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A Recognizing Technique Specific Disease on a Chest X-Ray with Support for Image Clarity and Deep Learning

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Abstract*:* This study was to predict 14 demonstrative signs in 3 conspicuous public chest X-ray datasets: MIMIC-CXR, Chest-Xray8, CheXpert, as well as a multi-site conglomeration of each of these data sets.The multi-source data set is compared with the smallest inconsistency, recommending one method to reduce the slope. In this research experiment using 5 CNN models, where for pre-processing using the CLAHE and SuCK methods, which help make the image look clearer and more contrasting. Based on experiments on the chest thorax there are 3 datasets, namely 1000, 5000 and 10000 datasets, as well as 2 pre-processing methods, namely CLAHE and SuCK. After the experiment, the CNN model which has the highest accuracy was used using 1000 datasets with CLAHE namely the DenseNet 121 model at 95%, and SUCK at 100%, for the total 5000 data sets the highest accuracy was using CLAHE, namely the Resnet 50V2 model at 83% and with SuCK, namely DenseNet 121 by 86%. For the number of 10000 datasets, the highest accuracy with CLAHE is the Inception V3 model of 63%, while the SUCK model of ResNet 50V2 is 87%. With several experiments, it is proven that the SuCK method produces better accuracy than CLAHE. This research can be continued with the use of test images for a more diverse chest thorax.

Keywords: *: medical imaging, chest x-ray classifier, computer vision, CLAHE, SuCK*

1. Introduction

We have already known that people in today's world are facing a lot of health problems, so it becomes important to prevent this disease before it occurs. One way to detect the disease suffered by the patient is to do an x-ray of the patient. Here, we analyse the extent to which a sophisticated deep learning classifier is prepared to generate indicative labels from X-ray images. Chest X-ray imaging is a significant screening and indicative apparatus for several life-threatening diseases, however because of the deficiency of radiologists, this screening instrument can't be utilized to treat all patients [1] [2]. Profound learning-based clinical picture classifiers are one likely arrangement [3] [4], with critical earlier work focusing on chest X-ray explicitly, utilizing enormous scope openly accessible datasets [6], exhibiting radiologist-level precision in demonstrative characterization [7][8]. Regardless of the problem

In the seemingly obvious case of carrying out indicative devices empowered through AI technology [9], basically to be able to move such techniques from paper to practice requires careful ideas [10]. The model may display differences in execution across protected subgroups, and this may lead to different subgroups receiving different treatment [11]. During assessment, AI calculations typically improve to adjusting precision on various subgroups. While some change in execution is undeniable, relieving any precise predisposition against safeguarded subgroups might be wanted or expected in a deployable model. In this paper, we analyse whether state-of-the-art (SOTA) deep neural classifiers prepared on huge public clinical imaging datasets are fair across various subgroups of safeguarded ascribes. We train classifiers on 3 enormous, public chest X-ray datasets: MIMIC-CXR [5], CheXpert [6], Chest-Xray [3] as well as an extra dataset framed of the conglomeration of those three datasets on their common names. For each situation, we execute chest X-ray pathology classifiers through a deep convolutional neural network (CNN) chest X-ray pictures as information sources, and improve the multi-mark likelihood of 14 symptomatic names at the same time. Specialists have noticed wellbeing differences as for race [12], sex [13], age [14], and socioeconomic status [12].

2. Literature Review

Studies of disease determination based on chest x-ray will perform a balance of odds test as our decency metric taking into account the clinical demonstrative setting requirements [15]. In particular, we looked at differences in the true positive rate (TPR) across the various subgroups per attribute. High TPR dissimilarity indicates that a weakened individual from a protected subgroup will not render true—i.e., true positive—findings to the same extent as everyone else, even in high-precision calculations. We tracked three important findings: First, that there is no doubt that there are broad examples of trends in SOTA classifiers, displayed in TPR variation across data sets. In addition, the degree of divergence for most of the fit properties/data sets was essentially unrelated to subgroup relative disease enrollment. This finding proposes that underrepresented subgroups may be defenseless against abuse in efficient delivery, and that such weaknesses cannot be substantially overcome through addressable basically through expanding subgroup patient count. Finally, we find that utilizing the multi-source dataset which joins the wide range of various datasets yields the least TPR variations, proposing utilizing multi-source datasets may battle predisposition in the information assortment process. As specialists progressively apply man-made reasoning and AI to accuracy medication, we trust that our work exhibits how prescient models prepared on enormous, even datasets can in any case yield different effect.

Chest X-Ray Classification. With the releases of large public datasets like ChestXray [3], CheXpert [6], and MIMIC-CXR [5], many researchers have begun to train large deep neural network models for chest X-ray diagnosis [4] [6]. Prior work [8] demonstrates a diagnostic classifier trained on Chest-Xray can achieve radiologist-level performance. Deep Learning in doing the Medical Image Analysis. There have been previous reviews on the field of deep learning in medical image analysis [17] [18].

However, based on their researches, deep learning in chest radiography is far from exhaustive in terms of the literature and methodology surveyed, the description of the public datasets available, or the discussion of future potential and trends in the field. Image Recognition of Lung Disease. A multi-scale adaptive residual neural network (MARnet) can be used to identify chest X-ray images of lung disease [19]. MARnet achieves accuracy (ACC) of 83.3% and the area under ROC curve (AUC) of 0.97 in the identification of 4 kinds of typical lung X-ray images including nodules, atelectasis, normal and infection. Another study by detecting pneumonia in the lungs caused by a bacterial infection. In this study, we used two well-known convolutional neural network models Xception and Vgg16 for diagnosing of pneumonia. In this experiment used transfer learning and fine-tuning in our training stage and the results showed that Vgg16 network exceed Xception network at the accuracy with 0.87%, 0.82% respectively [20]. Basically, pneumonia which can save millions of lives by detecting illness early. This study uses machine learning techniques to analyse chest X-ray images and predict Pneumonia. This study proposed a model by using some of the machine learning classifiers like Logistic Regression (LR), Neural Network (NN), and Support Vector Machine (SVM) that can detect the presence or absence of Pneumonia in chest X-ray images[21].

3. Materials and Methods

Since we carried out to select 1 out of the 3 different kinds of datasets to research, one that was promising is the chest X-ray dataset. The dataset consists of 14 types of thorax diseases (14 diseases and one for “No Findings” which indicates a healthy thorax). The 14 types of thorax diseases are Atelectasis, Consolidation, Infiltration, Pneumothorax, Edema, Emphysema, Fibrosis, Effusion, Pneumonia, Pleural Thickening, Cardiomegaly, Nodule, Mass and Hernia. Due to the problem of long training time, we decided to only use 10 out of the 14 types of diseases. Our work was to determine a computer vision model to detect each of these types of diseases.

Actually, the research carried out the state-of-the-art computer vision models to classify chest X-ray images into 10 diagnostic categories. The dataset was split into 80-10-10 train-validation-test split with no patient shared across splits. We train the dataset into each corresponding 5 state-of-the-art computer vision models. Therefor Stages of the research process to classify diseases by using chest X-Ray can be seen in Fig.1.

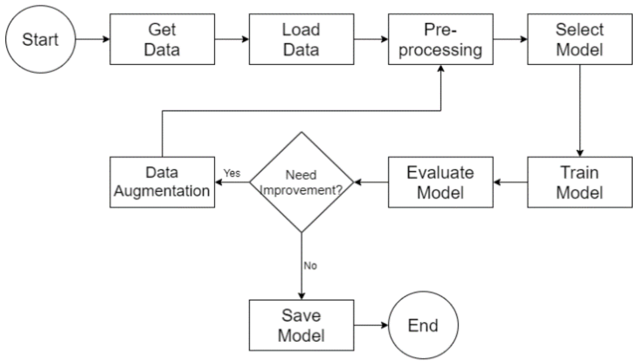

Fig 1. Stages of the research process to classify diseases by using chest X-Ray

Figure 1.0 informs the stages of the research process starting with preparing and loading data. After that, this experiment performs some data pre-processing and selects the CNN model to be used, and trains each data. After training, the output will be evaluated to find out whether it needs improvement or not. If they don't need it, then would store the processing results with the CNN model. It was continued in this experiment by doing some data augmentation and repeating the data training process again.

A. *Data pre-processing*

In this stages would collect the chest X-ray dataset which they have an approximately 112,000 images with 30,000 unique patients with each image having dimensions of approximately 3000 x 3000 pixels. First, we select datasets with only 10 of those diseases, after that would remove the remaining datasets. After removing, the dataset now has 102,000 images. Next, we would eliminate starting from the type of disease with the least data until the remaining 10 types of thorax disease. In this experiment added CLAHE and SUCK method into these models. With these methods, we hoped that the accuracy of these models will increase significantly. We divided the training into 3 amounts of datasets: 1000, 5000, and 10000 datasets.

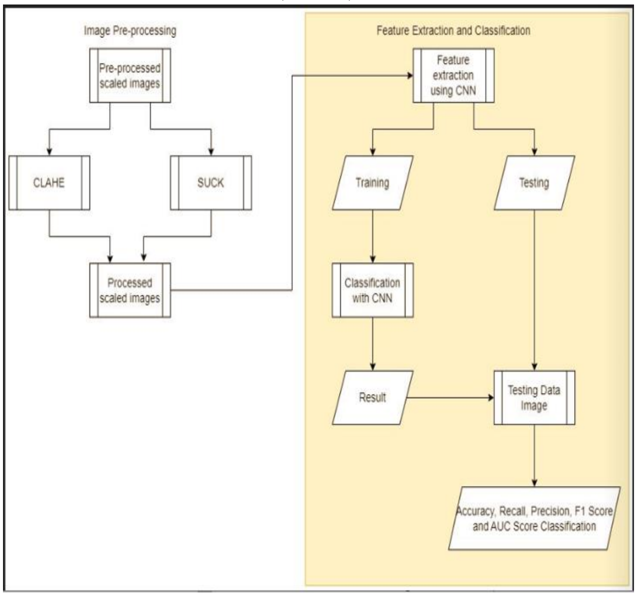

Fig. 2 The stages of the thoracic disease classification process are supported by the CLAHE and SUCK methods in pre-processing

Figure 2.0 inform the optimal process flowchart in this study. In this process chart is well illustrated to achieve optimal results for classification accuracy. At first the Dataset was carried out by the convolution filter process by applying the CLAHE and SUCK methods. This method would help us get a clearer and brighter image while reducing noise and increasing the brightness of the Data. Then the feature extraction process is carried out and continued with the classification process. To find out the results, a performance evaluation process was carried out from several CNN models using the chest thorax dataset to obtain the optimal percentage of classification accuracy.

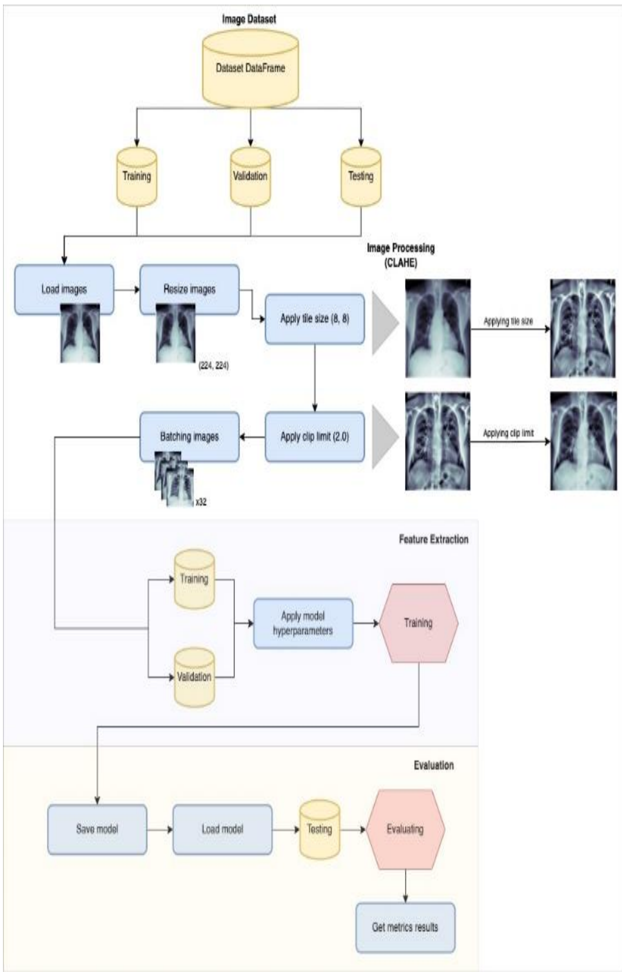

Fig. 3 Chest X-Ray pre-processing using CLAHE method

In Figure 3.0 The collection of chest thorax dataset images is carried out in 3 main processes, namely testing, validation and training. For the initial process, data loading is carried out, and the next resizing process is carried out for each image, which is processed using the CLAHE method. Furthermore, the training and validation process is carried out after image feature extraction is carried out for each image of the chest thorax by applying hyper parameters. If it is appropriate, save the model and load the model to carry out the evaluation process using data testing to get metric results.

Basically, CLAHE is an extension of HE, where the histogram made from this method gives a limit value. The limit value is the maximum height limit of the histogram. The CLAHE calculation process is calculated by the histogram limit clip limit, where the clip limit is calculated by the equation. In the equation, the value of M is the area size, N is the grayscale value, and a is the clip factor as an addition to the limits of the histogram with a value between 0-100.

$$\beta = \frac{M}{n}(1 + \frac{\alpha}{100}(s_{max} - 1) \tag{1}$$

An overview of the stages of processing chest thorax image data using SuCK can be seen in Figure 4.0

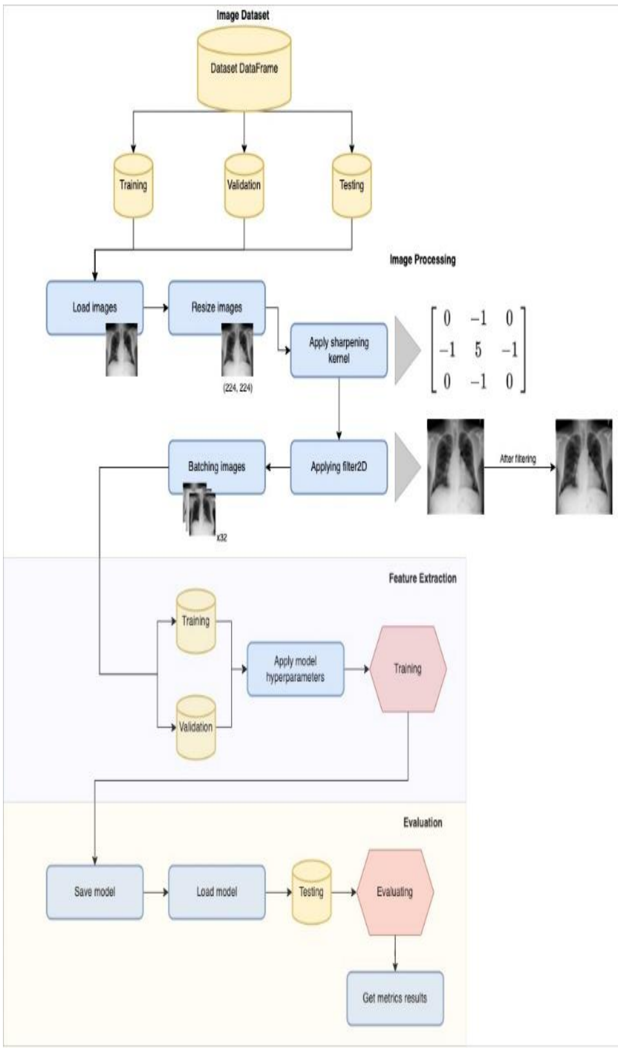

Fig. 4 Chest X-Ray pre-processing using SUCK method

Figure 5.0 illustrates the sharpening process for a typical x-ray image using the SuCK method. Sharpening using convolution/kernel values which is very useful for images that look smooth or blurry, becomes clearer by clarifying the interpretation of the image itself and the results can also look better than the previous image. In this image you can see the stages of the process of sharpening a chest X-ray image that has been affected by a disease or that is still healthy using SuCK methods.

Training process

We initialize 121-layer DenseNet, EfficientNetB0, InceptionV3, ResNet50V2, and MobileNetV2 with pre-trained weights from ImageNet and train multi-label models with binary cross entropy loss using a single NVIDIA GPU with 16GB of memory from Kaggle. We then apply normalization. We then batched the dataset of 32 as it is the most optimal value for state-of-the-art computer vision models. We use the Adam optimizer with a learning rate of 0.0005. We got the learning rate after doing the learning rate scheduler from the previous training and got the best learning rate of 0.0005. For training, we ran for 5 epochs which took approximately 10 hours per model. If the loss validation results do not increase for 2 consecutive epochs, the training will be terminated. The output of these models is a dimensional array with 10 values between 0-1 that indicates the probability of each disease label.

Evaluation on testing dataset

After doing the training process without using the CLAHE and SUCK methods, where in each CNN model the feature extraction process is carried out and then evaluates it on each of the testing datasets. Each evaluation requires processing time for each model, after which it is continued to measure the AUC score for each CNN model. The experimental results can be seen in Figure 6.0

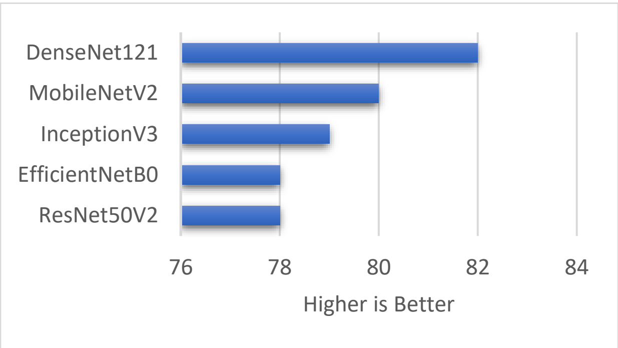

Fig. 6 AUC score for each state-of-the-art computer vision models on the testing dataset

In Fig 6.0 inform the result of the CNN model such as DenseNet121 has the highest AUC score which is 82. The AUC scores were not high enough because it had not used any advanced pre-processing method. After CLAHE and SUCK methods were used and splitting into 3 amounts of datasets. We evaluated every model and measured these models' AUC, Precision, Recall, and F1 scores. Each graph below was split based on the method and amounts of datasets. Precision is the match between the part of the data taken with the actual tested data. As seen on the picture below, is the formula of precision. TP or True Positive is the measurement of how the model predicts true positive as positive. TP is then divided from the sum of FP and TP. FP, short for False Positive is the measurement of how the model predicts a negative data as a positive value [16].

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

Recall is the success rate of the model on measuring how a class diversifies within different classes. As seen on the picture below, describes the formula of recall. Just like the precision formula, recall uses FN as its measurement to see positive values treated as negative values [16].

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

F1-score is simply the mean harmonic of precision and recall. F1-score measures how well our model performs on the testing dataset especially seeing how it can cleverly differentiate across other classes on the dataset [16].

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

To find out the accuracy results on several CNN models supported by the CLAHE and SuCK methods so that the image is more visible and contrasting for experiments in research, it can be shown based on the number of datasets that can be depicted in the graph below:

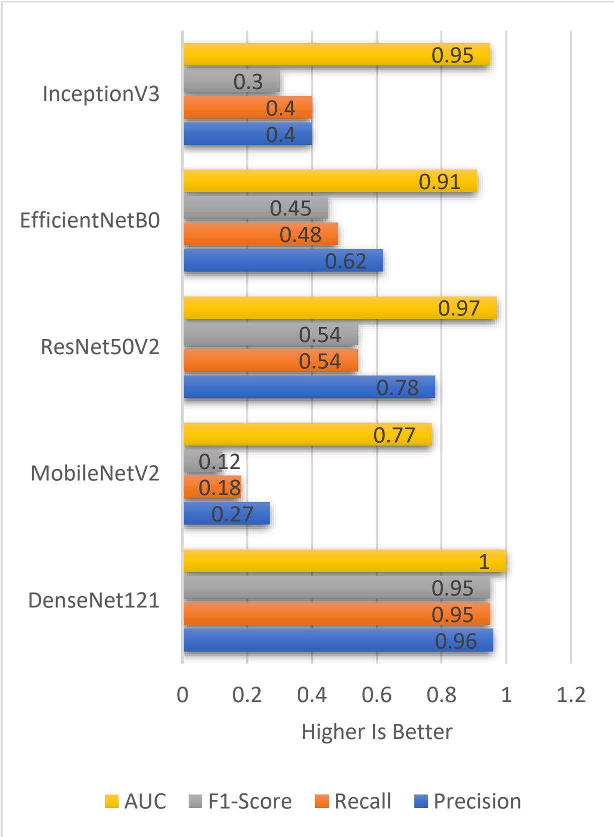

Fig. 6 Combined Information Performance Graph from AUC, F1, Recall, and Precision Score with several CNN models and the CLAHE method with a total of 1000 data sets

Figure 6 illustrates the combined results of the percentage of accuracy on the AUC, F1 score, recall and precision sequentially on each CNN model using the CLAHE method with a total of 1000 datasets. In this experiment, the DenseNet121 model has the highest accuracy of 100%, 95%, 95% and 96%. Furthermore, the Resnet 50 V2 model is 97%, 54%, 54% and 78%.

In this experiment, it can be seen that the average precision and recall in several CNN models is still less than 75%. Based on this experiment, It is only the Densenet 121 model which is supported by the CLAHE method, is very feasible in recognizing the disease based on a chest x-ray. In general, these experiments used the CLAHE method, the classification results used several CNN models for accuracy, Recall and Precision, only the ResNet 50 V2 model had good accuracy. However, for several other CNN models, the accuracy is not good for recognizing disease using chest x-rays.

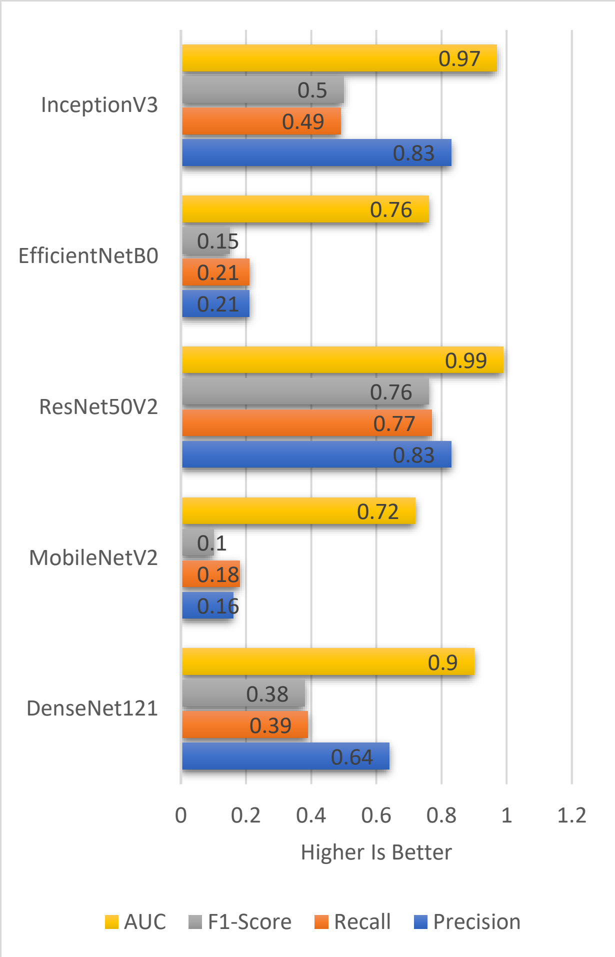

Fig. 7 Combined Information Performance Graph from AUC, F1, Recall, and Precision Score with several CNN models and the CLAHE method with a total of 5000 data sets

Figure 7 illustrates the combined results of the percentage accuracy on AUC, F1 score, recall, and precision sequentially for each CNN model using the CLAHE method with a total of 5000 datasets. In this experiment the Resnet50 V2 model has the highest accuracy of 99%, 76%, 77% and 83%. Furthermore, the Inception V3 model is 97%, 5%, 49%, and 83%.

In this experiment, it can be seen that the average precision and recall of some CNN models is still less than 75%. Based on this experiment carried out only the Resnet 50V2 model supported by the CLAHE method is highly feasible in recognizing disease based on chest X-rays. In general, in these experiments used the CLAHE method, the classification results carried out several CNN models for accuracy, Recall and Precision, only the ResNet 50 V2 model had good accuracy. However, for several other CNN models, the accuracy is not good for recognizing disease using chest x-rays.

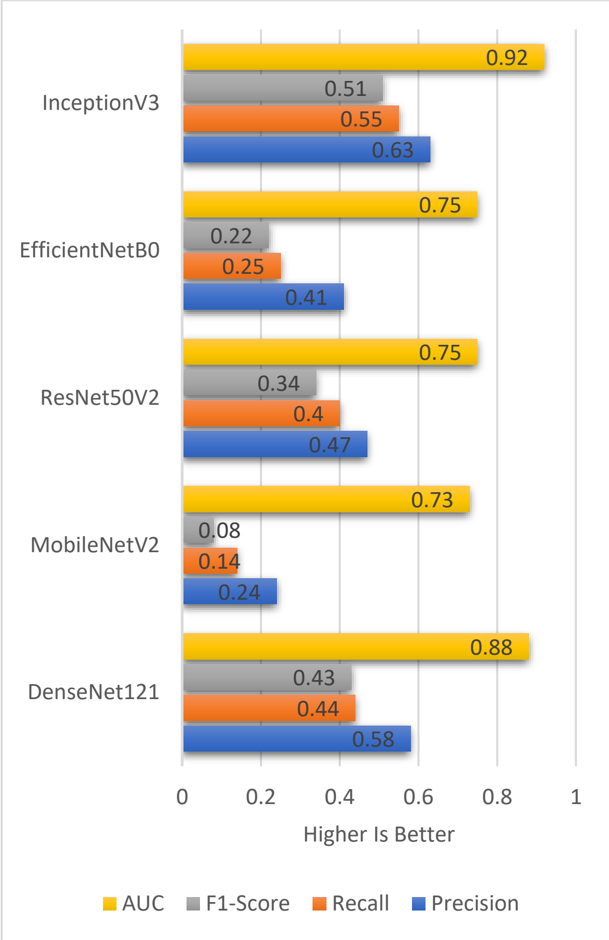

Fig. 8 Combined Information Performance Graph from AUC, F1, Recall, and Precision Score with several CNN models and the CLAHE method with a total of 10000 data sets

Figure 8 illustrates the other experiment the combined results of the percentage of accuracy on the AUC, F1 score, recall and precision sequentially on each CNN model using the CLAHE method with a total of 10000 datasets. In this experiment, the inception V3 model has the highest accuracy of 92%, 51%, 53% and 63%. Furthermore, the Densenet 121 model is 88%, 43%, 44% and 58%. In this experiment, it can be seen that the average precision and recall in several CNN models is still less than 50%.

Based on experiments using 10000 datasets that there is no CNN model that is feasible in recognizing disease based on chest X-rays. This happens because the average accuracy is less than 50%. Thus it will be a concern to find the right method or algorithm in recognizing several types of diseases using chest x-rays. So it is hoped that this activity will be an improvement in future research.

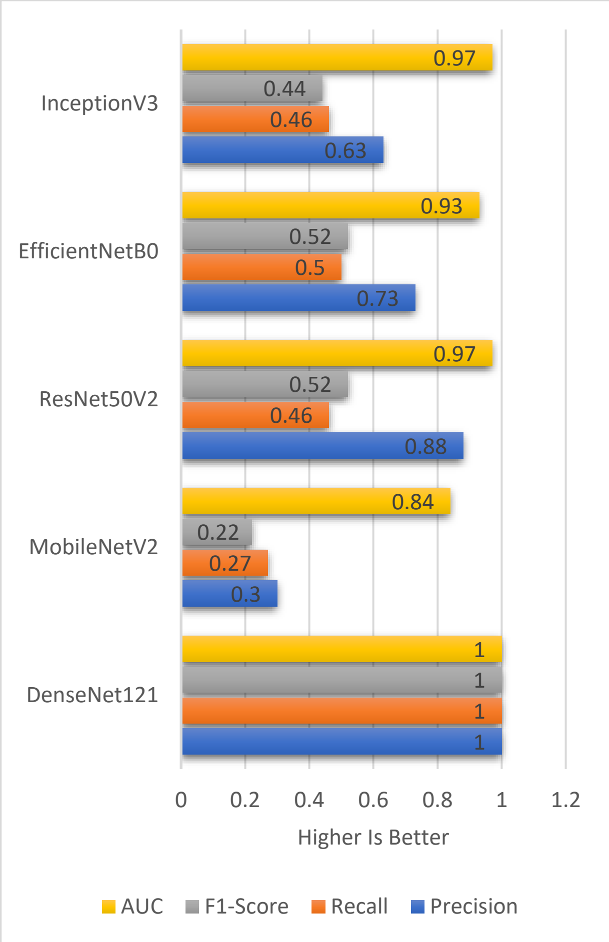

Fig. 9 Combined Information Performance Graph from AUC, F1, Recall, and Precision Score with several CNN models and the SuCK method with a total of 1000 data sets

Fig. 9 Inform the combined results of the percentage of accuracy on the AUC, F1 score, recall and precision sequentially on each CNN model using the SuCK method with a total of 1000 datasets. In this experiment, the DenseNet121 model has the highest accuracy of 100%, 100%, 100% and 100%. Furthermore, the EfficientNetB0 model is 93%, 52%, 50% and 73%.

In this experiment, it can be seen that the average precision and recall of some CNN models is still less than 50%. So it is illustrated that the Pre-processing method with SuCK is not suitable for recognizing disease using chest x-rays. In this study, it was illustrated that only the CNN DenseNet 121 model supported by the SuCK method had an accuracy of up to 100% in recognizing disease using chest x-rays. So this illustrates that the DenseNet 121 model is very suitable in recognizing disease using chest X-rays for a dataset of 1000 data.

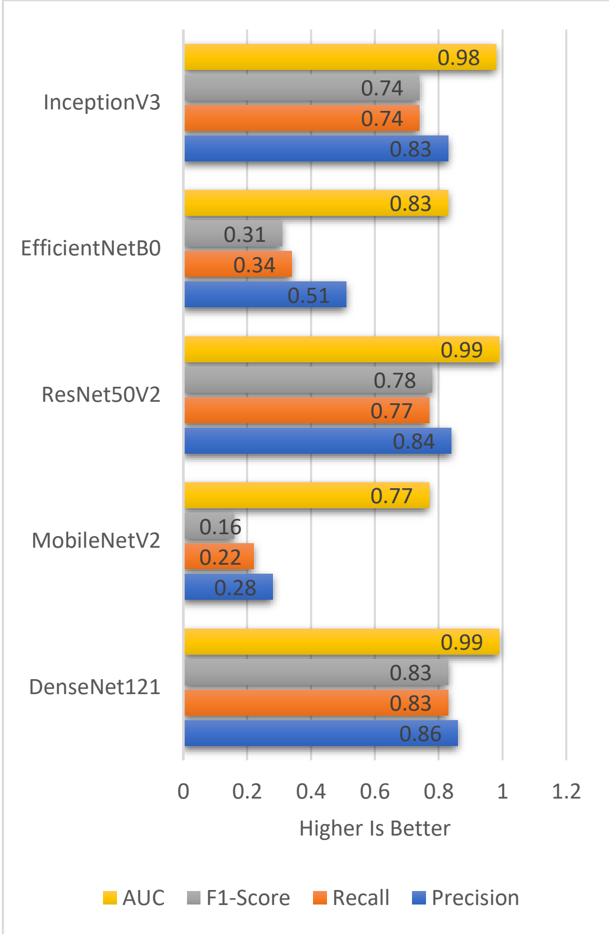

Fig. 10 Combined Information Performance Graph from AUC, F1, Recall, and Precision Score with several CNN models and the SuCK method with a total of 5000 data sets

In Figure 10 illustrates the combined results of the percentage of accuracy on the AUC, F1 score, recall and precision sequentially on each CNN model using the CLAHE method with a total of 5000 datasets. In this experiment, the DenseNet121 model has the highest accuracy of 99%, 83%, 83% and 86%. Furthermore, the Resnet 50 V2 model is 99%, 78%, 77% and 84%, followed the Inception V3 model is 98%, 74%, 74% and 83%.

In this experiment used the 5000 datasets. They can be seen that the precision and recall average of several CNN models is still quite good, where the average is above 70%. Based on this experiment, it can be seen that some models have accuracy and precision for recognizing diseases with chest X-rays, which can be above 70%, such as Densenet 121, Resnet V2 50 and Inception V3 models. Based on this experiment it can also be concluded that the number of data sets using a total training dataset of 5000 using both the CLAHE and SuCK methods produces a fairly good accuracy for disease recognition based on chest X-rays.

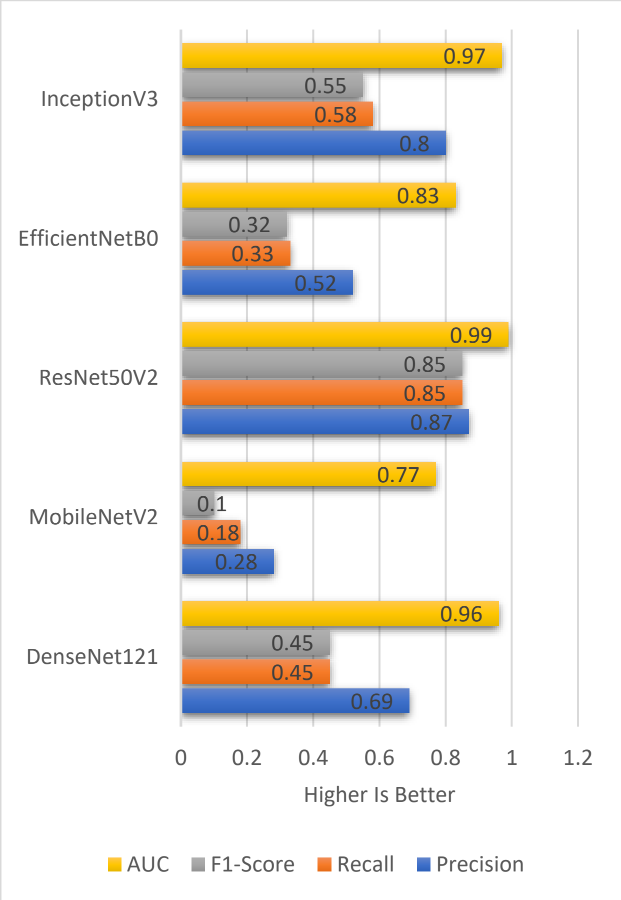

Fig. 11 Combined Information Performance Graph from AUC, F1, Recall, and Precision Score with several CNN models and the SuCK method with a total of 10000 data sets

Figure 11 illustrates the combined results of the percentage of accuracy on the AUC, F1 score, recall and precision sequentially on each CNN model using the SuCK method with a total of 10000 datasets. In this experiment, the ResNet 50 V2 model has the highest accuracy of 99%, 85%, 85% and 87%. Furthermore, the Inception V3 model is 97%, 55%, 58% and 80%.

The experiment illustrates that the precision and recall average are only on Resnet V2 50 and Inception V3 models with an average of around 70%. Based on this experiment, even though it uses a dataset of 10,000 data, the accuracy can be more than 70%, which is supported by the SuCK method for pre-processing. So with this method and the CNN Resnet V2 50 model it is very feasible to recognize chest X-ray images. In addition, it can also be concluded that using the SuCK method is much better than using CLAHE with a total of 10,000 data sets used.

Conclusions

1. Based on the experimental results using 3 kinds of datasets, namely 1000, 5000 and 10000 data. The CNN models used are the DenseNet121, Inceptikon V3, ResNet 50 V2, MobileNet V2, and EfficientNetBO models. As for pre-processing using the CLAHE and SuCK methods. In addition, this experiment shows that the SuCK method has the highest accuracy compared to the CLAHE method.
2. In this experiment, although an increase in the number of datasets, it almost always leads to an increase in accuracy, this did not happen in this study. In our opinion, this is due to process overfitting. Overfitting is a situation where the model tries to learn all the details including noise in the data and tries to fit all the data points into the line. This means that noise or random fluctuations in the training data are picked up and studied as a concept by the model. The problem is that this concept does not apply to new data and negatively affects the ability of the model to generalize in calculating precision.
3. Chest X-ray photo research can be continued to the next stage, by adding several other types of diseases. It is also hoped that further research can determine the disease more accurately to support medical personnel.

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Author contributions

Abdul Haris Rangkuti : Conceptualization, Methodology, Software, Field study Roderik Yohanes Mogot **:** Coding, Writing-Original preparation, Software, Validation., Field study Verdiant Jonathan Kusuma **:** Coding, Validation and Testing.

Conflicts of interest

The authors declare no conflicts of interest.