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.**

Also by using GAN, we try to solve the class imbalance problem.We try to implement DC-GAN(Deep Convolution GAN) for Chestxray8 dataset and for the disease like hernia and pneumonia.We also aim to compare the values of implementation of model using GAN and without GAN. 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, Densenet, GAN**

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.

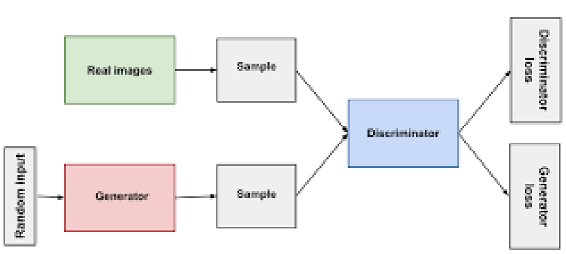

Fig. 1. GAN architecture

Generative Adversarial Networks (GANs) have shown great promise in medical image processing and analysis, and have numerous applications in this field. GANs can be used to generate synthetic medical images that are similar to real medical images, which can be used for data augmentation, to balance imbalanced datasets, and to simulate rare conditions or imaging modalities. 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 pretrained 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.

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

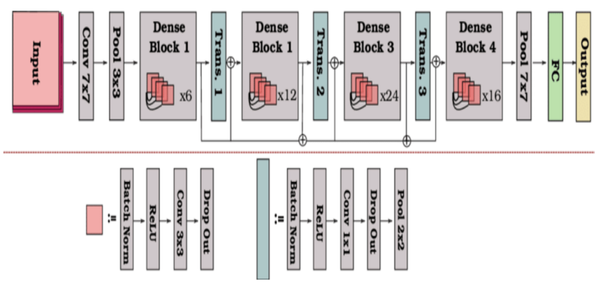

Fig. 2. DenseNet121 architecture

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.

Initially we utilized a pre-trained model and implemented a Densenet121 architecture to train on the ChestXray8 dataset. The dataset used for training had class imbalance, which can lead to biased models. To address this issue, we used DC GAN to generate new images for the two under sampled classes, namely Pneumonia and Hernia. The generated images were then incorporated into the dataset to retrain the Densenet121 model. To evaluate the effectiveness of the generated images, we compared the results by training the model both with and without the inclusion of GAN-generated images. This approach helped to balance the dataset and improve the accuracy of the model's predictions, resulting in a more robust and reliable model.

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.

After applying GAN, the AUC ROC curve can potentially improve, indicating a more accurate and robust classification performance. In terms of performance metrics, before GAN, the algorithm may have shown lower accuracy, precision, recall, and F1-score. On the other hand, after GAN, the algorithm's performance metrics may have improved, demonstrating a higher accuracy, precision, recall, and F1-score. Overall, the implementation of GAN can potentially enhance the machine learning algorithm's classification performance and improve its performance metrics.

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

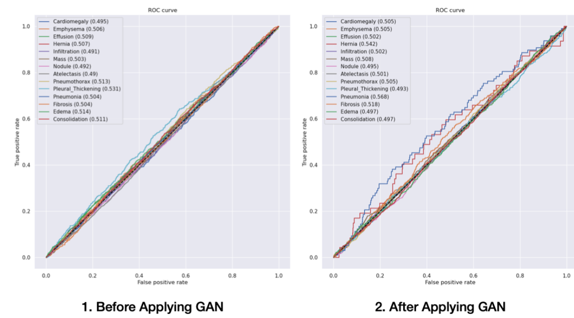

Fig. 3. AUCROC graph for different diseases

Pathology	AUC	Threshold Value	Sensitivity	Specificity	Accuracy	Precision	Recall	F1 Score
Cardiomegaly	0.494855	0.343657	0.117	0.903911	0.888095	0.0239262	0.115118	0.0396181
Emphysema	0.505611	0.0116233	0.699	0.335638	0.34086	0.015142	0.697495	0.0296405
Effusion	0.509377	0.065181	0.219	0.804608	0.765427	0.0744035	0.219036	0.111076
Hernia	0.506724	0.00748285	0.659	0.363044	0.373286	0.0358031	0.65838	0.067913
Infiltration	0.49141	0.421593	0.012	0.992136	0.89577	0.135593	0.0113218	0.0208986
Mass	0.502662	0.0141144	0.564	0.456872	0.459468	0.0252711	0.563284	0.0483721
Nodule	0.49217	0.0030304	0.772	0.234098	0.24756	0.0252305	0.771365	0.0488628
Atelectasis	0.489713	0.00467447	0.013	0.990185	0.896187	0.123626	0.0130095	0.0235417
Pneumothorax	0.513364	0.0401755	0.706	0.335524	0.342279	0.019398	0.704097	0.0377558
Pleural_Thickening	0.530575	0.0135977	0.643	0.426549	0.42871	0.011286	0.64011	0.022181
Pneumonia	0.504465	0.34835	0.381	0.64024	0.630857	0.0380313	0.380108	0.0691445
Fibrosis	0.503643	0.0153543	0.396	0.634499	0.632053	0.010872	0.392857	0.0211585
Edema	0.5139	0.018043	0.662	0.367974	0.372508	0.0161808	0.660682	0.031588
Consolidation	0.510999	0.0123411	0.537	0.49069	0.491949	0.0291696	0.536072	0.0553286

1. Before Applying GAN

Pathology	AUC	Threshold Value	Sensitivity	Specificity	Accuracy	Precision	Recall	F1 Score
Cardiomegaly	0.504968	0.105896	0.707	0.312017	0.32048	0.0220337	0.705964	0.0427336
Emphysema	0.505178	0.0259855	0.291	0.736077	0.729164	0.0169109	0.289017	0.0319523
Effusion	0.501908	0.0136756	0.919	0.0910025	0.150362	0.0724229	0.918953	0.134264
Hernia	0.542459	0.0110536	0.596	0.517635	0.517715	0.00166749	0.574468	0.00332533
Infiltration	0.501601	0.179124	0.199	0.810664	0.746208	0.109771	0.198415	0.141345
Mass	0.507525	0.0192542	0.179	0.854629	0.836944	0.0317913	0.177879	0.0539419
Nodule	0.495319	0.00195826	0.956	0.0589442	0.0829882	0.0272212	0.954495	0.0529328
Atelectasis	0.500512	0.000911353	0.886	0.132159	0.20981	0.104951	0.885516	0.187661
Pneumothorax	0.504511	0.116507	0.624	0.398754	0.403141	0.0203061	0.622155	0.0393285
Pleural_Thickening	0.493282	0.0286252	0.294	0.72538	0.720671	0.0114943	0.291209	0.0221156
Pneumonia	0.568331	0.526118	0.381	0.747714	0.746625	0.00424628	0.371134	0.0083965
Fibrosis	0.518123	0.0294912	0.574	0.476789	0.477815	0.0118343	0.571429	0.0231884
Edema	0.496957	0.00353626	0.957	0.0652991	0.0800679	0.016954	0.955117	0.0333166
Consolidation	0.497198	0.00237429	0.952	0.0602254	0.086713	0.0300802	0.950902	0.0583157

2. After Applying GAN

Fig. 4. 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 use GAN. GAN was only applied to two classes and yielded improved AUC ROC scores. However, further work can explore the use of GAN for all imbalanced classes to determine its effectiveness in improving classification performance. The comparison of the results before and after applying GAN can provide insights into the algorithm's ability to accurately classify all classes, including the imbalanced ones. The use of GAN for all classes can potentially lead to better classification performance and address the challenge of imbalanced data. Future work can also focus on optimizing GAN's hyperparameters to improve its performance and explore other deep learning techniques that can enhance the classification performance of imbalanced datasets.

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