Classification of Pneumonia Using Transfer Learning Resnet50

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***Abstract*—Pneumonia is a serious threat to human health, particularly in countries where dense populations and high pollution levels are the main problem. Early diagnosis would be a great way to reduce the harm caused by pneumonia, developing an algorithm that could evaluate and identify chest X-ray images would be crucial. The method we used is a CNN architecture called RedNet50 transfer learning, which has a high image recognition capability. The dataset used to train the model comes from Kaggle, which includes extracted chest X-ray images from three classes, namely COVID-19, Viral Pneumonia, and Normal. In this case, we are only using Viral Pneumonia and Normal classes. The results are pretty satisfying with accuracy reaching 94%, with the model only needing 18 epochs to converge.**

***Index Terms*—pneumonia, resnet-50, CNN**

I. Introduction

Pneumonia remains a serious threat to human health, particularly in developing countries where billions of people suffer from energy shortages, high pollution levels, and dense populations. According to estimates from the World Health Organization, air pollution-related illnesses, such as pneumonia, claim the lives of about 4 million people annually. Each year, almost 150 million individuals get pneumonia, with young children being the most affected. The issue could be made worse by a shortage of medical personnel and resources, particularly in nations with less developed medical technology [1].

Developing an algorithm that can evaluate a chest X-ray image and identify automatically if a patient has pneumonia is crucial. The most effective way to diagnose pneumonia at the moment is using a chest X-ray, which is also essential for epidemiological research and therapeutic therapy. However, using X-rays to detect pneumonia is a difficult task that requires radiologists' competence. However, convolutional neural networks may now be accurately used for image processing and recognition thanks to the development of deep learning, offering new methodological and technological support for medical diagnosis.

Since its 2006 approach by Geoffrey Hinton, Yoshua Bengio, and Yann LeCun, deep learning has advanced significantly as a subfield of machine learning [2]. The common term for this type of pattern analysis technique is deep learning. Convolution neural network (CNN) models are one of the three main research approaches for deep learning. CNNs are known for their remarkable learning efficiency. Fukushima presented a neural cognitive machine based on a hierarchical structure with a similar structure in 1980, following the proposal and establishment of a hierarchical structure of "receptive field" cells responsive to local portions of visual input space in 1962 by biologists Hubel and Wiesel. It is regarded as the earliest engineering application of the CNN network and introduces the ideas of pooling and convolution. [3] The structure of classical CNN is indicated by LenET-5, which was constructed and trained by LeCun et al. [4].

There are several uses for CNN in the medical domain, including disease prediction, image interpretation, patient classification, and disease analysis. [5] By comparing the CT image data of patients diagnosed with COVID-19 and patients with typical pneumonia, Wang et al. used CNN technology to train a deep learning model and achieve an area under the curve (representing the algorithm's performance) during the COVID-19 outbreak of new acute infectious diseases. A single case takes 10 seconds to diagnose [6].

By monitoring the exposure history of COVID-19 in the early stages of the pandemic, Feng employed the logical regression method to select and prioritize several distinct physiological measures, such as body temperature and heart rate, based on regular clinical indicators. The Lasso recursive machine learning technique was then employed to create a backup model for early case diagnosis in suspects without a CT scan [7].

II. Methodology

The technique used to detect COVID-19 is deep learning. The deep learning used is CNN (Convolution Neural Network). The reason for using the CNN technique is that the dataset used is in the form of an image. Then, the type of CNN architecture used is ResNet50 transfer learning. The reason ResNet50 architecture is used is because it has a high accuracy of 98.05%. This accuracy is the highest when compared to Inception-v3, ResNetv2, and others. ResNet50 has a high image recognition capability but it requires large training data and takes a long time to train the data [8].

ResNet-50 has 50 convolution layers, which allows the model to capture complex features in images. ResNet with

50 layers uses a bottleneck design for its building blocks. The bottleneck residual block uses a 1x1 convolution, known as a "bottleneck", which reduces the number of parameters and multiplication of the matrix [8].

A. Dataset

The dataset used comes from Kaggle. The dataset is in the form of extracted Chest X-ray images. There are 3 classifications in the dataset, namely Covid-19, Viral Pneumonia, and Normal. Then, the data on the dataset has been separated into train data and test data. The dataset distribution can be seen on the figures 1

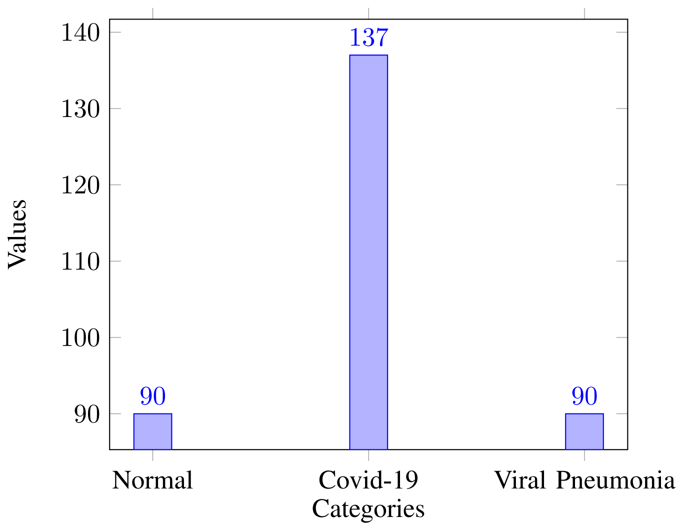

Fig. 1. Dataset Distribution

B. Classification

The flowchart diagram is shown in figures 2. Before we process the dataset further, we split the data set into train and test again even though the dataset was already split. Then, the resnet-50 transfer learning model was defined. Not to forget, we also declare early stopping so that the model does not perform excessive computation. The number of epochs initialized is 50 but of course the model does not need to run that much because of early stopping. Early stopping is based on the test loss value and accuracy of the model. Then, the model is evaluated using the library classification report. Then, testing is done on the model that has been made.

III. Experimental Result

A. Evaluation Method

The following criteria are used to evaluate the method.

- After running 18 epochs, the accuracy, loss, and convergence speed of the training sets.
- Confusion Matrix, accuracy, precision, recall, and F1 score of the model.

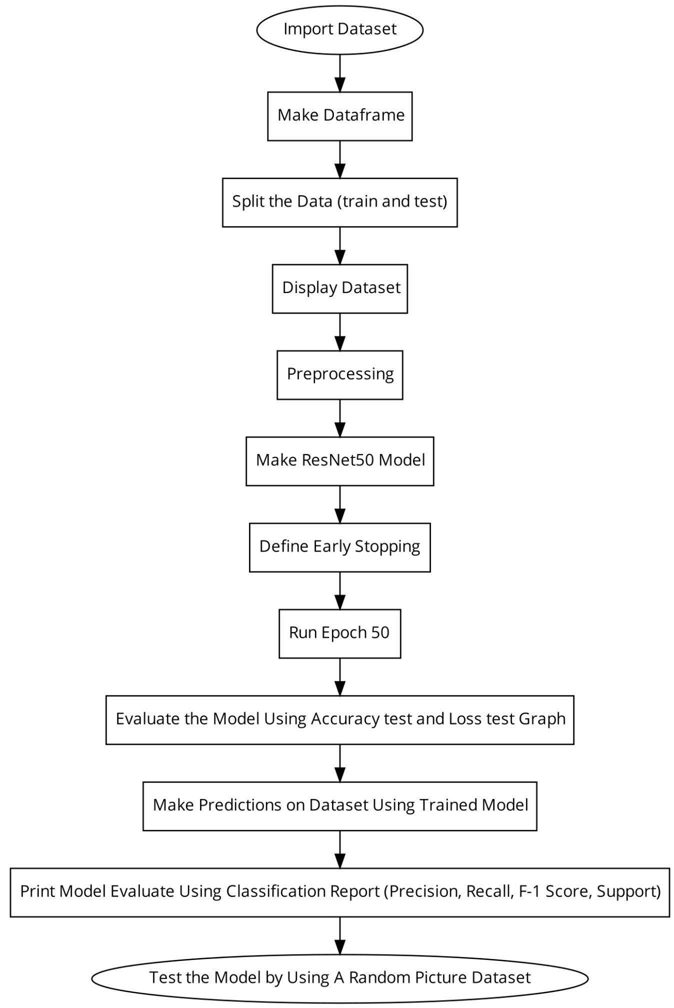

Fig. 2. Flowchart

B. Model Evaluation

The training terminates early after 18 of the 50 epochs because the model does not show any improvement beyond 10 epochs. The model develops as Figures 3 and 4 illustrate. Figure 3 demonstrates that following the 8^{th} epoch, the model's accuracy did not increase; it reaches 100% accuracy while the validation accuracy falls to 94.44%.

In the meantime, the model's loss lowered even with incremental reductions, and on the 18^{th} epoch, it finally settled at 0.0016. Additionally, the model's validation loss decreased with very little increments, reaching 0.1557 on the 18^{th} epoch.

Figures 3 and 4 show that the model is not overfitting because both the validation and overall accuracy increased. The validation loss of the model decreased in tandem with the model's loss. This suggests that there is no overfitting of the model.

C. Confusion Matrix, Accuracy, Precision, Recall Rate, and F1 Score

We laid out the confusion matrix to evaluate the model's strengths and weaknesses and comprehend the specific faults

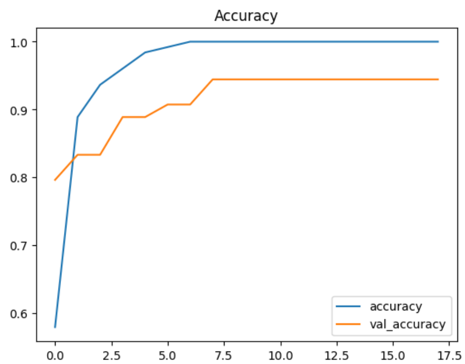

Fig. 3. Model's Accuracy Progress

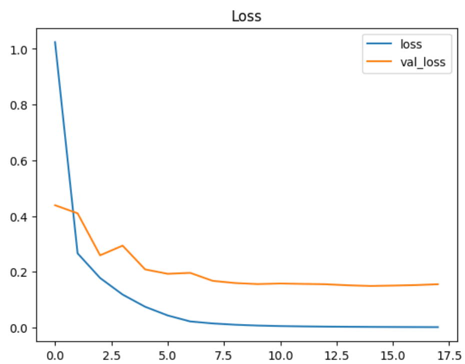

Fig. 4. Model's Loss Progress

in the classification prediction. Additionally, Figure 5 displays the relevant outcomes. By determining the computational model's F1 score, recall, specificity, accuracy, and precision, the optimizer was thoroughly assessed.

According to Figure 6, 0.94 is the highest F1-Score. With a precision of up to 0.97, it also possesses a very high accuracy in predicting viral pneumonia. To further illustrate this, Figure 7 displays some of the model's attempts to predict specific

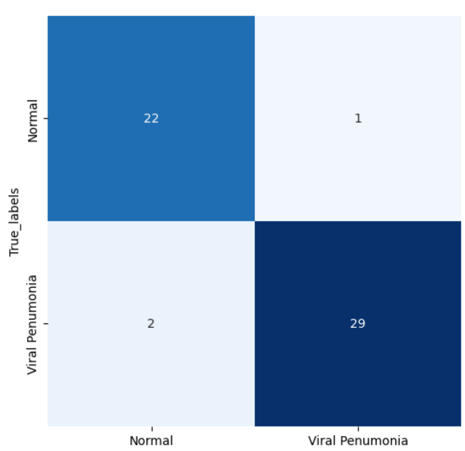

Fig. 5. Confusion Matrix

	precision	recall	f1-score	support
Normal	0.92	0.96	0.94	23
Viral Pneumonia	0.97	0.94	0.95	31
accuracy			0.94	54
macro avg	0.94	0.95	0.94	54
weighted avg	0.95	0.94	0.94	54

Fig. 6. Classification Report

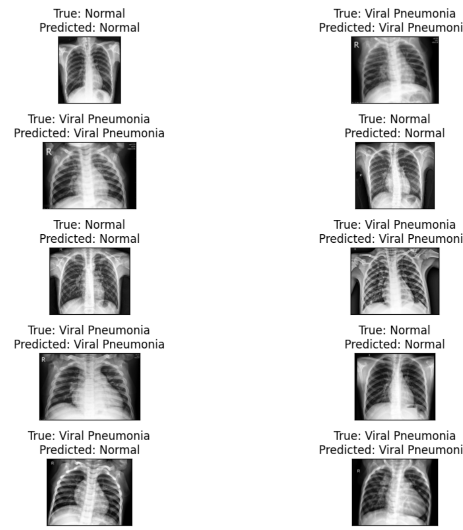

Fig. 7. Prediction

images. Nine out of ten images are correctly predicted by the model; one image is incorrectly predicted to be a viral pneumonia instead of a normal image.

IV. Conclusion

To conclude, the ResNet50 convolutional neural network model was used to classify pneumonia images. After 18 epochs, the model ended early with validation accuracy reaching 94% and validation loss that went down to 0.1557. The ResNet50 model is a great model with high success as it converges quickly, has only 18 epochs needed, and has a pretty high accuracy. This model could efficiently help doctors improve the speed and accuracy of pneumonia diagnosis. The only thing lacking in this model is its inability to explain the results obtained.

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