DETECTION OF LUNG CANCER MALIGNANCY TYPES ON CT-SCAN USING THE CONVOLUTIONAL NEURAL NETWORK METHOD AT PHC HOSPITAL SURABAYA

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ABSTRACT

There are many uses for digital image processing, ranging from tumor and cancer detection in the body to reading blood cells. The rate of lung cancer represents about 13.27% of the total cancer cases, and this shows that lung cancer is the main type of disease in men. Lung cancer is one of the most dangerous and life-threatening diseases in the world. In Indonesia, lung cancer is more often detected when patients are at an advanced stage. Therefore, in this paper, we applied Deep Learning to solve a lung cancer malignant detection system; it is used to detect and classify nodule areas. So that lung cancer detection can be obtained with accurate results. This paper explains the working system for detecting lung cancer malignancies using a Convolutional Neural Network (CNN) and the model architecture for training the dataset using the EfficientNet model. This study collected 800 lung CT images from PHC Surabaya Hospital in DICOM format. A total of 13 layers with EfficientNet architecture and classification layers for each type of cancer class have been used in the model. The experimental results of the model achieved satisfactory results with an accuracy of 99.46%, with a maximum epoch of 30 and a mini-batch size of 128.

Keywords: *Convolutional Neural Network, CT-Scan, Lung Cancer, Malignancy Detection*

1. INTRODUCTION

Lung cancer is one of the most dangerous and life-threatening diseases in the world. Lung cancer is the abnormal growth of lumps in the lung tissue which can be benign or malignant. Current estimates provided by the "World Health Organization" (WHO) say that around 7.6 million deaths worldwide every year are due to lung cancer. According to public statistics in America, lung cancer is the deadliest cancer killer of people in the United States [1], [2]. If lung nodules are not detected and diagnosed early, they can become cancer that can grow and spread to other organs in the body. Therefore, subject detection of nodules in the lungs plays an important role in the early diagnosis of lung cancer and in improving patient survival rates. In Indonesia, lung cancer is more often only detected when it is at an advanced stage. Lung cancer is very difficult to detect because it appears and shows symptoms at an advanced stage. Therefore, to minimize this incident, cancer detection is not only based on complaints from patients, but diagnosis and stage detection of lung cancer must be holistic by carrying out physical examinations and radiological and laboratory supporting examinations [3].

Several studies have applied artificial intelligence techniques for this purpose, for example: using artificial neural networks to detect lung cancer [4], or using support vector machine techniques [5], [6], *K-nearest neighbor* [7], or using genetic algorithms [8], as well as fuzzy techniques [9], [10]. One of the newest and best methods for detecting lung cancer is to use Convolution Neural Networks (CNN) to help extract features from images. Then the extracted features are used to classify images [11]. To apply several machine learning techniques for detection and classification of lung cancer images, there is a need to use data as input to the algorithm that has been applied. Various methods are used to diagnose lung cancer, especially MRI, X-ray, and CT. X-ray chest radiography and Computer Tomography

(CT) are two well-known imaging modalities commonly used in the identification of various lung diseases [12], [13]. Apart from that, there are many public databases that are used for scientific research purposes such as ELCAP *Public Lung Image Database*, LIDC Database, and Data Science Bowl 2017 [1].

CT images are still the most effective way to detect lung cancer. Therefore, it is very important to classify pulmonary nodules on CT images. Initial classification of lung nodules from CT images can be performed with a fast and accurate Computer-Aid Diagnosis (CAD) system for lung nodule classification. Classification of lung nodules is important for the diagnosis of lung cancer based on CT images for example nodule, non-nodule, cancer, and non-cancerous [14]. CNN have achieved remarkable achievements in many aspects of medical imaging, such as ultrasound [15], [16]; MRI [17]; and CT [18].

In general, the detection and classification of lung cancer via CT images involves 3 tasks, namely: 1) tumor detection or segmentation; 2) cancer prognosis; and 3) carcinoma classification. The task of segmenting a tumor goes through two steps, starting with candidate selection and following confirmation of the tumor [19]. In the lung cancer detection system, the data collection was collected using the CNN technique with the AlexNet architecture to assist classification with 3 types of classes: normal, benign, and malignant. The obtained model provides high accuracy, reaching 93.548% when applied to the collected dataset, also providing precision up to 97.1015%, sensitivity up to 95.714%, and specificity reaching around 95%.

2. RESEARCH METHODOLOGY

2.1 Dataset

The object of this research is a CT-Scan image showing a tumor in the lung lungs patients obtained from PHC Surabaya Hospital. Image database containing annotation collected nodules during the CT-Scan process. The dataset obtained contains 7500 CT Scans covering 800 nodules to be classified. Every candidate has their position in coordinates and classification as non-nodular or nodular. It is worth noting that There is Lots of candidates per nodule. The dimensions of these images are 512x512xZ, where Z is varying in length depending on the height of the scanned patient. We cut every picture candidate to get 50x50 ROI area image based coordinate candidate.

2.2 Research Flow

The flow that will be carried out in this research consists of: (1) data collection, (2) input data, (3) data preprocessing, (4) training, (5) validation, and (6) testing. The research flow is visualized in Figure 1.

2.2.1 Data collection

The data used was obtained from the results of collaboration with PHC Surabaya Hospital. This data is the result of a doctor's diagnosis of patients at PHC Surabaya Hospital. The data obtained is in the form of digital images of the thorax from a CT-Scan machine. The data is divided into four diagnostic classes, namely Large Benign, Small Benign, Malignant, and Normal. To obtain this data, researchers obtained permission from the hospital to obtain a code of ethics with certain conditions in accordance with hospital regulations.

2.2.2 Input Data

The input data used in this network is in the form of thorax images from 4 diagnoses of lung conditions, namely Benign Large, Benign Small, Malignant, and Normal in the form of digital images. The image size for network processing is 224x224 pixels. There are 200 data for each class so the total data is 800 images. Data from the four classes is divided into two types of data groups, namely training data and testing data. The group division for the training process is 60% and data for the testing process is 40%.

2.2.3 Nodule Area Detection

Done detection of tumor nodules contained in the image using Faster R-CNN. At this stage 2 sub-stages that are labeled nodules and getting the nodule area. First, to get a picture nodule The image labeling process is carried out. Namely, first labeling objects that are considered tumor nodules on a CT scan of the lungs, by giving a box delimiter for objects in the network input image. Will The process of detecting objects including tumors is carried out using Faster. Explanation process flow of how detection works nodules are easier explained in Figure 2.

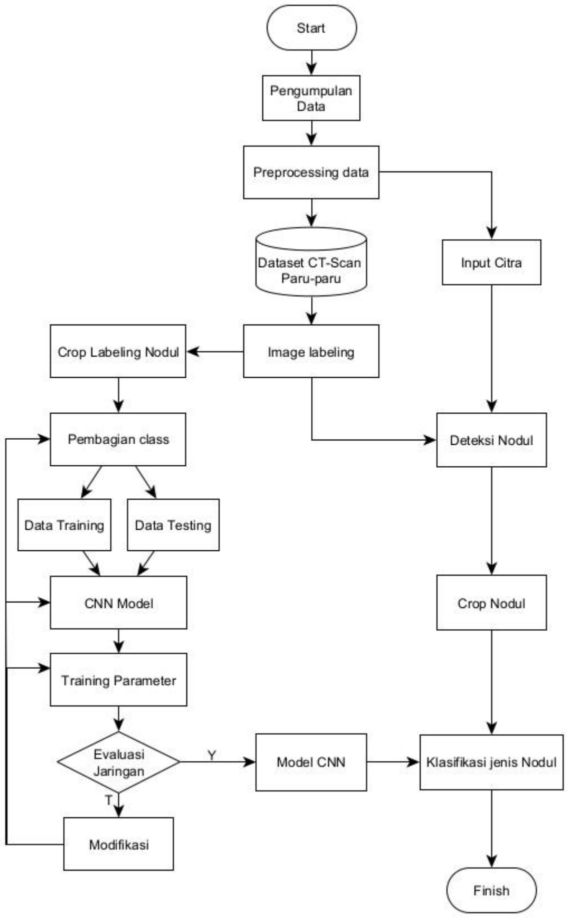

Figure 1. Flow Chart System Detection

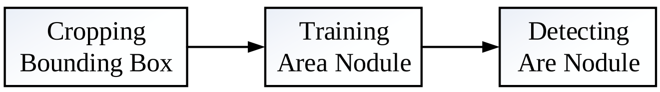

Figure 2. Flow detection of nodule

Figure 2 is a channel from detection nodules starting by labeling the tumor nodule area and then doing training on the bounding box that has been labeled. Detection of these nodules helps differentiate an object that can be said to be a tumor from an object that is similar to a tumor. Several objects similar to tumors include an alveolus, which is captured by a CT scan, and its shape and characteristics are the same as nodules/tumors. Apart from the alveoli, other organs near the lungs are captured by CT scans with characteristics and shapes that are the same as nodules/tumors. The first thing to do before classification type cancer lungs are to detect presumed nodule areas as nodule/tumor.

2.3 EfficientNet Architecture CNN Model

The objective of planning the network architecture *CNN* built is to classify cancer lungs on a CT scan. The plan is to apply the network with training data so that the system can learn to recognize tumor objects. If the network obtained good results in distinguishing type cancer lungs on CT-Scan, then the trials were carried out on validation data. The network can classify test data if the data is validated and shows good results. Based on the characteristics of each image that must be detected. Features owned by each object's competitors are very complex. Therefore, that built network requires sufficient input data as well as a very deep network to reach the desired accuracy. In this research, a proposed method, *CNN*, with architecture EfficientNet, with this feature no longer builds or designs architecture CNN from the start, using transfer learning is sufficient to cut part classification from transfer learning using classification layers alone. These features can improve model accuracy using EfficientNet transfer learning and cutting classification layer sections from EfficientNet. This feature also allows the model to learn functions confirming identity that more layers. A transfer learning process is carried out from the architectural model EfficientNet to overcome limitations of the amount of data and hardware used.

Figure 3 is a transfer learning model from CNN with the architecture EfficientNet. Transfer learning process in general done by freezing the initial convolution layer and just modify it layer end to form fully-connected layers and classification. Development system done by modifying the layers The final convolution can be trained with our model, so that the parameters and weights the network can adapt to new data in the form of trained thorax image. Based on extraction features on layers initial convolution of features level low applied throughout picture covers edge, pattern, color is feature general, while at deeper layers it functions to identify feature to be more specific in the image such as texture or shape.

3. RESULTS AND DISCUSSIONS

3.1 EfficientNet Architecture Model Testing

In the following section, we describe the EfficientNet architecture used as a model for transfer learning. The model has been previously trained with the ImageNet dataset. In this research, we use the training results to retrain with a different dataset. Thus, transfer learning networks can be used to train unrelated categories in large Collections (*ImageNet*).

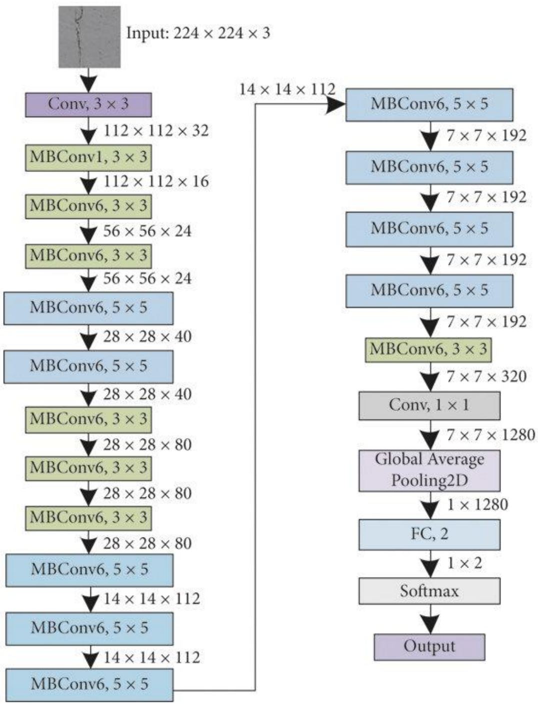

Figure 3. EfficientNet Architecture Structure

Table 1. EfficientNet Architecture Model

Layers (types)	**Output Shape**	**Param**
input_2 (InputLayer)	[(None, 224, 224, 3)]	0
rescaling_1 (Rescaling)	[(None, 224, 224, 3)]	0
stem_conv (Conv2D)	(None, 112, 112, 24)	648
stem_bn (BatchNormalization)	(None, 112, 112, 24)	96
stem_activation (Activation)	(None, 112, 112, 24)	0
block1a_project_conv (2D Conv)	(None, 112, 112, 24)	5184

block1a_project_bn (BatchNormalization)	(None, 112, 112, 24)	96
block1a_project_activation (Activation)	(None, 112, 112, 24)	0
block1a_add (Add)	(None, 112, 112, 24)	0
block1b_project_conv (2D Conv)	(None, 112, 112, 24)	5184
block1b_project_bn (BatchNormalization)	(None, 112, 112, 24)	96
block1b_project_activation (Activation)	(None, 112, 112, 24)	0
block1b_drop (Dropout)	(None, 112, 112, 24)	0
block1b_add (Add)	(None, 112, 112, 24)	0
block7e_expand_conv (Conv2D)	(None, 7, 7, 3072)	1572864
block7e_expand_bn (BatchNormalization)	(None, 7, 7, 3072)	12288
block7e_expand_activation (Activation)	(None, 7, 7, 3072)	0
block7e_dwconv2 (Depthwise Conv2D)	(None, 7, 7, 3072)	27648
block7e_bn (BatchNormalization)	(None, 7, 7, 3072)	12288
block7e_activation (Activation)	(None, 7, 7, 3072)	0
block7e_se_squeeze (Global AveragePooling2D)	(None, 3072)	0
block7e_se_reshape (Reshape)	(None, 1, 1, 3072)	0
block7e_se_reduce (Conv2D)	(None, 1, 1, 128)	393344
block7e_se_expand (Conv2D)	(None, 1, 1, 3072)	396288
block7e_se_excite (Multiply)	(None, 1, 1, 3072)	0
block7e_project_conv (Conv2D)	(None, 7, 7, 512)	1572864
block7e_project_bn (BatchNormalization)	(None, 7, 7, 512)	2048
block7e_drop (Dropout)	(None, 7, 7, 512)	0
block7e_add (Add)	(None, 7, 7, 512)	0
top_conv (Conv2D)	(None, 7, 7, 1280)	655360
top_bn (BatchNormalization)	(None, 7, 7, 1280)	5120
top_activation (Activation)	(None, 7, 7, 1280)	0
flatten_1 (Flatten)	(None, 62720)	0
fc1 (Dense)	(None, 200)	12544200
batch_normalization_1 (BatchNormalization)	(None, 200)	800
dropout_2 (Dropout)	(None, 200)	0
fc2 (Dense)	(None, 100)	20100
dropout_3 (Dropout)	(None, 100)	0
fc3 (Dense)	(None, 50)	5050
pred (Dense)	(None, 4)	204

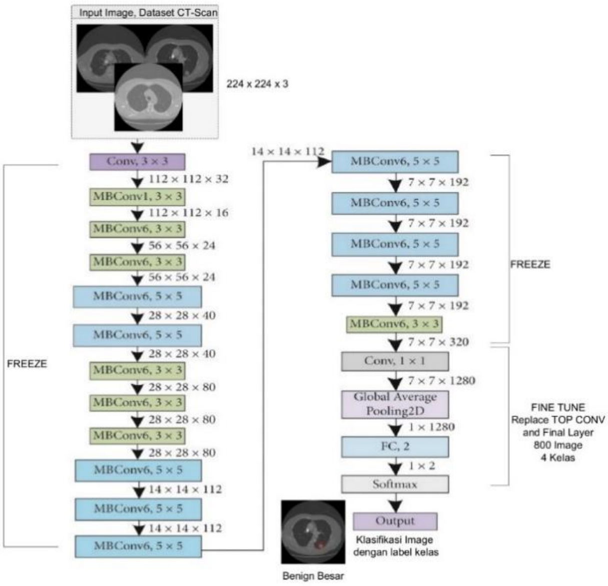

Figure 4. EfficientNet architectural structure

In table 1 above is the architecture of *EfficientNet*. The *CNN* architecture consists of several layers: *Convolution Layer*, *BatchNormalization*, and *Classification Layer*. A series of *Convolution Layers* and *BatchNormalization* act as feature extraction divided into several parts. The first part consists of two Convolution layers with 24 -24 units each along with a *BatchNormalization layer* measuring 112×112 and Relu activation. Meanwhile, the other also has two Convolution layers but each numbering 48, 80, 96, 160, 176, 192, 304, 320, 512, 640, 960, 1056, 1824, 3072 and 1280 units as well as *BatchNormalization and Relu activation* layers.

Figure 4 shows the *EfficientNet* architectural structure used in *transfer learning* by replacing the *Top Conv layer* and a *final layer* or *Fully-Connected Layer*. The *EfficientNet* model from the results of transfer learning with *ImageNet* is a network that has extracted features accurately and informatively. This was used in this research for a new task to classify types of lung cancer on CT-Scan images of the lungs. The transfer learning used is by replacing the Top Conv layer with a new network that has never been trained before. The aim is that the network can learn specific features in new data in the form of lung cancer CT scan images which can increase accuracy. Meanwhile, in blocks Conv 1 to Top Conv layers remain frozen and low level features are utilized which are applied to the entire image including edges, patterns and colors which are common features.

3.2 CNN Model Accuracy

Model accuracy tests were carried out to find out the ability of architectural models to classify disease on CT-Scan images. Apart from that, the training results of the transfer learning model use *EfficientNet* Accuracy results are obtained as in Figure 5 and loss in Figure 6.

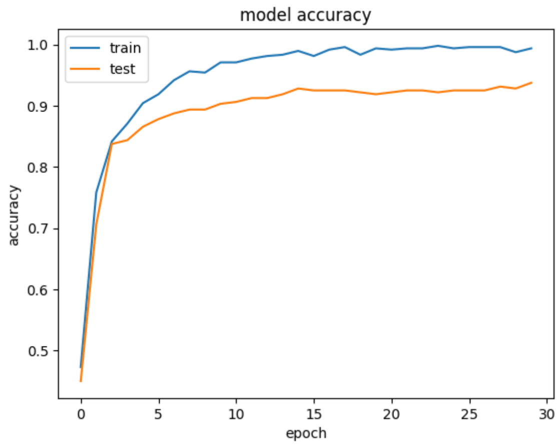

Figure 5. Model Accuracy

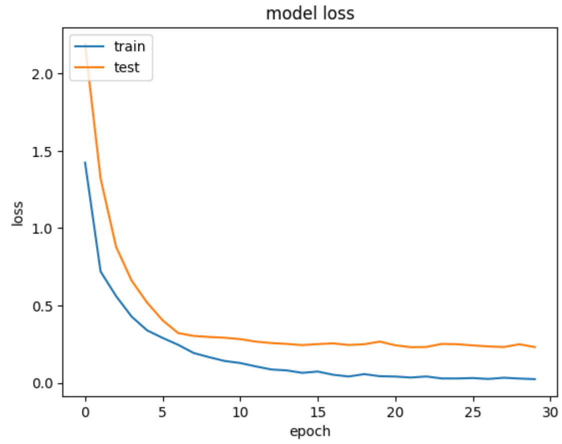

Figure 6. Loss Model

Model training results on train data and test data. Based on the results of trials by training 800 lung CT-Scan images with 4 different classes, and divided based on 60% train data and 40% test data with the CNN method, the accuracy of the train data was 99.46% and a loss of 0.14%. Obtained 93.75% for test data and loss of 23.16% which is visualized in the graphs in Figure 5 and Figure 6.

4. CONCLUSION

The system successfully detect nodule areas cancer in the picture CT Scan and classify type cancer in nodules using the method *CNN* by utilizing a *transfer learning* model *EfficientNet*. This system is necessary for development technique detection in the nodule area so that the system detection can detect the nodule area sufficiently accurate.

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