thickening	0.814794	0.45797	0.816	0.681937	0.685852	0.0721289	0.814871	0.132527
Pneumonia	0.806693	0.61158	0.663	0.804744	0.803155	0.0356983	0.658436	0.0677249
Fibrosis	0.786121	0.428276	0.719	0.719237	0.719188	0.0179471	0.7125	0.0350123
Edema	0.914408	0.496351	0.907	0.804607	0.806238	0.0714594	0.904372	0.132453
Consolidation	0.81782	0.560865	0.776	0.743196	0.744347	0.101687	0.775031	0.179785

Fig. 3. Performance metrics

V. Conclusion

This paper explores the use of DenseNet121, for accurately classifying various chest diseases using the publicly available ChestXray8 dataset. The results demonstrate that the model achieved high accuracy in classifying chest diseases, showcasing the potential of deep learning in medical image analysis. The training dataset had significantly fewer examples of certain diseases, which resulted in ignoring the small set of examples that led to misclassification .Therefore, in order to solve the class imbalance issues, we will apply some of the existing approaches, such as SMOTE, under sampling, and oversampling, whichever delivers the highest accuracy for the fewer class examples.

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