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Pleural Effusion Detection Using Deep Neural Networks

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ABSTRACT-Pleural effusion is an anomalous lung condition characterized by a build-up of fluid between the two layers of the pleura, which causes specific symptoms such as angina and dyspnea. In Indonesia, pleural effusion cases alone account for 2.7% of other respiratory conditions, with an estimated number of victims in general at more than 3000 people per 1 million population annually. Pleural effusion is a severe case and can get death if not treated instantly. On the basis of a study, as numerous as 15% of 104 cases diagnosed with pleural effusion died within 30 days. This paper proposes a deep learning model that automatically detects pleural effusion based on chest x-ray images. In this paper, we evaluated two deep learning algorithms namely VGG 19 and Vision Transformers on the dataset subsampled from ChestX-ray14. The number of data samples considered for our study is 2000 chest x-ray images, that includes 1000 images for pleural effusion and 1000 images for a normal lung condition. As a result of this study, the accuracy obtained from VGG19 and Vision Transformers are 89% and 81% respectively. Obtained results indicate that our model can be used to assist radiologists to diagnose the presence of pleural effusion up to some extent

KEYWORDS:: Deep learning, Pleural effusion, VGG19, Vision Transformers

I. INTRODUCTION

The lungs are a pair of air-filled organs that are a vital part of the respiratory system where oxygen from the air is exchanged for carbon dioxide from the blood. If the lungs are impaired, it will directly affect the respiratory system which can be lethal. The pleura is a two-layered membrane that lines the lungs and the inside of the chest cavity. Between the layers, there is a pleural cavity that generally contains about 10-20 ml of pleural fluid that serves as a lubricant that assists in the easy movement of the lungs and inflation during breathing. However, if the fluid is excess and accumulates, it can press the lungs, causing chest pain and difficulty in breathing; this condition is called Pleural Effusion. This abnormal lung condition is characterized by a build-up of fluid between the two layers of the pleura, which is generally caused as a result of disruption in the balance between production and reabsorption. With normal resorption, pleural effusion can occur if pleural fluid formation continues to increase to 30 times. On the other hand, decreased resorption of pleural fluid alone won't produce a significant expansion of fluid in the pleural cavity, given the normal rate of pleural fluid formation is very slow. Other diseases can also cause pleural effusion, either forming from the lungs (such as tuberculosis, pneumonia), the pleural membrane or extrapulmonary (such as congestive heart failure). Pleural effusion is a common health condition.

In Indonesia, pleural effusion cases alone account for 2.7 of other respiratory conditions, with an estimated number of cases in general (transnational) at further than 3000 people per 1 million population annually. Victims also come from any age group, although it generally occurs in women than in men. Pleural effusion is a severe case and leads to death if not treated immediately. According to a study, 15% of 104 cases diagnosed with pleural effusion lost their lives within 30 days.

II. RELATED WORK

This section is an overview of some previous similar studies in completing the task in the form of classification of chest x-ray images using similar algorithms.

.D. Apostolopoulos et.al. delved into the transfer learning approach on a huge dataset of X-ray images from cases with Covid-19, pneumonia, and healthy cases using a pre-trained model VGG19. They achieved the best results with the proposed model which gives an accuracy of 97.8, (2020).[1]

T. Ozturk, M, et al. carried out the Automated discovery of COVID-19 cases using deep neural networks with X-ray images of cases with COVID19, Pneumonia, and healthy cases. The pretrained model-DarkCovid Net provides an accuracy of 87%[2]

P.K. Setel. et al. carried out the discovery of coronavirus complaint (COVID-19) grounded on deep features and support vector machine using pre-trained models-ResNet50 and SVM. They achieved the best results with the proposed models which give an accuracy of 95.4 2020. [3]

Albahli used a deep neural network to distinguish covid-19 from other casket conditions using X-ray images. The pre-trained model that was used is ResNet15 which gives an accuracy of 87% (2020)[4].

J. Civit et al. used a deep learning system for COVID-19 opinion aid using X-ray pulmonary images with a pre-trained model VGG16 which gives an accuracy of 86% (2020). [5]

Ahuja et al. used a Deep transfer learning-grounded automated discovery of COVID-19 from lung CT checkup slices. The pre-trained model that was used is ResNet18 which has an accuracy of 99.4(2020)[6]

III. METHODOLOGY

3.1 CHEST X-RAY IMAGE DATASET

Effusion and normal chest x-ray images used in this study were collected from the National Institute of Health (NIH). Our study dataset contains 2000 images which are subsampled from chest x-ray 14 each with dimension of 1024 X 1024. The input shape of the images used for vision transformer and VGG19 are 32X32 and 224X224 respectively. Therefore we reshaped our dataset images into dimensions expected by Vision transformer and VGG19 for further procedures. The sample chest x-ray images dataset is given in Figure 1.

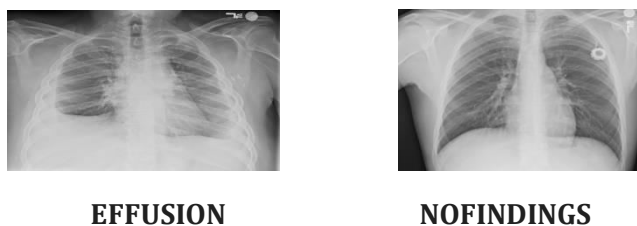


FIG 1sample image

3.2 VGG 19

VGG19 convolutional neural network that has a depth of 19 layers trained on imagenet dataset. In our study, we used Imagenet weights to use the knowledge gained by VGG19 on thousands of images. The VGG19 pre-trained imagenet weights can classify up to 1000 objects. We set our pretrained unchanged and flattened the final output layer of VGG19. Then we added one dense layer with two output neurons and softmax activation function for classifying the pleural effusion and Normal condition of the given chest xray images. The weights of this dense layer is updated using the images from the training set.

3.3 VISUAL EXPLANATION OF VGG19 THROUGH GRAD-CAM

The Gradient-weighted Class Activation Mapping (Grad-CAM), uses the gradients of the target concept lung chest- x-ray during a classification network flowing into the ultimate convolutional layer to produce a coarse localization map highlighting the important regions in the image for predicting the concept. We combine Grad-CAM with existing fine-grained visualizations to make a high-resolution class-discriminative visualization, Guided Grad-CAM and apply it to image classification. Grad-CAM is a class-discriminative localization technique that generates visual explanations for VGG 19 model without requiring architectural changes or retraining. We evaluate Grad-CAM for localization and faithfulness to the model, where it outperforms baselines



Fig 3. a original image

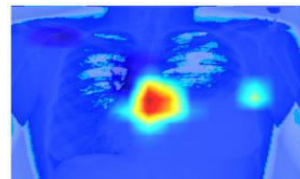


Fig 3.b grad cam image

3.4 VISION TRANSFORMERS

ViT divides a picture into a grid of square patches. Each patch is flattened into one vector by concatenating the channels of all pixels in a patch and then linearly projecting it to the desired input dimension. Patch encoding takes inspiration from the BERT architecture on tokenizing the input sequences. i.e. Prepending the class information to the sequence of embedded patches Patch encoding takes inspiration from the BERT architecture on tokenizing the input sequences. i.e. Prepending the category information to the sequence of embedded patches, During pre-training and fine-tuning, a classification head is attached to the function and therefore the classification is by a multi-layer perceptron with GELU Multi-layer perceptrons (MLPs). MLP-Mixer contains two sorts of layers: one with MLPs applied independently to image patches (i.e. mixing the per-location features), and one with MLPs applied across patches.

IV. EXPERIMENTAL RESULTS

We experimented with two deep learning models namely pre-trained VGG19 and Vision Transformers are performed in order to classify chest X-ray images. The models were trained through chest x-ray images with VGG19 and Vision Transformers. . The experiments were carried out through a computer with an Intel i5 10200H 2.4 GHz processor, and 8 GB RAM. The working environment was Tensorflow and the programming language was Python. The model training was performed by determining 50 epochs and a batch size of 256. The learning rate was determined as 0.001. The chest x-ray dataset used in the training of Vision Transformers and VGG19 models are divided into 80% training and 20% validation.

PARAMETERS OF VGG19

The model training was performed by determining 10 epochs and a batch size of 32. The learning rate was determined as 0.001 and the validation split was determined as 0.1 with adam optimizer

PARAMETERS OF VISION TRANSFORMERS

The model training was performed by determining 50 epochs and a batch size of 256. The learning rate was determined as 0.001.

Algorithm	Precision	Recall	F1score	Accuracy
Vgg19	0.92	0.87	0.89	89%
ViT	0.86	0.91	0.89	81%

Table 1 classification report of models

The Table 1 describes the classification report of two algorithms i.e., VGG19 and Vision transformers. VGG 19 model has achieved the highest accuracy when compared to the vision transformers.

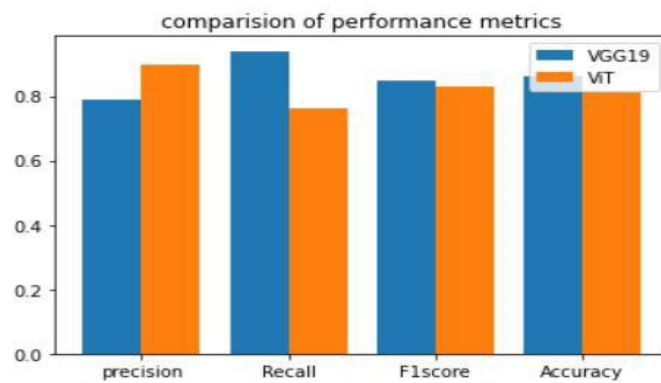


Fig 4 Performance metrics of Vit and VGG19

Figure 4 describes the performance of precision, recall, f1score, and accuracy of two deep learning models namely VGG19 and Vision Transformer.



Fig 5.a original image

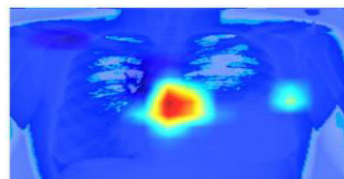


Fig 5.b GRAD-CAM

The Figure 5.a and 5.b describes the original image of the chest x-ray and the grad cam image of the pleural effusion chest x-ray. Grad-cam produces a coarse localization map highlighting the important regions in the image for predicting the pleural effusion.

	NoFindings	Effusion
NoFindings	19	145
Effusion	180	57

Table2:Confusion Matrix Of VGG19

Table 2 describes the confusion matrix of the VGG19 model. It depicts the values of true positive , true negative,false positive and false negative of effusion and no finding classes.

	NoFindings	Effusion
NoFindings	11	159
Effusion	183	49

Table 3 Confusion Matrix Of ViT

Table 3 describes the confusion matrix of ViT model. It depicts the values of true positive,true negative, false positive and false negative of effusion and nofinding classes.

V. CONCLUSION

In this paper, we experimented with two deep learning models VGG19 and Vision Transformers to predict the abnormality in chest x-rays. VGG 19 model has achieved the highest accuracy of 89% when compared to Vision Transformers. The vision transformer model has achieved an accuracy of 81%. The results of the evaluation and analysis show that the model built to perform a task in the form of pleural effusion classification based on x-ray images shows promising results on the tested metrics, with 89% accuracy for VGG19 and 81% for vision transformers. To provide more explainable results, we adopted the GRAD CAM model to produce a heatmap to show the area it focuses on when making its prediction. This heatmap can also be used to locate the area most indicative of pleural effusion; thus, we hope it can be an alternative to improve the medical diagnosis performance in identifying the disease. Therefore, further study is expected to use a more significant amount of image data to produce a better performance model in image classification and object localization.

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