Classification of Lung Cancer with Convolutional Neural Network Method Using ResNet Architecture

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Abstrak

Lung cancer has become one of the most frightening specters in the world of health, leading many people to death each year. Therefore, the classification of lung cancer types is very important to determine the appropriate treatment steps. Considering that lung cancer treatment in the early stages is far more effective and efficient, accurate classification is the key to improving survival rates. This research focuses on the classification of three common lung cancer types: Adenocarcinoma, Large Cell Carcinoma, and Squamous Cell Carcinoma. To achieve optimal results, this study utilizes the ResNet architecture, a deep neural network model that has demonstrated its capabilities in various fields. Before being used on the model, the dataset containing lung X-ray images of patients undergoes preprocessing. At this stage, each image is resized to 256x256 pixels to ensure uniformity and compatibility with the model. Furthermore, this research trains various ResNet models, ranging from ResNet50, ResNet101, to ResNet152, which is the model with the most parameters. By comparing the performance of each model, this study finds that all trained ResNet models are capable of producing good accuracy in classifying lung cancer types. Among these models, ResNet152 demonstrates the most superior performance with an accuracy of 89%. This result suggests that the ResNet architecture has great potential to be used as an aid in classifying lung cancer types with a high level of accuracy. This research makes a significant contribution to the effort to improve the diagnosis and treatment of lung cancer, paving the way for a brighter future for lung cancer patients.

Kata Kunci: Computer Vision, Convolutional Neural Network, ResNet, Image Classification, Lung Cancer

I. INTRODUCTION

According to WHO, lung cancer is one of the diseases with the highest mortality rates each year [1]. Lung cancer often does not show early symptoms, hence the need for early diagnosis and treatment [2]. Regular medical checkups and the use of cutting-edge medical technology are vital in improving the chances of survival and quality of life for patients. Important steps such as raising awareness of risk factors, providing effective treatment, and developing more advanced diagnostic technologies are priorities in addressing the major challenges posed by lung cancer.

Several studies on lung cancer detection in CT scan images using the CNN method, one of which is Onkar et. al. [3] which discusses the classification of lung and colon cancer using Convolutional Neural Network by analyzing the condition and function of organ tissue. Fajar et. al. [4] detected lung cancer nodules in CT scan images using Mask R-CNN. Most existing studies simply categorize tumors as benign or malignant [5], [6], [7]. This study overcomes these limitations by exploiting the full potential of the ResNet architecture within a Convolutional Neural Network (CNN) framework. This study used convolutional neural networks (CNN) to classify three types of lung cancer: adenocarcinoma, large cell carcinoma, and squamous cell carcinoma. Accurate classification of these specific cancers has the potential to significantly improve lung cancer management and patient outcomes. By achieving accurate classification of these specific cancers, this research has the potential to significantly improve lung cancer management and patient outcomes.

The utilization of computer vision in image detection has become increasingly popular nowadays [5]. Convolutional Neural Network (CNN) has become one of the computer vision methods that can be used to detect and recognize objects in an image [6]. CNN has proven to be effective in detecting lung diseases through CT Scan images [7], [8], [9], [10]. ResNet, including ResNet50, ResNet 101, and ResNet152, is one of the well-known CNN architectures that excel in CT Scan detection due to its ability to train Deep Neural Network (DNN) deeply and address the vanishing gradient problem [11]. The utilized lung images are LDCT CT Scan, which can detect lung nodules as small as 5 millimeters, compared to conventional CT Scan that are less detailed [12], [13]. LDCT is also recommended by many health organizations such as the National Cancer Institute (NCI) and the European Respiratory Society (ERS) for lung cancer screening [14], [15], [16].

Lung cancer are commonly suffered and have become a significant problem nowadays [17]. Lung cancer detection using ResNet in previous research has shown a promising level of accuracy [18], [19], [20]. However, it did not utilize LDCT Scan images as its dataset. ResNet (Residual Neural Network) has emerged as a frontrunner in cancer image detection due to its remarkable performance, attributed to its deep architecture, robust feature learning capabilities, excellent generalization abilities, and consistent effectiveness demonstrated in numerous studies. ResNet's deep architecture enables it to extract intricate features from cancer images with high precision, even in low-resolution or low-quality images. Its exceptional generalization ability empowers the model to perform effectively across diverse datasets, encompassing a wide range of cancer image variations. These attributes establish ResNet as one of the most promising deep learning models for cancer image detection and hold immense potential to revolutionize early cancer diagnosis and treatment. Therefore, this study focuses on utilizing the ResNet architecture as a whole to classify the three types of lung cancer, namely Adenocarcinoma, Large Cell Carcinoma, and Squamous Cell Carcinoma, using LDCT CT Scan images of the lungs.

II. METHOD

This research utilizes a Convolutional Neural Network (CNN) with ResNet architecture for lung cancer classification. The process begins with collecting Low-Dose Computed Tomography (LDCT) images of patients with suspected lung cancer. Next, the collected images undergo pre-processing steps to improve their quality for analysis. After image preparation, the CNN method with ResNet architecture is implemented. Following the processing, model testing and evaluation are conducted on the processed images to obtain the final accuracy of the lung cancer classification (Figure 1).

A. Data Collection

At this stage, the collection of data sets related to the image or Low Dose CT (LDCT) of the lungs and about the CNN algorithm in particular that relates to the Residual Neural Network architecture (ResNet). The data collection for this study is a dataset taken from Kaggle's open source (https://www.kaggle.com/datasets/mohamedhanyyy/chest-ctscan-images) that contains a collection of Low Dose CT (LDCT) in the lungs consisting of lung cancer and normal lung images. The data set contains 1,000 images in which the images are divided into four classes, three classes for lung cancers: Adenocarcinoma, Large Cell Carcinoma and Squamous Cell carcinoma; and one class for normal lung conditions.

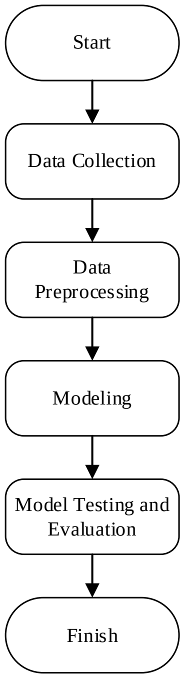

Figure 1. Research Work Procedures

B. Data Preprocessing

Following data collection, a data preprocessing stage is implemented to organize, modify, and clean the data. This step ensures the generated data is of higher quality and more suitable for the subsequent model development phase. Notably, all images were resized to a standard resolution of 256x256 pixels before being fed into the model. Figure 2 illustrates this preprocessing step in detail.

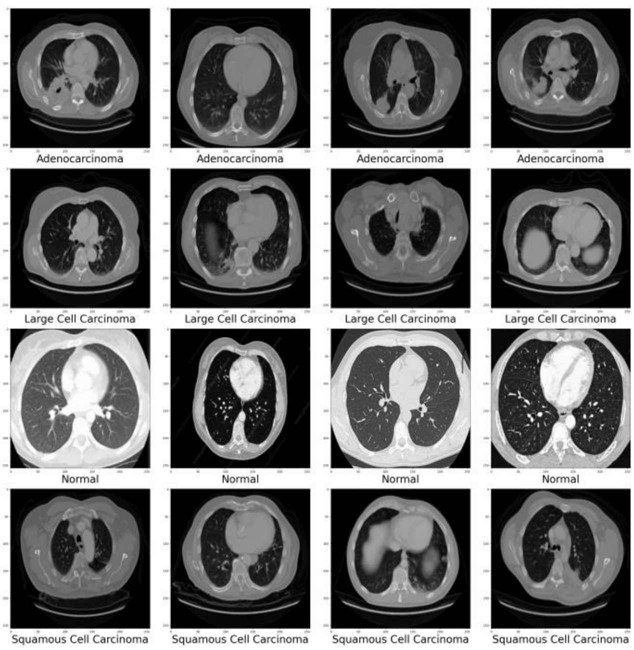

Figure 2. Dataset Image After Preprocessing

In Figure 3 is a division of 1000 image datasets divided into 3 data files namely test, train, valid. Tests refer to a test set, Train denotes a training set, and Valid signifies a validation set. The training set comprises 70%, the test set accounts for 20%, and the validation set makes up 10%.

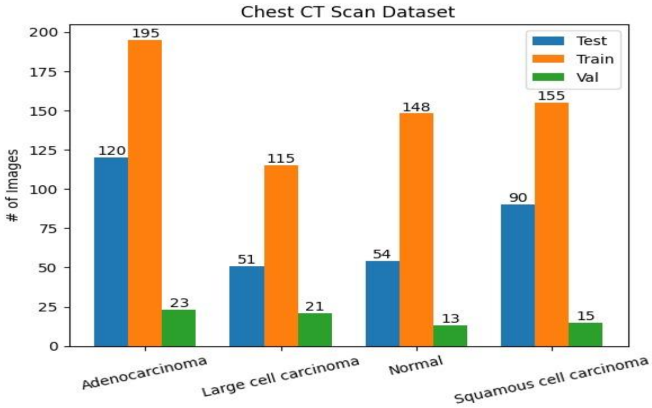

Figure 3. Graphic Multiple Images on Each Test, Train, and Validation

Image augmentation is the process of creating new examples of training from existing ones. This process can help fight overfitting and improve the performance of the inner nerve network for computer vision tasks such as classification, segmentation, and object detection. In the image augmentation process, where preprocessing_function is used to process image input before it is used in the model. Rotation_range allows for random rotation of images. Width_shift_Range and height_shif_ranger function in random horizontal and vertical shifts on images. Shear_ranges function as the geometric transformation that bends images. Zoom_ranga functions as a random zoom or shrink on pictures.

C. Modeling

This studywe used the Convolutional Neural Network (CNN) method with ResNet architecture to classify cancer in the lungs [21]. For the classification of cancer in the lungs, the Convolutional Neural Network (CNN) model created can detect a variety of diseases and distinguish one disease from another [22].

The ResNet architecture is a replicated network model often used in the field of image processing and image recognition developed by Microsoft Research in 2015 [23]. ResNet is one of the key innovations in computer vision that enables deeper network training without experiencing vanishing gradient problems.

Figure 4 illustrates the layer structure of the ResNet architectures, specifically ResNet50, ResNet101 and ResNet152. ResNet50, a widely recognized variant, comprises 50 total layers: 48 convolutional layers, a single MaxPool layer, and one average pooling layer. ResNet101, another variation, features a deeper structure with 100 convolutional neural network (CNN) layers and a single fully connected layer. Additionally, the text mentions ResNet152, another variant with 152 layers. [24].

Figure 4. Layer Structure on ResNet Architecture

Increased depth of neural tissue can generally lead to decreased accuracy and increased error. ResNet solved this problem by implementing Residual Learning, a technique that allows the network to pass several layers and prevent the Vanishing Gradient Problem as showm in Figure 5.

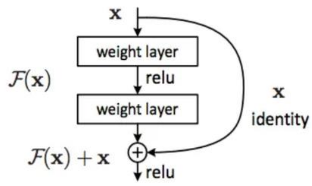

Figure 5. Residual Learning Block

D. Model Testing and Evaluation

At this stage, testing is done with data testing on all trained ResNet models. With the tests that have been carried out, an evaluation of the performance of the model that has been trained can be performed. The evaluation results obtained, used as indicators for comparison of the model.

III. RESULT

A. Training and Validation Result

The use of early stopping may prevent the training and validation process from reaching 100 epochs. The training and validation process will cease when there is no longer a significant improvement in the loss value. Each ResNet model with the lowest validation loss will be utilized during the testing phase to assess its performance in classifying lung cancer.

The ResNet50 model we developed for the lung cancer classification task underwent just 46 epochs of training and validation. The ResNet50 model achieved its best validation loss on the 36th epoch. At that epoch, the training accuracy was 94.62%, the validation accuracy was 90.28%, and the validation loss was 0.4365. The graph showing the training accuracy compared to the validation accuracy, as well as the graph displaying the training loss in relation to the validation loss, can be found in Figure 6.

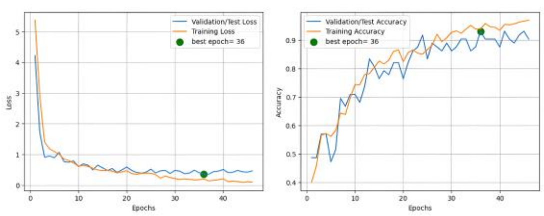

Figure 6. Training Accuracy Compared to Validation Accuracy and Training Loss Compared to Validation Loss of Resnet50.

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The ResNet101 model for lung cancer classification undergoes 100 epochs of both training and validation. The lowest validation loss recorded by ResNet101 is 0.4087, achieved during the 32nd epoch. At that epoch, the training accuracy reached 92.66%, while the validation accuracy stood at 87.50%. A graph comparing the training accuracy to the validation accuracy and a graph comparing the training loss to the validation loss can be found in Figure 7.

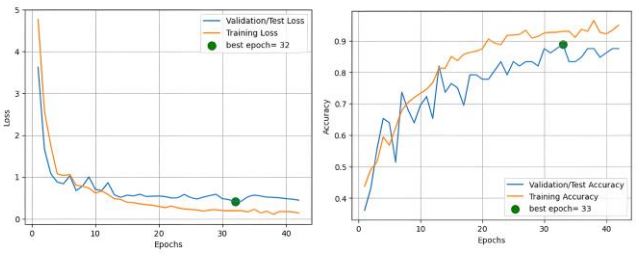

Figure 7. Training Accuracy Compared to Validation Accuracy and Training Loss Compared to Validation Loss of Resnet101

For the ResNet152 model, the training and validation process extended to 38 epochs. ResNet152 reached a validation loss of 0.3737 as the lowest point at the 28th epoch. At that epoch, the training accuracy reached 90.21%, while the validation accuracy was recorded at 87.50%. Figure 8 plots the training accuracy against the validation accuracy and the training loss against the validation loss over the epochs.

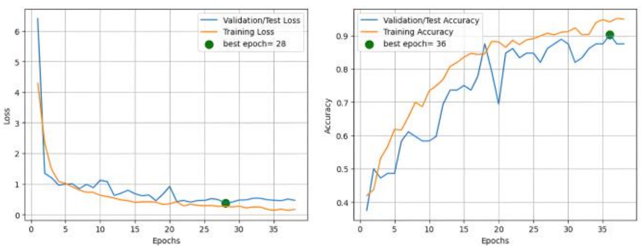

Figure 8. Training Accuracy Compared to Validation Accuracy and Training Loss Compared to Validation Loss of Resnet152

B. Testing Results

The optimal weight achieved during the training phase is utilized in the ResNet model. Subsequently, all ResNet models are evaluated using the test set. The testing set in this study consists of 319 lung cancer images, each resized to 256×256 pixels.

To assess and measure the performance of the model in classifying lung cancer, the metrics utilized are accuracy, precision, recall, and F1 score. The formulas for these four metrics are as follows:

$$\text{accuracy} = \frac{\text{number of correctly classified images}}{\text{total number of images}} \quad (1)$$

$$\text{precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (2)$$

$$\text{recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad (3)$$

$$\text{F1} - \text{score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (4)$$

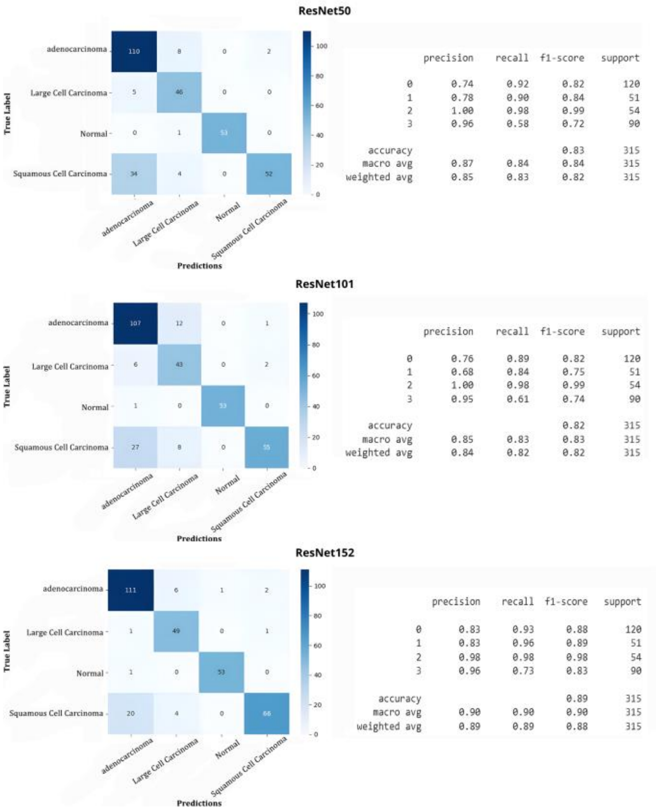

Figure 9. Classification Report and Confusion Matrix From All Resnet Model Evaluations Resulting From Lung Cancer Classification (Adenocarcinoma, Large Cell Carcinoma, Squamous Cell Carcinoma and Normal)

The accuracy, precision, recall, and F1 score values on the testing data set for all designed ResNet models are shown in Figure 9. Evaluations were performed, calculated for each class in the image in order of Adenocarcinoma (0), Large Cell Carcinoma (1), Normal Lung (2), and Squamous Cell Carcinoma (3). ResNet152 has the highest accuracy of 89%. The second highest accuracy was 83% obtained from ResNet 50.ResNet101 achieved 82% accuracy and was the lowest accuracy of the three models. Overall the ResNet152 model achieved the highest results while ResNet101 showed the lowest results, in other words the ResNet152 model has the best performance and quality in the classification of lung cancer namely Adenocarcinoma, Large Cell Carcinoma and Squamous Cell Carcinoma and normal lungs. However, this designed model can still be developed to be better by performing segmentation techniques on the image.

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IV. DISCUSSIONS

In applying CNN models using ResNet50, ResNet101 and ResNet152 architectures in lung cancer classification, ResNet152 achieved 89% better accuracy than ResNet50 and ResNet101. All models we designed using the three ResNet models achieved very high accuracy. It means that the models we designed are considered to have excellent performance and quality in detecting lung cancer.

Table 1. Comparison With Previous Studies

Name	Classes	Model	Accuracy (%)	Loss
Ours	Adenocarcinoma, Large Cell Carcinoma, Squamous Cell Carcinoma and normal lung	ResNet 152	89%	0,33
U. Khultsum et al.[25]	Bengin and Malignant	MobileNet	96,70%	0,19
A. Vierisyah et al.[26]	Bengin and Malignant	ResNet101	95,10%	-
T. D. Putra et al.[27]	Cancerous and normal patients	ANN	92,79%	-
Fajar et. al. [4]	large benign size, small benign, and malignant	Mask R-CNN	85,2%	-
Putri Pratiwi et al.[28]	positive lung cancer and negative lung cancer	K-Fold Cross Validation	92,00%	-

Table 1 explains that U. Khultsum et al. [25] got high accuracy results for lung disease classification using the MobileNet model. They only used it on benign tumor types and potentially cancerous malignant tumors. A. Vierisyah et al. [26] got good accuracy results with the ResNet101 model . However, a lot of overfitting occurred in the results of the study. T. D. Putra et al. [27] studied lung cancer patients medical records and compared them with patients with normal lungs using an ANN model and got high accuracy results. As is the case with the research of Putri Pratiwi et al. [28] experimented with medical record data of lung cancer positive and lung cancer negative patients.

While this study's accuracy may be slightly lower than some prior research, it demonstrates significant gains in overall effectiveness. This is attributable to our success in overcoming the challenge of overfitting, a common issue that can inflate accuracy results in previous studies. This study's approach enables the detection of specific lung cancer subtypes, including adenocarcinoma, large cell carcinoma, and squamous cell carcinoma. This represents a significant advancement over prior research, which could only differentiate between benign and malignant tumors.

All these studies successfully demonstrated that machine learning is good at diagnosing, detecting, and classifying lung diseases. Although, the previous studies did not focus on lung cancer specifically but only on its outline (benign and malignant cancer) [25], [26], [29]. In this study's, the classification of lung cancer (Adenocarcinoma, Large Cell Carcinoma, Squamous Cell Carcinoma and Normal) by utilizing the ResNet model showed good results. Of the three models used (ResNet50, ResNet101, and ResNet152, ResNet152) obtained the best results with 89% accuracy. Thus, it can be said that the model we developed is better at detecting lung cancer. However, this research model can still be improved by adding image data from lung LDCT.

V. CONCLUSION

This study proposes a novel approach for lung disease classification using a ResNet-based model. The model aims to differentiate between three types of lung cancer is adenocarcinoma, large cell carcinoma, and squamous cell carcinoma, in addition to normal lung tissue. To ensure model generalizability, we implemented a comprehensive data preprocessing step prior to training, validation, and testing. This preprocessing included image augmentation techniques and the application of early stopping during model training. Our results revealed that ResNet-152 outperformed other ResNet models in classifying lung cancer. Overall, the proposed model offers a promising solution to assist medical personnel in achieving more efficient lung disease detection.

To enhance the generalizability and effectiveness of future research, we recommend exploring alternative deep learning architectures. These architectures could include Inception, DenseNet, EfficientNet, or even other CNN variations. Additionally, utilizing the most recent dataset directly acquired from a hospital setting is highly recommended. This approach ensures that the utilized data is more representative of real-world scenarios and reflects the latest medical advancements. By employing images directly obtained from hospitals, future research can achieve a stronger foundation and produce more clinically relevant results.

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