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Implementation of Convolutional Neural Network for Classification of Density Scale and Transparency of Needle Leaf Types

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ABSTRACT

Crown density and transparency are among the parameters in determining forest health using magic card. This is still less effective because it only relies on direct vision. Therefore, a more sophisticated and accurate application using digital image technology is needed. Convolutional Neural Network (CNN) is designed to help recognize objects in images with various positions. There are 1000 images of needle leaf types with ten classes of crown density and transparency for every kind of needle leaf, including araucaria heterophylla, cupressus retusa, pine merkusii, and shorea javanica, which are classified using AlexNet. AlexNet is a CNN architecture that has eight feature extraction layers. The AlexNet model succeeded in classifying coniferous trees on the scale of density and crown transparency with an accuracy level of 87.00% for araucaria heterophylla, cupressus retusa 96.00%, merkusii pine 86.00%, and shorea javanica 95.00%. Although some errors were still found in classification, this was caused by similar patterns and similar image positions. It is hoped that the results of this research will be used in monitoring forest health in the future.

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1. INTRODUCTION

A forest is an ecosystem consisting of a large area of land that contains various kinds of natural resources for life. It is characterized by the dominance of trees in its environment, which are connected and cannot be separated [1]. Indonesia is one of the countries that has the largest area of tropical rainforest in the world and is number three after Brazil and Africa which has high biodiversity [2]. Wan Abdul Rachman Grand Forest Park (Taman Hutan Raya Wan Abdul Rahman or Tahura WAR) is a forest area declared a conservation area by the government, and its management is divided into several blocks [3]. Indonesia has various types of forests, including healthy and unhealthy ones. Forest health can be seen from the condition of the trees that make up the forest. A tree is considered healthy if it can perform its physiological functions well. It is resistant to disturbances such as pest attacks and other environmental factors [4]. Forest health can be monitored using the Forest Health Monitoring (FHM) method. Parameters used in this method include crown ratio (Live Crown Ratio-LCR), crown density (Cden), crown transparency (Foliage Transparency-FT), dieback (CDB), crown diameter (Crown Diameter Width-CdWd) [5].

The intensity of sunlight entering and remaining in the tree crown can be measured using a crown density and transparency scale card. Crown density and transparency are among the parameters in determining forest health. Density that has a value of ≥55% and transparency of 0-45% can be said to be a healthy forest [6]. The crown density and transparency assessment percentage are the same for all tree types. Conifers (softwood) or needle-leaf wood are one type of tree that produces wood. The use of density and transparency scale cards, also known as magic cards, is still less effective because they only rely on direct sight and then adjusted to the scale on the card, the accuracy of which is only calculated according to the eye, so a more sophisticated and accurate application is needed. Therefore, computational techniques using digital images are applied to facilitate the process.

Deep learning is part of machine learning that allows computers to learn lessons from past experiences [7]. In deep learning, artificial neural networks and various machine learning algorithms have more than one layer level, imitating the structure of biological neural networks. This layer level is widely used to extract features, perform transformations, and analyze patterns using learning methods that can be supervised or unsupervised [8]. Observations made with deep learning can take the form of analysis and classification of image patterns. An essential type of network in the deep learning domain is a convolutional neural network (CNN). CNN can process large amounts of data to achieve promising results. The aim is to process two-dimensional data with a basic convolutional layer [9]. CNN has several architectures, one of which is AlexNet [10]. AlexNet was one of the first deep convolutional networks to achieve high accuracy on the ImageNet LSVRC-2012 challenge, with an accuracy of 84.7%. AlexNet can receive input or image input in the form of RGB. AlexNet is an architectural model consisting of 5 convolution layers, three pooling layers, two dropout layers, and three fully connected layers, and it utilizes the Rectified Linear Unit (RELU) activation function [11].

Previous research related to the use of the AlexNet architecture for weed detection. An image dataset containing 15336 segments with a granularity of 3249 soil, 7376 soybeans, 3520 grasses, and 1191 broadleaf weeds was used. Partition for train and test has been done with a ratio of 70:30. Simulation results show that the conventional Artificial Neural Network (ANN) algorithm provides an accuracy of 48.09%. In comparison, the AlexNet algorithm provides an accuracy of 99.8% on the test dataset [12]. Previous research related to the use of density and canopy transparency scale cards has been used to assess the state of forest health in the plant and animal collection area of the Wan Abdul Rachman Grand Forest Park, Lampung Province [13]. This research uses AlexNet architecture training because this model can classify images with various classes. Therefore, this study aimed to classify the level of density and transparency of needle leaves based on scale cards on four different types of trees. The dataset applied is a collection of needle leaf images with four variations of needle leaf types. One thousand images represent each type of needle leaf, and each image is classified into ten classes based on a scale of density and degree of transparency, ranging from 5% to 95%.

2. RESEARCH METHODOLOGY

In this research, the CNN algorithm with the AlexNet architectural model was used to classify the density level and transparency level of the needle leaf crown. The research process is described in detail, as shown in figure 1[14].

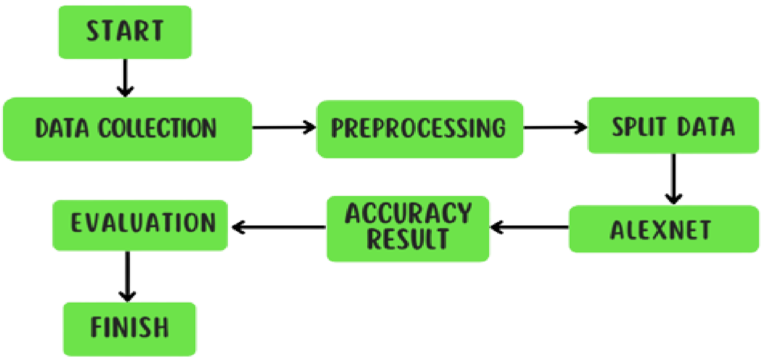

Figure 1. Research Method

2.1 Data Collection

The first step is to collect images of needle leaves used in this research. Image capture was carried out from March to May 2023 in two locations, namely Tahura WAR Kemiling, Bandar Lampung, and the University of Lampung area. The types of needles used in the research include araucaria heterophylla, cupressus retusa, pine merkusii, and shorea javanica.

2.2 Preprocessing

Preprocessing is the initial step to prepare the original data or image before the data is applied to the CNN algorithm [15] and simplifies computing time for large tasks [16]. The needle leaf images that have been collected are then labeled or classified based on density scale class and title transparency. This labeling was assisted by 15 respondents who were students at the University of Lampung. The dataset that has been labeled is then changed to the image pixel size of 224 x 224 [17]. This dataset has different numbers for each class, so it is necessary to apply data augmentation methods [18]. Data augmentation is a technique that may be used to improve data significantly [19]. The data augmentation method functions to increase the number of images. The augmentations used are vertical flip, horizontal flip, and zoom [20].

2.3 Split Data

After the dataset is prepared, the next step is to separate the data into three parts: training, testing, and validation. Training data is needed to train the model [21]. In this case, about 70% of the images are used for training data. Test data is used to test the model's performance [22], covering around 20% of the total image. Validation data supports the model training process with training data [23]. In the process of training with training data, validation is also used to check the suitability of the data received by the model. This validation data comprises approximately 10% of the total images.

2.4 AlexNet Model

The research uses the AlexNet model. AlexNet is one of the CNN designs that won achievements in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) competition 2012. The competition focused on large-scale image classification tasks [24]. AlexNet consists of eight layers, including 5 convolution layers, some of which are followed by max-pooling layers, Rectified Linear Unit (RELU) activation, as well as 3 fully connected layers with a softmax activation function [25]. Training models using the AlexNet architecture, tools such as Google Colab and Jupyter Notebook are used. In this process, several control parameters are set, such as the number of epochs, batch size, optimizer choice, and learning rate, all of which play an essential role in determining the extent of the model's success in the training and testing stages [26]. The parameter values applied in AlexNet modeling are shown in table 1.

Table 1. Parameter Values

Hyperparameter	Type/Values
Epoch	20
Batch size	8
Optimizer	Adam
Learning-rate	0.0001

Table 1 above contains the hyperparameter values applied in this research, including 20 epochs. Epoch is a parameter that determines the number of iterations in the training process. Batch size indicates the number of samples taken from the training data and grouped in one batch. The batch-size value is 8, while the optimizer used is Adam, and the learning rate is set at 0.0001. The learning rate plays a role in regulating the algorithm's speed to achieve an optimal model.

2.5 Accuracy Results

AlexNet training model accuracy indicates the model's ability to recognize, apply, and classify patterns. A high level of accuracy in training models indicates that the model has mastered the training data well. However, this only sometimes reflects how much a model can perform when anomalies exist in never-before-seen data.

2.6 Evaluation

The confusion matrix measured the evaluation of density scale classification results and crown transparency. Confusion matrices are used to describe model performance, and from confusion matrices, standard metrics can be calculated and used to evaluate model performance [27]. Which includes accuracy, precision, recall, and F1-score values to describe the extent of the model's success [28].

3. RESULTS AND DISCUSSION

This section will present the results and analysis of density and transparency classification for needle leaf types using CNN with the AlexNet architecture. The evaluation and implementation results of the classification process will be described in this section. The main focus of this section is to review the accuracy levels and evaluation models for each type of coniferous tree.

3.1 Data Collection

This research uses images depicting four different varieties of needle leaves. For each type of needle leaf, crown density and transparency scale classes ranging from 5% density to 95% transparency were identified based on the assessments of 15 respondents.

3.2 Preprocessing

The dataset, which consisted of 100 images for each class, was then saved to google drive and Tesla's computer. Each needle leaf-type image is placed in the directory corresponding to its class label. The amount of data for each type of needle leaf for the crown density and transparency scale is shown in table 2.

Table 2. Needle Leaf Type Image Dataset

Kelas		Jenis Pohon			
Kerapatan	Tranparansi	Araucaria Heterophylla	Cupressus Retusa	Pinus Merkusii	Shorea Javanica
5%	95%	100	100	100	100
15%	85%	100	100	100	100
25%	75%	100	100	100	100
35%	65%	100	100	100	100
45%	55%	100	100	100	100
55%	45%	100	100	100	100
65%	35%	100	100	100	100
75%	25%	100	100	100	100
85%	15%	100	100	100	100
95%	5%	100	100	100	100
Total		1000	1000	1000	1000

Table 2 above is a dataset that has undergone a process of changing pixel values and augmentation to produce the same number of images for each class.

3.3 Split Data

Once the dataset is ready, the next step is to divide it into three parts, namely 70% training data, 10% validation data, and 20% testing data. This data division produces 700 data points for training, 100 data points for validation, and 200 data points for testing on each type of coniferous tree.

3.4 AlexNet

This research uses the AlexNet model running on a Tesla K80 GPU by using parameter values according to table 1. The model processes an input layer measuring 224 x 224 pixels with three color channels (RGB). The AlexNet model uses 11 layers with ReLu activation after the convolution layer. The pooling layer in the AlexNet model used is max pooling. The max pooling layer connected to the convolution layer has a filter size of 3x3, with a function to reduce the dimensions of the needle leaf image and the number of parameters required for the network. The results of the arrangement of convolution layers and max pooling are the features that have been extracted, which are then forwarded to the fully connected layer with 4096 neurons per layer. The fully connected layer also has an activation function, namely softmax. AlexNet has an advantage in the number of parameters, which means AlexNet is a CNN architecture that prioritizes model depth. AlexNet has 11 layers, and its training parameters reach 70 million parameters. This depth helps carry out the model training process on the dataset. The AlexNet architecture on needle leaves is shown in figure 2 [29].

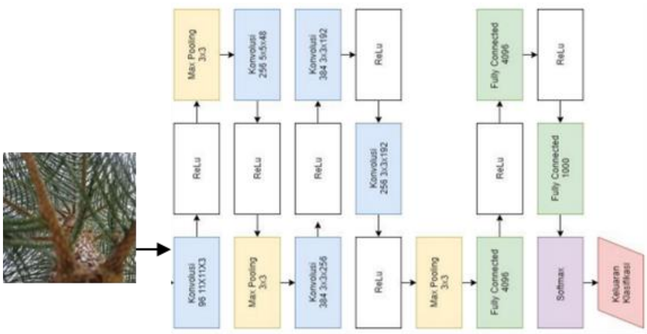

Figure 2. AlexNet architecture on needle leaves

3.5 Accuracy Result

The accuracy results of the AlexNet model on coniferous trees based on crown density and transparency classes are as follows:

a. Araucaria Heterophylla

The level of model accuracy on the Araucaria heterophylla tree using GPU Tesla K80 obtained an accuracy of 87.00%.

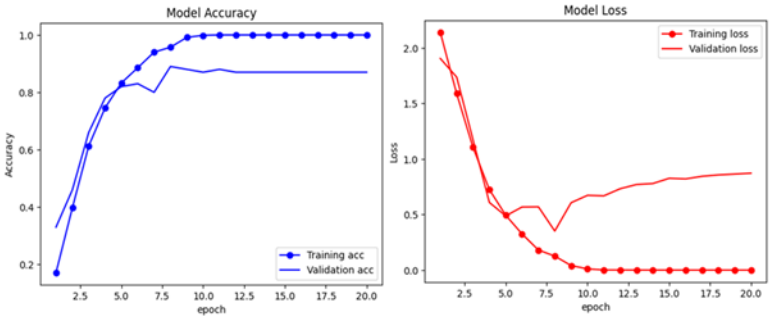

Figure 3. Accuracy and loss graph of AlexNet araucaria heterophylla model with Tesla K80 GPU

The graph shown in figure 3 above depicts the accuracy and loss results during the AlexNet model training process using the Tesla K80 GPU. In general, the model accuracy level increases from epoch to epoch. It can be seen that there was a decrease in accuracy at the 6th epoch, then increased at the 7th epoch but decreased again at the 10th epoch. After that, there was an increase in accuracy at the 14th epoch, and remained stable until the 20th epoch. It should be noted that instability in accuracy levels during the training process is considered normal, as the model adapts to data it has never encountered. Accuracy on training data reached 100%, while on validation data, it was 87.00%. The loss graph on the AlexNet model for the Araucaria Heterophylla tree shows a decrease, although it fluctuates. An increase in losses was seen in the 10th epoch, then fell again before experiencing an enhancement in the 6th epoch, followed by a decline in the 8th epoch. Increased losses occurred once again in the 9th epoch. The final value of a loss on the training data is around 0.0070%, while on the validation data, it reaches 87.21%. The graph of the AlexNet model using the Tesla K80 GPU shows that the increase in loss only occurs slowly from epoch to epoch, which shows that the process of testing this model does not require effort.

b. Cupressus Retusa

The model accuracy level for the Cupressus retusa tree using the Tesla K80 GPU obtained an accuracy of 96.00%.

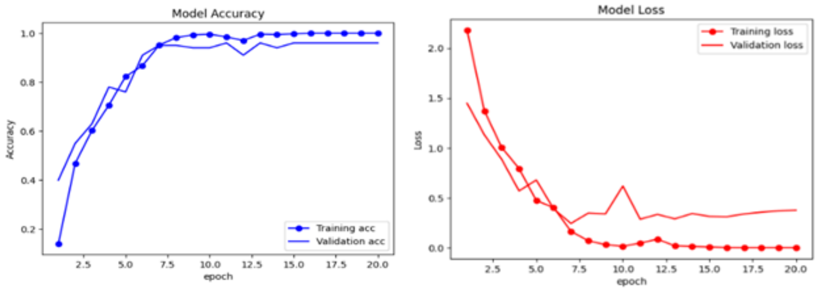

Figure 4. Accuracy and loss graph of AlexNet cupressus retusa model, with Tesla K80 GPU

The image above shows the instability of the model accuracy level, which can be seen from epoch 3 to epoch 14, which continuously fluctuates between increasing and decreasing. However, the graph shows a more consistent increase in epoch 15 to 20. The accuracy level on the training data reached 100%, while on the validation data, it reached 96%. Meanwhile, in the graph of the loss value of the AlexNet model for the Cupressus Retusa tree, there is a decrease even with fluctuations. The increased loss occurred at epochs 5, 8, and 10, then decreased before rising from epoch 14 to epoch 20. The final loss value on the training data was around 6.49%, while on the validation data, it reached 37.54%.

c. Pinus Merkusii

The model accuracy level for the Cupressus retusa tree using the Tesla K80 GPU obtained an accuracy of 86.00%.

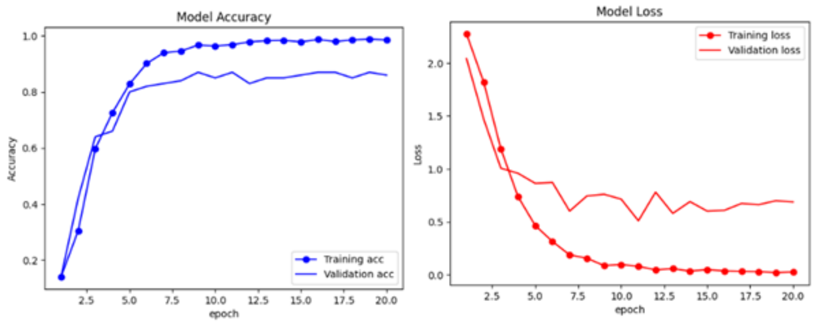

Figure 5. Accuracy and loss graph of the AlexNet pine merkusii model with Tesla K80 GPU

The image presented depicts the model's accuracy level, which experienced fluctuations until it reached epoch 20. Instability in the accuracy level during the testing process is considered normal because the model still adapts to data that has never been encountered before. The accuracy rate on training data reached 98%, while on validation data, the accuracy rate reached 86%. Meanwhile, the loss value graph shows a decline, although with fluctuations. An increase in loss was seen at epoch four and continued to fluctuate until epoch 20. The final loss value on the training data was around 0.78%, while on the validation data, it reached 68.89%.

d. Shorea Javanica

The model accuracy level for the Cupressus retusa tree using Google Colab obtained an accuracy of 95.00%.

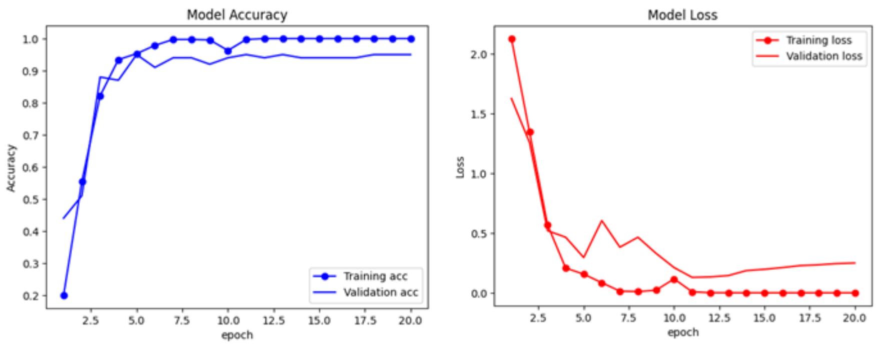

Figure 6. Accuracy and loss graph of AlexNet shorea javanica model, with Tesla K80 GPU

The image above shows that the model accuracy level at epoch 4 decreased and began to increase at epoch 5. This increase became more stable, starting from epoch 10 to epoch 20. Fluctuations in accuracy levels during the testing process are considered standard because the model is still adapted to data that has never been studied. Accuracy on training data reached 100%, while on validation data, it reached 95.00%. Meanwhile, the loss value graph has decreased, although with fluctuations. There was an increase in loss at epoch 6, followed by a decrease at epoch 7, which continued to fluctuate until epoch 10. After that, a more stable decrease started from epoch 11 to epoch 20. The final loss value on the training data was around 0.0013%, while it reached 0.25% on validation data. The graph of the AlexNet model using a Tesla K80 GPU shows that the improvement only occurs slowly from epoch to epoch, indicating that this model does not require much effort during the testing process.

3.6 Evaluation

The evaluation model for images of coniferous trees based on canopy density and transparency classes is as follows:

a. Araucaria Heterophylla

The accuracy results of the AlexNet model test for the Araucaria heterophylla tree on the K80 GPU machine were 93.00%.

Table 3. Precision, recall, f1-score AlexNet architecture of araucaria aeterophylla trees

Needle Leaf Density and Transparency Classes	Result		
	Precision	Recall	F1-Score

D5, T95	84.00%	84.00%	84.00%
D15, T85	100%	80.00%	89.00%
D25, T75	100%	96.00%	98.00%
D35, T65	100%	100%	100%
D45, T55	100%	100%	100%
D55, T45	74.00%	81.00%	77.00%
D65, T35	95.00%	90.00%	93.00%
D75, T25	100%	100%	100%
D85, T15	88.00%	100%	93.00%
D95, T5	100%	100%	100%
Accuracy		93.00%	
Eror		7.00%	

Table 3 shows that in classes with densities of 15, 25, 35, 45, 75, and 95, the highest precision values were achieved, reaching 100%. Meanwhile, density class 55 has the lowest precision value, 74.00%. This happens because there are six false positive (FP) values in the density class 55, which should partly be three values for the density class 5, 2 values for the density class 25, 2 values for the density class 15, and 1 value for the density class 85. The precision value reflects the extent to which the model can identify samples that belong to the positive class (true positive, TP) among samples that are predicted to be in the positive class (TP and FP). Meanwhile, density classes 35, 45, 75, 85, and 95 obtained the highest recall values, reaching 100%. Density class 15 has the lowest recall value, namely 80.00%. This is caused by three false negatives (FN) in density class 55, which should be predicted as one value of density class 5 and 2 values of density class 25. Recall measures the extent to which the model can identify all samples that should be included in the positive class (TP), among all actual samples is the positive class (TP and FN).

b. Cupressus Retusa

The accuracy results of the AlexNet model test for Cupressus retusa trees on Google Colab were 95%.

Table 4. Precision, recall, f1-score AlexNet architecture of cupressus retusa trees

Needle Leaf Density and Transparency Classes	Result		
	Precision	*Recall*	*F1-Score*
D5, T95	87%	80%	83%
D15, T85	94%	100%	97%
D25, T75	100%	100%	100%
D35, T65	100%	100%	100%
D45, T55	93%	100%	97%
D55, T45	95%	100%	98%
D65, T35	100%	90%	95%
D75, T25	92%	100%	96%
D85, T15	86%	90%	88%
D95, T5	100%	95%	98%
Accuracy		95%	
Error		5%	

Table 4 shows the precision, recall, and f1-score values of the AlexNet cupressus retusa tree architecture. The best precision values were obtained by classes with 25, 35, 65, and 95 densities, namely 100%. The lowest precision value was obtained by density class 85, namely 86%. This value is generated because there are 5 FP values in density class 85, which should be three in density class 5. The precision value shows how good the model is at determining samples correctly predicted as the positive class (TP) among samples predicted as positive class (TP and FP) . The highest recall value was obtained by almost all classes, namely 100%, except for classes with densities of 5, 65, 85, and 95. The lowest recall value was obtained by classes with density 5, namely 80%. This value was accepted because there were 5 FN values in density class 5, which were predicted as one as density class 15, 1 as density class 45, and 3 as density 85. The highest f1 score value was found in density classes 25 and 35, namely 100%, while The lowest f1 score was obtained by density class 5. This error could occur because image characteristics were found that were almost similar, so the model was mispredicted.

c. Pinus Merkusii

The accuracy results of the AlexNet merkusii pine tree test model on the Tesla K20 GPU were 86%.

Table 5. Precision, recall, f1-score AlexNet architecture of merkusii pine trees

Needle Leaf Density and Transparency Classes	Result		
	Precision	Recall	F1-Score

D5, T95	100%	68%	81%
D15, T85	71%	80%	75%
D25, T75	89%	93%	91%
D35, T65	83%	79%	81%
D45, T55	64%	100%	78%
D55, T45	86%	90%	88%
D65, T35	100%	95%	98%
D75, T25	69%	82%	75%
D85, T15	95%	95%	95%
D95, T5	100%	81%	89%
Accuracy		86%	
Error		14%	

Table 5 shows the precision, recall, and f1-score values of the AlexNet architecture for Merkusii pine trees. The best precision values were obtained by classes with 5, 65, and 95 densities, namely 100%. The lowest precision value was obtained by density class 45, namely 64%. This value is generated because there are 8 FP values in the density class 45, which should be 3 values in the density class 5, 2 as density 55, 1 as density 65, and 2 as density 75. The precision value shows how good the model is at determining samples correctly predicted as positive class (TP) among samples predicted to be in a positive class (TP and FP). The class obtained the highest recall value with a density of 45, namely 100%. The class obtained the lowest recall value with density 5, 68%. This value was obtained because there were 8 FN values in density class 5, which were predicted as two as density class 15, 1 as density class 25, 1 as density 35, 3 as density 45, and 1 as density 85. The highest f1 score was found in density class 65, namely 98%, while the lowest f1 scores were obtained by density classes 15 and 75.

d. Shorea Javanica

The accuracy results of the AlexNet pine tree merkusii test model on the K80 GPU machine were 94.99%.

Table 6. Precision, recall, f1-score AlexNet architecture shorea javanica tree

Needle Leaf Density and Transparency Classes	Result		
	Precision	Recall	F1-Score
D5, T95	100%	100%	100%
D15, T85	94.00%	100%	97.00%
D25, T75	90.00%	100%	95.00%
D35, T65	91.00%	83.00%	87.00%
D45, T55	100%	100%	100%
D55, T45	90.00%	90.00%	90.00%
D65, T35	95.00%	95.00%	95.00%
D75, T25	90.00%	82.00%	86.00%
D85, T15	100%	100%	100%
D95, T5	100%	95.00%	98.00%
Accuracy		98.00%	
Eror		2.00%	

Table 6 shows the precision, recall, and f1-score values for the AlexNet architecture on the Shorea Javanica tree. Density classes 5, 45, 85, and 95 have the best precision values. Meanwhile, density classes 25, 55, and 75 have the lowest precision values, 90.00%. Precision indicates the extent to which the model can identify truly True Positive (TP) samples among samples predicted to be in a positive class (TP and false positive, FP). The classes with the highest recall are classes 5, 15, 25, 45, and 85, while density class 75 has the lowest recall value, 82.00%. This low recall value is caused by the presence of 2 false negatives (FN) in density class 75, which was predicted as density class 25. Recall measures the extent to which the model can identify all samples that should be included in the positive class (TP), among all actual samples is the positive class (TP and FN). The highest F1 scores were found in density classes 5, 45, and 85, reaching 100%, while the lowest F1 scores were found in density class 75. This error can occur because the model faces very similar images, so the model makes prediction errors.

4. CONCLUSION

The conclusion obtained from the results of the research that has been carried out is that the AlexNet architecture can identify the scale of density and transparency of the needle leaf-type crown. The accuracy results obtained by the AlexNet architecture using the Tesla K80 GPU on needle leaf types are Araucaria heterophylla at 87.00%, cupressus retusa at 96.00%, pine merkusii at 86.00%, and shorea javanica at 95.00%. The value of the model's ability to predict density and crown transparency scale classes for four types of needle leaves (precision) and the value of the effectiveness of searching test data to detect density and transparency classes for four types of needle leaves (recall), applying the augmentation method, namely vertical and horizontal flip, and zoom. Obtained an average precision and recall of 94.10% and 93.00% respectively for the image of Araucaria heterophylla, the cupressus retusa image produced an average precision and recall of 95.00% and 96.00% respectively, for the pine merkusii image, the average was obtained. Precision and recall were 86.00% each, and for the shorea javanica image, the average precision and recall were 95.00% each.

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