

# Wood Classification of Japanese Fagaceae using Partial Sample Area and Convolutional Neural Networks<sup>1</sup>

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## ABSTRACT

Wood identification is regularly performed by observing the wood anatomy, such as colour, texture, fibre direction, and other characteristics. The manual process, however, could be time consuming, especially when identification work is required at high quantity. Considering this condition, a convolutional neural networks (CNN)-based program is applied to improve the image classification results. The research focuses on the algorithm accuracy and efficiency in dealing with the dataset limitations. For this, it is proposed to do the sample selection process or only take a small portion of the existing image. Still, it can be expected to represent the overall picture to maintain and improve the generalisation capabilities of the CNN method in the classification stages. The experiments yielded an incredible F1 score average up to 93.4% for medium sample area sizes (200 × 200 pixels) on each CNN architecture (VGG16, ResNet50, MobileNet, DenseNet121, and Xception based). Whereas DenseNet121-based architecture was found to be the best architecture in maintaining the generalisation of its model for each sample area size (100, 200, and 300 pixels). The experimental results showed that the proposed algorithm can be an accurate and reliable solution.

**Keywords:** wood, microscopic image, sample selection, classification, convolutional neural network

## 1. INTRODUCTION

Wood is the most dominant forest product for commercial use in various industries as raw material and to support the daily life of humans, such as building materials, furniture, craft arts, and many others. In identifying the wood, the visual inspection of various wood tissues is a common method (Hwang *et al.*, 2020). Wood species are very diverse, but still have

unique characteristics that can be distinguished from each other. Therefore, an accurate and reliable wood classification system based on the image classification method needs to be developed.

Several previous works related with microscopic analysis of the wood surface can be mentioned as follows. Saverio *et al.* (2020) investigate wood characteristics of 8-year-old superior teak from Muna Island by observing macroscopic and microscopic anatomical

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characteristics. This study showed differences in the characteristics of the higher wood portion, wood texture, growing ring width, and wood specific gravity which were categorized as a Strength Class of III (Savero *et al.*, 2020). Furthermore, Jeon *et al.* (2020) researched the anatomical characteristics of *Quercus mongolica* which was attacked by oak wilt disease, the anatomical structure of infected wood, deadwood, and healthy wood. The results of the study that showed a big difference between wood affected by oak wilt and healthy wood was the tyloses ratio (Jeon *et al.*, 2020). Finally, Jeon *et al.* (2018) conducted a study on the characteristics of Korean commercial bamboo species (*Phyllostachys pubescens*, *Phyllostachys nigra*, and *Phyllostachys bambusoides*). The research resulted in crystal properties, vascular bundle, fiber length, vessel diameter, and parenchyma, as well as the length and width of the radial and tangential sections (Jeon *et al.*, 2018).

Salma *et al.* (2018) proposed a wood identification algorithm by combining Daubechies Wavelet (DW) and Local Binary Pattern (LBP) methods (Salma *et al.*, 2018) as the pattern extractor. The pattern was then classified by using support vector machine (SVM) classifier. Sugiarto *et al.* (2017) developed a wood identification algorithm based on cooperation between the histogram of oriented gradient (HOG) and the SVM classifier (Sugiarto *et al.*, 2017). Meanwhile, Kobayashi *et al.* (2019) developed a method for statistically extracting the anatomical features of Fagaceae (Kobayashi *et al.*, 2019). This approach could help to reveal some new aspects of wood anatomy that might be difficult in conventional observation. The next reference is reported by Hadiwidjaja *et al.* (2019). The paper implemented the LBP and Hough transform methods to improve the extract of the wood feature.

Classification has become one of the main topics that has attached much attention in recent years. Many methods have been developed for classification

purposes. Nowadays, the convolutional neural network (CNN) emerges as a powerful visual model with an outstanding performance in various visual recognition and classification problems, for instance, as presented in the papers of Yu *et al.* (2017), and Levi and Hassner (2015). Yu *et al.* (2017) developed an efficient CNN architecture to boost the hyperspectral image classification discriminative capability. Levi and Hassner (2015) proposed a simple convolutional net architecture that can be used even when the amount of learning data is limited. Their method was evaluated with the Adience benchmark for age and gender estimation and successfully outperformed other current methods. The Adience dataset is a dataset of face images acquired at common imaging conditions. Therefore, variations of object appearance, poses, and environmental light are found since the photos were taken in free situations. The CNN method can provide excellent classification results, but it still has a challenge in the number of data sets needed to make the classifier well trained (Yu *et al.*, 2017; Levi and Hassner, 2015; Maggiori *et al.*, 2016; Marmanis *et al.*, 2015).

Several previous studies that became references in the use of CNN in the classification and identification process include works of Kwon *et al.* (2019), Kwon *et al.* (2017) and Yang *et al.* (2019). In the first paper, Kwon *et al.* (2019) used the ensemble model LeNet2, LeNet3, and MiniVGGNet4 to classified Korean softwood with the F1 score reaching 0.98. In the second paper, Kwon *et al.* (2017) developed an automatic wood species identification system utilising CNN models such as LeNet, MiniVGGNet, and their variants. The research showed a sufficiently fast and accurate result with 99.3% accuracy score by LeNet3 architecture for five Korean softwood species. In the last paper, Yang *et al.* (2019) used the ensemble methods of two different convolutional neural network models, i.e., LeNet3 and NIRNet. The ensemble methods were applied to lumber species with the average

F1 score of 95.31%.

In this wood classification research, we attempted to identify the microscopic wood image. By following the successful example in the paper discussed earlier, the CNN method becomes one of the potential approaches to solve the microscopic wood image classification. In overcoming the small number of wood datasets to train the CNN classifier, as mentioned in several studies in the paragraph above, to get a good CNN classifier requires an adequate quantity of datasets in the training process. A sample selection process is proposed before the microscopic image of wood dataset enters the classification stage using the CNN method. Inside the sample selection process, the wood image is cropped into several sections at a specific size. We assumed that even though it only uses certain image segments, it has some characteristics that can distinguish one species from another, such as vessel size, the density of vessels, colour, and transverse wood fibre.

The remaining part is organised as follows. Section 2 presents the data sets used in the research, the sample selection process, the proposed CNN architectures, and the proposed classification algorithm. Section 3

furthermore presents all experimental results started from the sample selection, training, and testing results. The last section, Section 4, provides the conclusion and future work.

## 2. MATERIALS and METHODS





















### 2.1. Wood Dataset

The wood species is commonly recognised by examining a small piece of wood as a sample. In this Japanese Fagaceae wood classification research, we observed the microscopic features of the wood. The commonly observed microscopic features are vessels, parenchyma, rays, and others (Schoch *et al.*, 2004; Prislán *et al.*, 2014). Observations are made by collecting micro cores and observing them under a light microscope (Prislán *et al.*, 2014).


































































This research used a wood dataset obtained from the Research Institute of Sustainable Humanosphere (RISH), Kyoto University, Japan. The dataset consisted of microscopic images of nine species of Fagaceae woods. Table 1 presents the list of wood.

Each image in the dataset was stored as a TIFF file

**Table 1.** Nine species of Japanese Fagaceae

Academic Name	Japanese Common Name	Number of Individual Wood	Number of Images	Data and Kyoto University ID (KYOW number)				
<i>Castanea crenata</i>	Kuri	10	20					
				10246	10293	10294	10997	10997
<i>Fagus crenata</i>	Buna	10	12					
				11596	12944	13755	13760	13830
<i>Fagus crenata</i>	Buna	10	12					
				458	972	1116	1294	8305
<i>Fagus crenata</i>	Buna	10	12					
				458	972	1116	1294	8305

**Table 1.** Continue

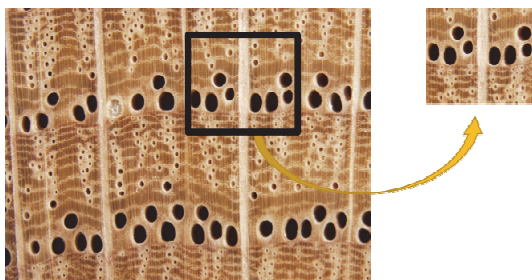
Academic Name	Japanese Common Name	Number of Individual Wood	Number of Images	Data and Kyoto University ID (KYOW number)				
<i>Fagus japonica</i>	Inubuna	9	12					
				354	1613	5368	8306	8308
								
				13836	13955	17510	18594	
<i>Quercus accuta</i>	Akagashi	10	19					
				342	1615	2867	2957	4920
								
				8312	9277	13837	14477	14679
<i>Quercus actissima</i>	Kunugi	10	30					
				60	1120	1617	5540	5668
								
				8314	8315	12092	15352	17763
<i>Quercus crispula</i>	Mizunara	10	18					
				62	411	462	2963	8203
								
				8320	10297	11421	13841	
<i>Quercus gilva</i>	Ichiigashi	10	26					
				2958	4973	5535	5663	8317
								
				9279	11593	13839	14829	18722
<i>Quercus glauca</i>	Arakashi	10	15					
				5536	5664	9280	12846	12847
								
				12942	13743	15619	17789	18774
<i>Quercus variabilis</i>	Abemaki	7	13					
				1620	6576	8332	8333	10328
								
				14129	17782			

with the  $4140 \times 3096$  - pixel dimension. The existing dataset was divided into three groups: training data, validation data, and test data. Data for test consisted of 27 images (3 images from each species), data for validation consisted of 18 images (2 images from each species), and data for train consisted of 120 images (as the rest of images).

## 2.2. Selection of Featuring Sub-images

The proposed method used a small segment of the image as an input. This procedure was defined by considering the size of the original image and limited dataset availability of 165 images. The image had a dimension of  $4140 \times 3096$  pixels with a size of approximately 38 MB. The implementation of an image processing algorithm on an image with a large size could cost the computer resources and computational time. Moreover, as informed from the previous section, the minimum number of datasets can result in overfitting and low generalisation capabilities of the CNN model.

The process of taking specific segments of the input image consisted of 3 categories based on the sample area size. The first category was small that would crop the image with a size of  $100 \times 100$  pixels and produced 1230 sample areas for each image. The second category was medium that would crop images with a size of  $200 \times 200$  pixels and produced 300 sample areas for each image. Moreover, the last one was the



**Fig. 1.** The illustration of the sample selection process on the image.

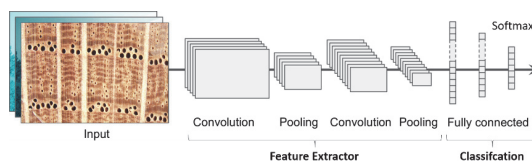
large category to crop images with a size of  $300 \times 300$  pixels and produced 130 sample areas for each image.

Fig. 1 depicts the more specific and detailed features provided by the selected area sample. The CNN model trained on specific and detailed features resulted in a CNN model that had excellent generational capabilities though with the limited dataset provided.

## 2.3. Implementation of Convolutional Neural Networks

CNN is a neural network architecture used for prediction when the input observations are images, which is the case in a wide range of neural network applications (Seth, 2019). In principle, CNN mimics the visual cortex. It is based on studies as conducted by Neocognitrons in 1980 (Fukushima, 1980), which gradually evolved into what is now called as convolutional neural networks (Géron, 2019). CNN is very similar to ordinary neural networks and still consists of neurons with weights that can be learned from data. Each neuron receives several inputs and performs a dot product. In general, CNN has three main layers: the convolution layer, pooling layer, and fully connected layer (Sewak *et al.*, 2018).

Fig. 2 shows that the typical CNN architecture piles up several convolutional layers (followed by activators), and pooling layer. Several convolutional layers (followed by activators), other pooling layers, and so on until the final layer produces several predictions (for instance, the softmax layer outputting several esti-



**Fig. 2.** Convolutional Neural Networks (CNN) architecture.

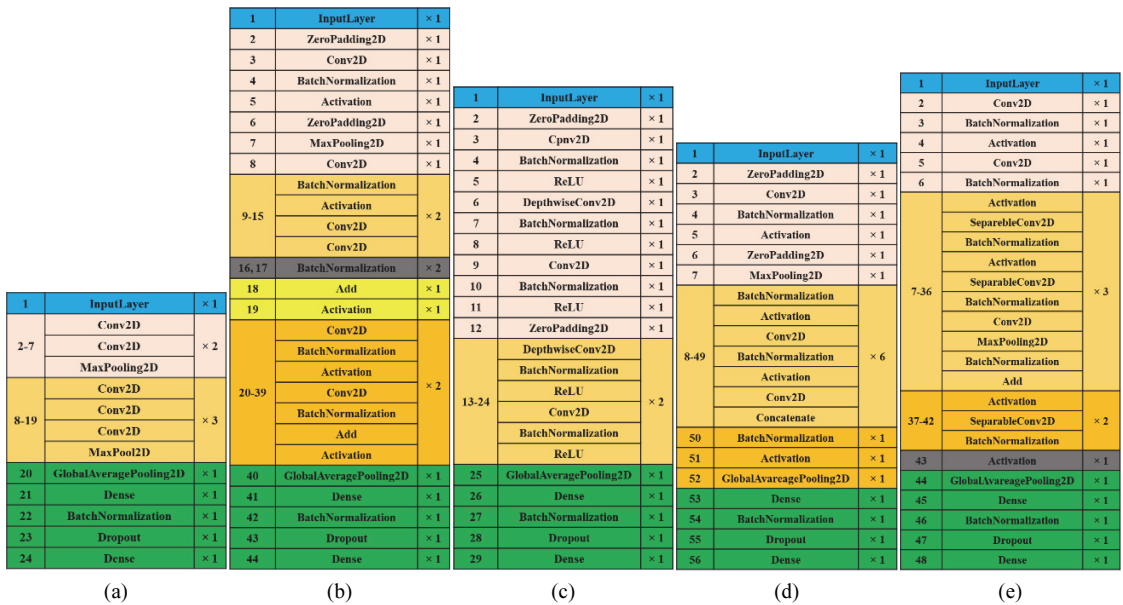
mated class probabilities) (Géron, 2019).

In practice nowadays, very few people train entire convolutional networks from scratch. They do not choose this way for several reasons, such as many data required in the process to train the CNN model; lots of parameters (weights) to be trained and to avoid overfitting. The transfer learning is a solution for the problem. Five CNN architectures have been designed by applying transfer learning to fit in the sample selected data set.

Transfer learning is a machine learning technique that reuses the trained and developed models from one task into the second task. It refers to the situation whereby what has been learned in one setting is exploited to improve optimization in another setting (Hussain *et al.*, 2019). Some examples of popular pre-trained models for transfer learning are VGG-16,

MobileNet, ResNet-50, and DenseNet.

Fig. 3 illustrates the architecture of each model. Each base architecture was cut into a particular network depth, such as VGG16 (Simonyan and Zisserman, 2014) at the 19<sup>th</sup> layer, ResNet50 (He *et al.*, 2016) at the 39<sup>th</sup> layer, MobileNet (Howard *et al.*, 2017) at the 23<sup>rd</sup> layer, DenseNet121 (Huang *et al.*, 2017) at the 51<sup>st</sup> layer, and Xception (Chollet, 2017) at the 42<sup>nd</sup> layer. All layers were cut after the specified layers. Furthermore, a new fully connected layer would be used to fit the nine species/class of wood. The use of shallow network depth aimed to prevent the network from losing the essential features of the wood. The deeper the network, the more detailed the features will be produced; and this can affect the sample selected image with the features that are sufficiently detailed to be lost.



**Fig. 3.** Five architectures of CNN, VGG16 (a), ResNet50 (b), MobileNet (c), DenseNet121 (d), and Xception (e) based architecture. For each architecture, the first column is the layer number, the second and the third one is the layer type, and the number of blocks, respectively. Colour differences indicate the differences in architectural blocks. Light blue blocks indicate input layers, green blocks indicates fully connected layers, and light orange, grey, gold, yellow, and orange blocks indicate feature extractor layers.



## 2.4. Proposed Algorithm

Algorithm development consisted of two main steps. The training process initiated the step (Fig. 4) followed by the testing process (Fig. 5) as the second step.

The training process began with a sample selection process, as described in subsection 2.2. Furthermore, each architecture as in subsection 2.3 was trained in each sample selection size category (small  $100 \times 100$  pixels, medium  $200 \times 200$  pixels, and large  $300 \times 300$ ), therefore each architecture could produce 3 models, and in total for 5 architectures, there would be 15 models.

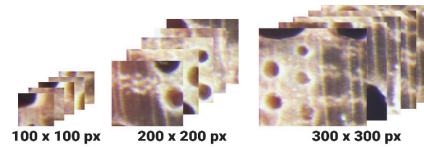
In the testing process, augmentation data would be added to the test sets. The addition of data augmentation aimed to add data variation and make the testing process able to describe a more general situation. The augmentation process was carried out by rotating the image, thereby increasing the total number of test data to 54 images. Furthermore, test sets entered the sample selection stage. However, the difference was that not all sample areas for each image was going to be used. The optimal number of sample areas would be sought, which could produce high accuracy while still consid-

ering computational costs. For example, for one image with a sample area of one size (100, 200, or 300), it would take five images. Furthermore, all sample area images were classified by each CNN model. From all prediction results, the mode value was searched to be the final prediction result for each image (the real image). Fig. 5 illustrates this process.

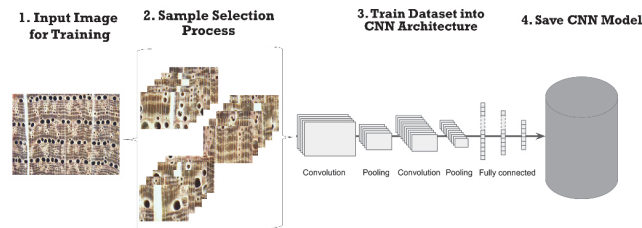
## 3. RESULTS and DISCUSSION

### 3.1. Sample Selection Process Analysis

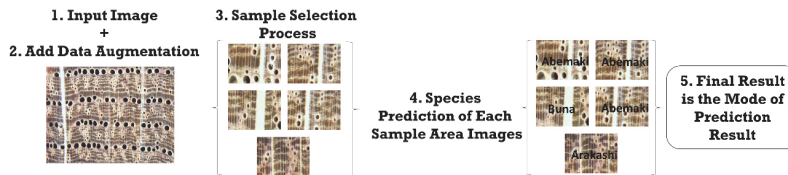
In the proposed algorithm, as described in subsection 2.4, every wood image data must be entered into the sample selection process. The sample selection process produced three categories of sample areas (small, medium, and large) as illustrated in Fig. 6.



**Fig. 6.** Sample selection results for *Quercus variabilis* species (small, medium, and large sample area).



**Fig. 4.** The training process in getting the CNN model.



**Fig. 5.** The testing process in getting the classification result.

The training process used all sample areas from each original image (1230 sample areas for small size, 300 sample areas for medium size, and 130 sample areas for large size). Meanwhile, for the testing process, we sought the most optimal number of sample areas with accuracy and computational cost. Fig. 7 presents ten trials using different numbers of data samples (1, 3, 5, 7, 9, 11, 13, 15, 21, and 25).

Large sample area sizes and VGG16 architecture were used in this process. The results of this process analysis would be used in the next process. The most optimal result was achieved when the number of samples in the test set was 5. The next process was to

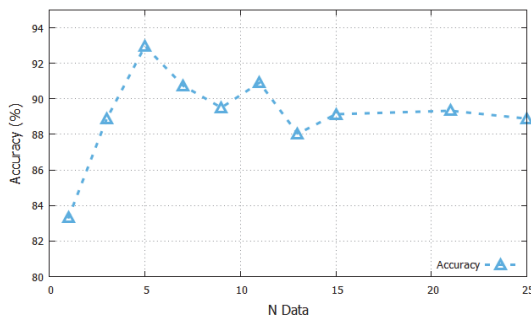


Fig. 7. The correlation between the number of test sets and the resulting accuracy.

evaluate 15 CNN models using the number of sample areas defined in this section.

### 3.2. Training Process Analysis

The training process for all CNN models used the same parameters to produce the valid benchmarks. The first training experiment set the following parameters: the number of epochs (30 epochs), learning rate (0.0001), and the optimiser (Adam optimiser). If the training accuracy has not increased in 10 epochs, the training process would be terminated without waiting for the maximum number of epochs. Furthermore, if in 5 epochs training process did not increase, the learning rate would be reduced by multiplying it by a factor value of 0.6. By lowering the learning rate, the process of updating the weight became smoother to increase accuracy. A total of 15 training processes have been completed. Fig. 8 displays a history of training from the VGG16 architecture with a sample size area of 200 pixels.

Fig. 8 shows the architecture designed to accept wooden datasets properly. From each epoch, score accuracy continued to increase, and score loss continued to decrease. Scores between the validation and the

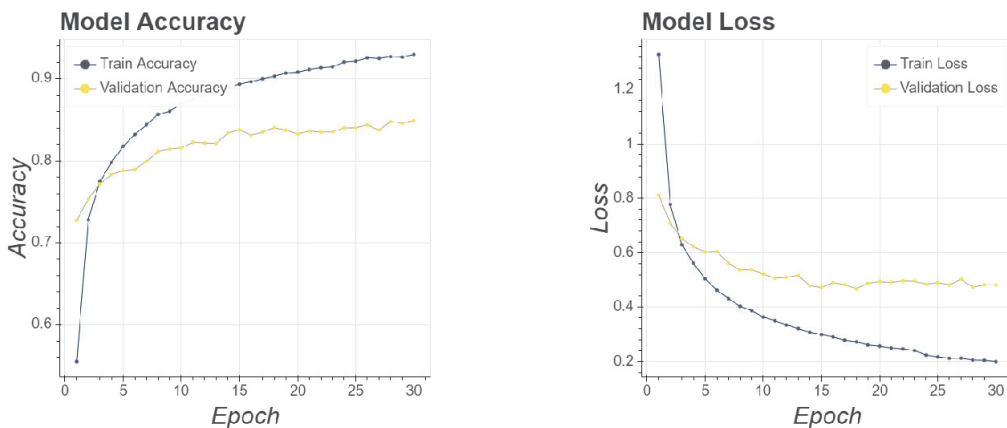


Fig. 8. The accuracy and loss progressions are plotted based on the results of the CNN model with the partial sample area.



training were not far apart showing that the model did not overfitting. Furthermore, to test the performance and generalisation of the models, a testing process was carried out on the wood testing dataset that has been prepared.

### 3.3. Testing Process Analysis

The testing process was done by evaluating each CNN models with the prepared testing data set. In detailed, the results of the testing process are presented in Table 2.

Based on test results, the accuracy score generally increased following the size of the input image. With a sample area size = 100, the average F1 scores of VGG16, ResNet50, MobileNet, DenseNet121, and Xception were 92, 95, 86, 94, and 92% respectively. With a sample area size = 200, the average F1 scores of VGG16, MobileNet, DenseNet121, and Xception increased to 92, 87, 98, and 96% respectively, and for ResNet50 it decreased to 94%. Finally, for sample area size = 300, the average F1 scores increased for VGG16 and Xception to 94, and 98%, ResNet50 and MobileNet decreased to 89, and 84%, and for DenseNet121 it was unchanged from 98%.

Test result data in Table 2 provides a correlation

between the size of the sample area and the capabilities of the resulting CNN model. The size of the sample area is related to the number of features contained in the image. As shown in Fig. 6, the smaller sample area could make the surface features of the wood disappeared due to the cutting process. The samples of medium category area appeared as the most optimal size in maintaining features contained in wood images. This area could create samples containing the most detailed and specific wood features compared to other 2 categories. Proved by the average F1 score of the medium size, each CNN architecture achieved 93.4%. Although the large category sample area had more features, it was not more specific than the medium category sample area. Thus, the results from large area samples did not produce a more general CNN model compared to medium area samples.

Furthermore, Table 2 informs that the DenseNet121-based model became the most general CNN architecture for all sample area sizes and considered to be the best CNN model for Japanese Fagaceae wood identification. DenseNet121-based produced F1 scores above 94% for every size of the sample area (100, 200, and 300 pixels). Meanwhile, MobileNet-based became the CNN architecture providing the lowest accuracy. However, it should be taken into account to

**Table 2.** CNN models performance evaluation by applying the proposed algorithm

		VGG16	ResNet50	MobileNet	DenseNet121	Xception
Small	Precision	92%	93%	87%	95%	94%
	Recall	93%	94%	87%	94%	93%
	F1	92%	95%	86%	94%	92%
Medium	Precision	94%	96%	89%	98%	97%
	Recall	93%	94%	87%	98%	96%
	F1	92%	94%	87%	98%	96%
Large	Precision	95%	91%	87%	98%	98%
	Recall	94%	89%	85%	98%	98%
	F1	94%	89%	84%	98%	98%
Weight Size		60 MB	4.5 MB	1.3 MB	5.9 MB	30 MB

use, with the given size of the resulting weight to be the lightest. Although accuracy is not as high as other architectures, it can be the most portable architecture option in use.

To prove how the proposed algorithm could overcome the problems of generalization ability, dataset limitation, and accuracy, several comparisons have been made by making a CNN model that did not go through the sample selection process. In other words, it directly used the original image. As a sample of the training process carried out, Fig. 9 displays the history of the VGG16 architecture training process.

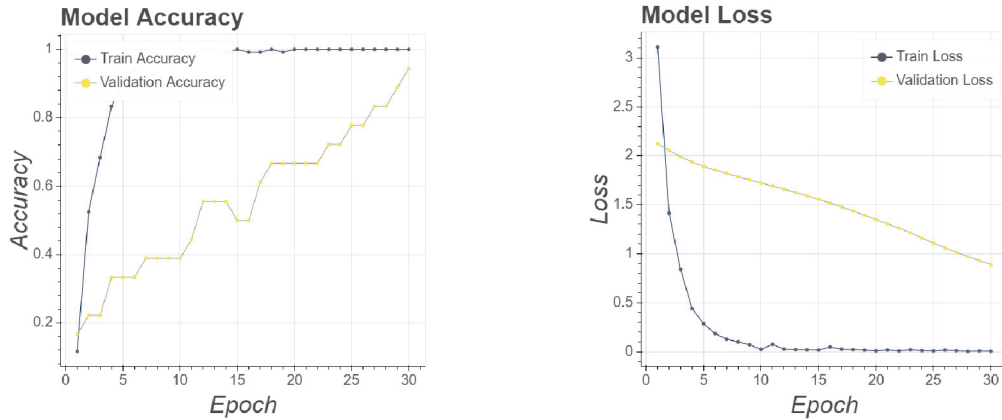
The training process used a similar architecture and parameters as in the training process described in Section 2.4. However, this stage excludes the sample selection process. It resulted in 94% validation accuracy values and validation loss values continuing to approach 0. Implementation of the partial sample area during the training stages does not significantly im-

prove compared to the step with the whole sample area. However, the testing stage obtained different results. As presented in Table 3, most of the CNN architectures provide parameters values at lower levels.

The unfavourable testing results in Table 3 indicated that the model was overfitting and had low generalizability. This comparison showed the advantages and benefits of using the sample selection process. With the similar limited dataset, the sample selection process could overcome the overfitting problem and the low generalizability of the CNN model.

#### 4. CONCLUSION

CNN has become a popular deep learning model widely used for image and visual analysis. In the applications, it requires many datasets to learn a robust classifier. In this wood classification research, the microscopic images taken from the laboratory were in



**Fig. 9.** The accuracy and loss progressions are plotted based on the results of the CNN model with the whole image area.

**Table 3.** CNN models performance evaluation without applying the proposed algorithm

	VGG16	ResNet50	MobileNet	DenseNet121	Xception
Precision	86%	88%	51%	71%	83%
Recall	81%	81%	63%	67%	70%
F1	80%	81%	54%	62%	70%

a limited number and had a large size of around 38 Mb and a dimension of  $4140 \times 3096$  pixels. Therefore, a well-designed algorithm has been proposed, which could handle the dataset limitations and identify wood species accurately and efficiently. The proposed algorithm principle was to implement the sample selection process before the dataset entered the classification stage using VGG16, ResNet50, MobileNet, DenseNet121, and Xception based architectures.

The experimental results showed that the sample selection process could produce CNN models with some good generalisation capabilities. The experimental results proved that by making sample areas more specific and detailed, it can produce a powerful CNN model. The medium area sample category ( $200 \times 200$  pixels) appeared as the most optimal sample area. While the CNN DenseNet121 architecture became the most optimal architecture when used with medium sample areas.

The availability of more microscopic images is recommended in the future to improve the classification accuracy of the proposed algorithm. The results of this wood classification research are expected to be widely used. With a small size of the CNN model, it can be potentially applied to the mobile devices.

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## DATA AVAILABILITY STATEMENT

The microscopic images used in the experiment are available from Kyoto University Research Information Repository (<https://repository.kulib.kyoto-u.ac.jp/dspace/>

handle/2433/250016).

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