CNN Architecture for Classifying Types of Mango Based on Leaf Images

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ABSTRACT

In such conditions, it is necessary to have a system that can automatically classify plant species or identify types of plant diseases using either machine learning or deep learning. The plant classification system for ordinary people who are not familiar with the field of crops is not an easy job, it requires in-depth knowledge of the field from the experts. This study proposes a system for identifying mango plant species based on leaves using the CNN method. The reason for proposing the CNN method from previous research is that the CNN method produces good accuracy. Most previous studies to classify plant species use the leaves of the plant. The purpose of this study is to propose a CNN architectural model in classifying mango species based on leaf imagery. The input image of colored mango tree leaves measuring 224x224 is trained based on the CNN architectural model that was built. There are 4 CNN architectural models proposed in the study and 1 transfer learning InceptionV4. Based on the evaluation test results of the proposed CNN architectural model, that the best architectural model is the third. The number of parameters of the third CNN architecture is 1,245,989 with loss values and accuracy during evaluation are 1,431 and 0.55. The largest number of parameters is transfer learning InceptionV3 21,802,784, but transfer learning shows the lowest accuracy value and the highest loss, namely 0.2, and 1.61.

INTRODUCTION

Processing the digital image, vision techniques computer, machine learning algorithms, and deep learning are increasingly being developed due to handling complex data and good precision results (Chouhan et al., 2019). The stages in developing a computer-based automation system (Yamparala et al., 2020) based on images need to be processed and segmented images (Razi, 2012), then learning to find out the pattern of an image (Chouhan et al., 2019) (Prasad et al., 2019) al., 2016). The goal of developing an automation system in agriculture is to help the agricultural team, as well as maximum agrarian output, and facilitate more efficient work (Yamparala et al., 2020) (Ranjan et al., 2015) (Arivazhagan et al., 2013) (Samajpati & Degadwala, 2016) (Mishra et al., 2021) (Zarrin & Islam, 2019). Not everyone knows the ins and outs of agriculture because not everyone studies in that field. Therefore, people in agriculture are trying to develop a system that can classify types of plants, identify plant diseases. The hope is that they can help others who do not study in agriculture to take good care of plants and help facilitate the work of caring for plants (Yamparala et al., 2020) (Aakif & Khan, 2015) (Prasetyo, 2016) (Arivazhagan et al., 2013)) (Samajpati & Degadwala, 2016) (Mishra et al., 2021). Farmers who work in the agricultural sector also

sometimes have difficulty identifying the type of plant or knowing the kind of plant disease because it does not have experience. In such conditions, a system that can automatically classify plant types or identify types of plant diseases is needed using machine learning (Yamparala et al., 2020) (Ranjan et al., 2015) (Prasetyo, 2016) (Arivazhagan et al., 2013)) (Rumpf et al., 2010) (Dutta & Basu, 2013) (Samajpati & Degadwala, 2016) (Mishra et al., 2021) (Zarrin & Islam, 2019) (Mia et al., 2020) (Srunitha & Bharathi, 2018) (Prasad et al., 2016) (Madiwalar & Wyawahare, 2017) (Kaur et al., 2019) and deep learning (Arya & Singh, 2019) (Chouhan et al., 2019) (Saldana Ochoa & Guo, 2019) (Aakif & Khan, 2015) (Delgado et al., 2019) (Singh et al., 2019) (Nafi'i yah, 2020). Automatic systems for detecting diseases in plants or classification of plant types are beneficial for new farmers and have no experience because they can help work. Classification of plants for ordinary people who are not familiar with crops is a difficult job, and it requires in-depth knowledge of the field from the expert.

Many studies related to the classification of plant species have been carried out using both machine learning and deep learning methods. We mentioned several studies related to plant species classification: classifying mango, papaya, coconut, and banana tree species using the CNN method (Saldana Ochoa & Guo, 2019); classifying types of mangoes, grapes, oranges, and apples based on images using CNN (Aakif & Khan, 2015); classifying mango species using machine learning (Ranjan et al., 2015); classifying mango tree species based on geometric features with ANN (Rumpf et al., 2010); classifying plant species using KNN, and Fuzzy Logic (Delgado et al., 2019); classifying types of mangoes with CNN (Zarrin & Islam, 2019); and classifying tuber types with CNN (Nafi'iyah, 2020).

Previous research shows that the classification of plant species is needed. Because not everyone knows the types of plants, and it takes experts and experts to know the types and characteristics of plants. This study proposes a system for identifying mango plant species based on leaves using the CNN method. The reason for proposing the CNN method from previous research is that the CNN method produces good accuracy. Most previous studies to classify plant species use the leaves of the plant. The CNN model proposed refers to research (Saldana Ochoa & Guo, 2019) (Aakif & Khan, 2015) (Zarrin & Islam, 2019) (Nafi'iyah, 2020). The purpose of this study is to propose a CNN architectural model in classifying mango species based on leaf imagery.

RESEARCH METHODS

1. Dataset

Table 1 describes the distribution of the dataset for training and testing. Table 1 describes the types of mangoes divided into 5, namely Alphanso, Amarpali, Ambika, Austin, Kent. The dataset is taken from Kaggle, and only five types of mango are used. Figure 1 is an example of a leaf image.

Table 1. Dataset Sharing

No	Type	Training	Test
1	Alphanso	24	12
2	Amarpali	24	12
3	Ambika	24	12
4	Austin	24	12
5	Kent	24	12

(a)   (b)
Figure 1. (a) Manga Type Alphanso (b) Amarpali

The dataset used is an image of colored mango tree leaves with a size of 224 x 224, as shown in Figure 1.

2. Proposed Research

This study proposes a CNN architectural model to classify the types of mangoes based on leaf images. Figure 2 illustrates the flow chart of this research. The 224x224 color input image is trained based on the CNN architectural model building. We propose 4 CNN models, Figure 2 describes the CNN architecture made with 4 models as shown in Table 2. The difference between the CNN architecture models is the number of convolution layers and the number of nodes in each convolution layer.
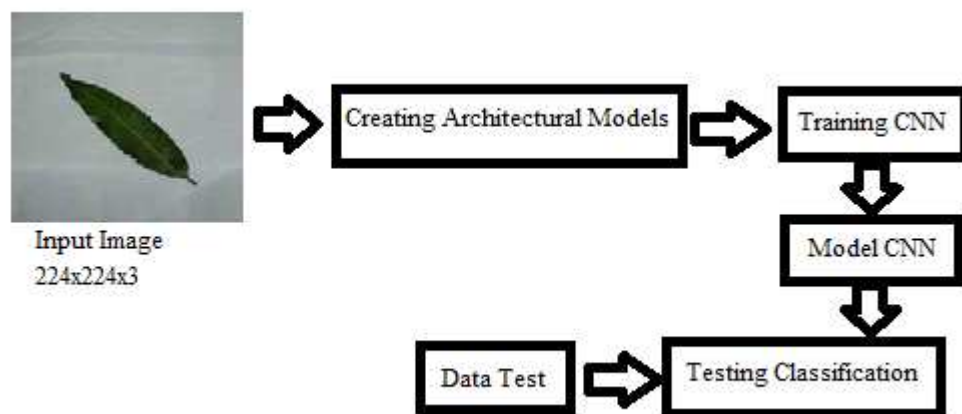

Figure 2. Research Diagram

3. Convolution Neural Network

The CNN architectural model proposed in the study is 5; the model is shown in Table 2. Table 2 shows the CNN model made by explaining the number of parameters.

Table 2. CNN Architecture Model

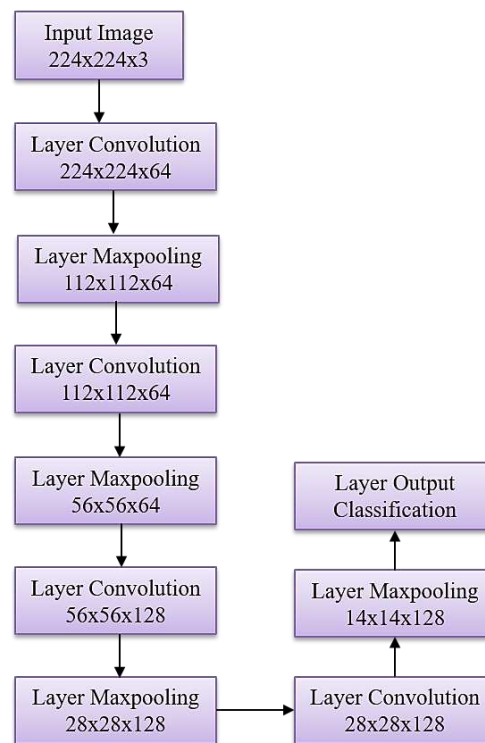| No	Model Type	Total Parameters
1	The First CNN Model	9700421
2	Second CNN Model	7407173
3	Third CNN Model	1245989
4	The Fourth CNN Model	549797
5	Transfer Learning InceptionV3	21802784

Figure 3. First CNN Architectural Model

Table 2 describes the total parameters of each CNN architectural model. Each architecture has a different number of layers and nodes in each hidden layer. The hidden layer in CNN consists of the convolution layer, the pooling layer, the activation layer, the fully connected layer, and the flatten layer. Each architecture from the first model to the fourth model in Table 2 is described in Figure 3, Figure 4, Figure 5, and Figure 6. Figures 3 and 4 are almost the same as the hidden layers built, only differing in the number of hidden layers. In figure 3 the number there are eight hidden layers, while in Figure 4, there are 10. Simultaneously, the number of nodes in each Convolution and Maxpooling layer is almost the same.
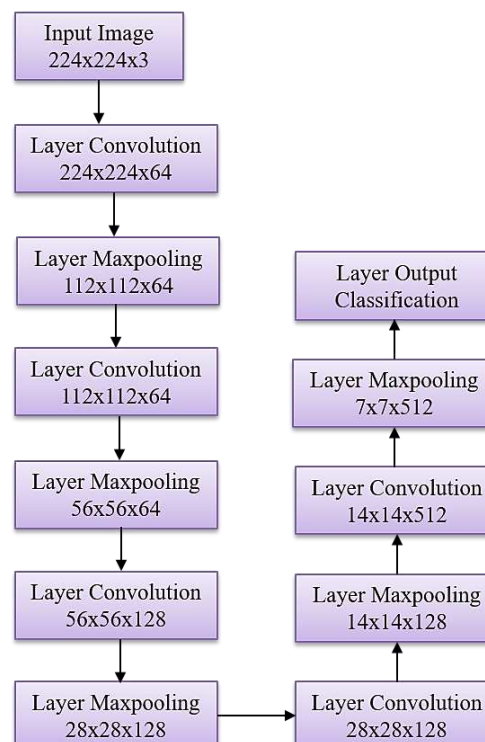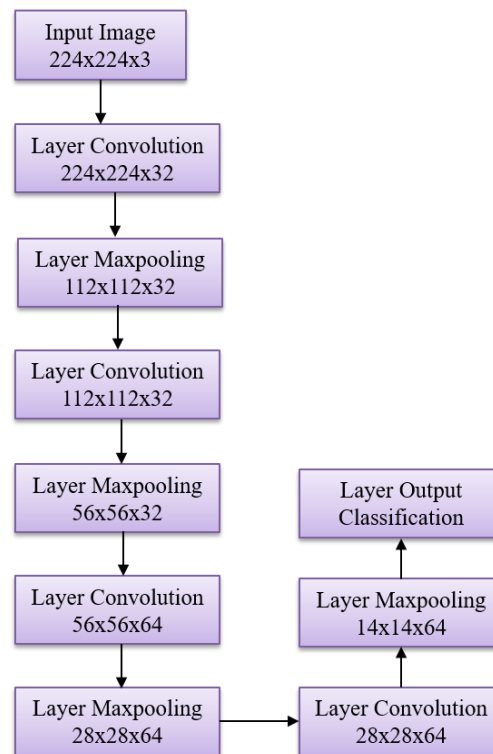
Figure 4. Second CNN Architectural Model

Figure 5. Third CNN Architectural Model

The explanation from Figure 3 to Figure 6 shows the CNN architecture built. The difference between each architecture is the number of convolution layers and max-pooling layer and the number of nodes in each convolution layer and max-pooling layer.
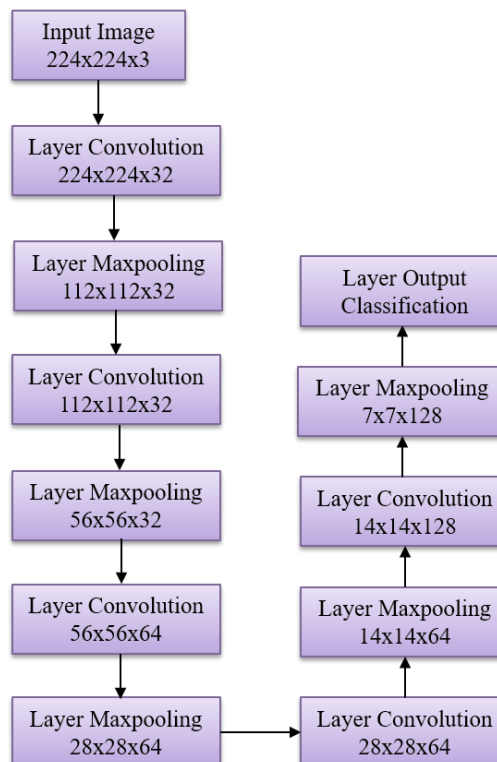

Figure 6. Fourth CNN Architectural Model

RESULTS AND DISCUSSION

This study proposes 4 CNN architectural models and uses InceptionV3 transfer learning. Each architectural model differs in the number of layers and nodes in the convolution layer, the max-pooling layer. The number of parameters of each CNN architectural model is different. The most significant number of parameters in the InceptionV3 learning transfer model. Simultaneously, the most considerable number of proposed model parameters is the first model in Figure 3. Each proposed architectural model is trained and evaluated, as many as 50 epochs of training are carried out. We understand that the number of datasets used is minimal, namely 24 of each type of mango shown in Table 1, so we also augment the training. When we did our training, we used error testing with categorical loss cross-entropy. Equation 1 describes the formula for calculating the error value. The error value can also be called the loss value, namely the loss value in training or evaluation is the value of the difference in calculations between the prediction results symbolized in $\hat{y}_i$ the actual data or the fact data symbolized in y_i. The greater the value of the difference between the predicted value and the actual value, the less good the model. The greater the accuracy value of a model, the better the model. The accuracy value is the same value between the actual value y_i and the predicted value $\hat{y}_i$. The loss and accuracy values of the four CNN architectural models that have been experimented are in Table 3.

$$Loss = \frac{1}{N} \sum_{i=1}^{N} -\left(y_i \log \hat{y}_i + \left((1 - y_i)\log(1 - \hat{y}_i)\right)\right) \tag{1}$$

Table 3. Accuracy and Error Results from Training and Evaluation

No	Type Model CNN	Training		Evaluation	
		Loss	Accuracy	Loss	Accuracy
1	The First CNN Model	1.396	0.35	1.26	0.48
2	Second CNN Model	1.4015	0.375	1.46	0.4
3	Third CNN Model	1.33	0.43	1.23	0.55
4	The Fourth CNN Model	1.446	0.325	1.431	0.367
5	Transfer Learning InceptionV3	1.61	0.2	1.61	0.2

The purpose of calculating the error value for each iteration in training is to improve each node's weight value in the convolution and max-pooling layers. The explanation of Equation 1 is that y is the actual data, while the algorithm's output data $\hat{y}$. Table 3 describes the error value and accuracy of the training and evaluation process of each of the proposed CNN model architectures and transfer learning. Each training and evaluation process of the CNN architectural model is shown in Figure 7 to Figure 11. Figure 7 describes the performance of the loss value and the accuracy of the first CNN architectural model. Each Figure 7 to 11, the left represents the performance accuracy, and the right part explains the value of the loss.
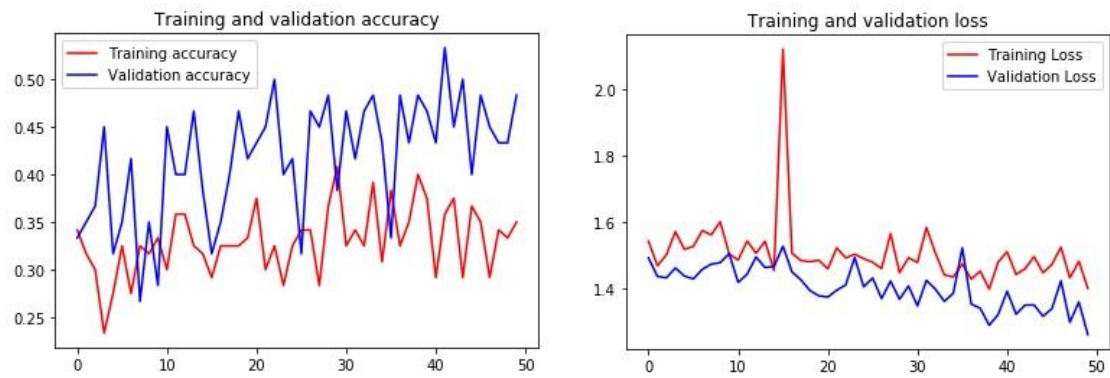
Figure 7. First CNN Model Loss Value and Accuracy Graph
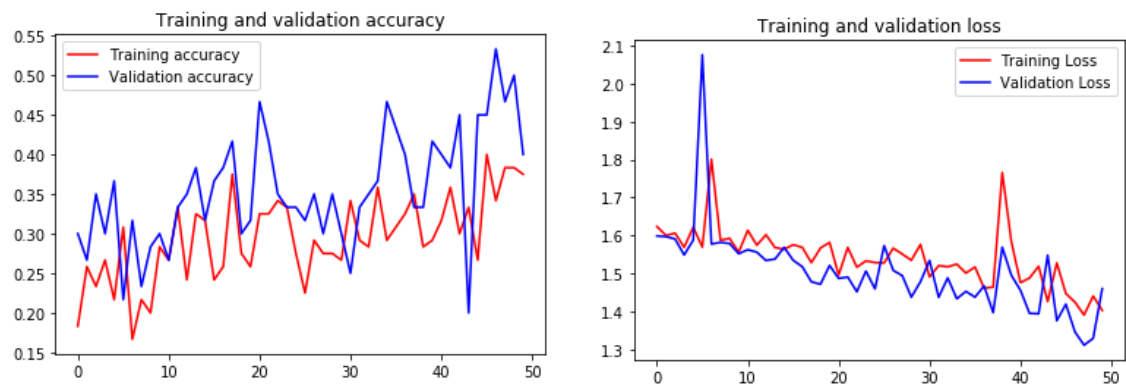

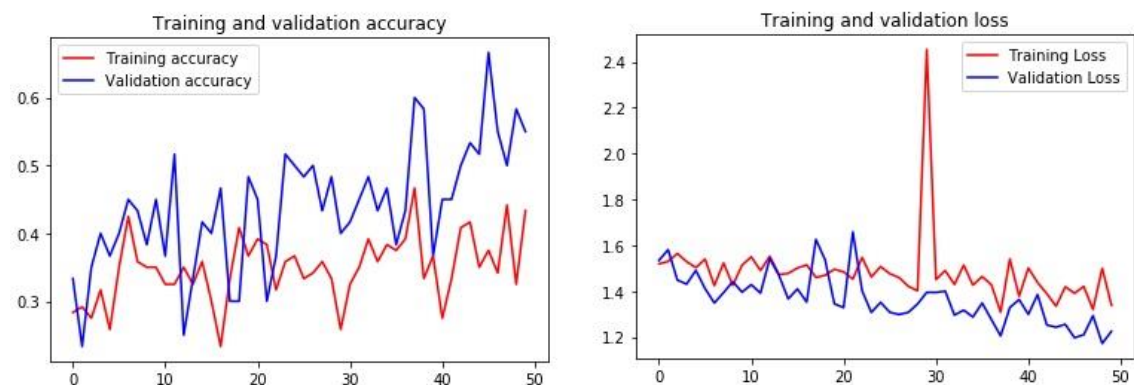Figure 8. Graph of Second CNN Model Loss and Accuracy

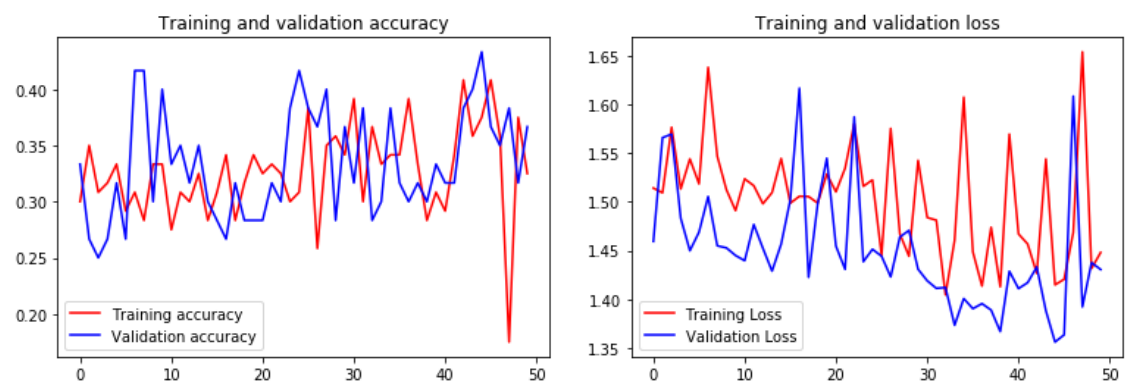Figure 9. Graph of Third CNN Model Loss and Accuracy

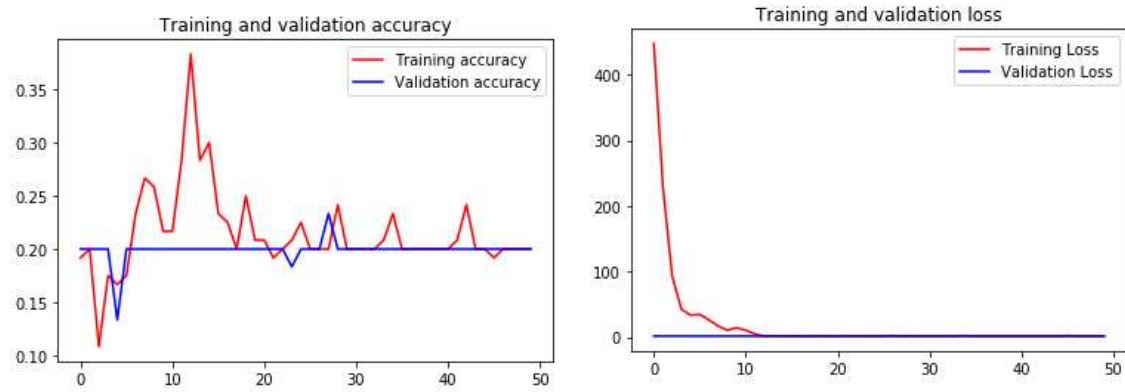Figure 10. Graph of the Value Loss and Accuracy of the Fourth CNN Model

Figure 11. Graph of Value Loss and Accuracy of CNN Transfer Learning Model

Figure 8 describes the performance of the loss values and the accuracy of the second CNN architectural model. Figure 9 represents the performance of the loss value and the accuracy of the third CNN architectural model. Figure 10 illustrates the implementation of the loss value and the accuracy of the fourth CNN architectural model. Figure 11 describes the performance of the loss value and accuracy of the CNN InceptionV3 transfer learning model. Based on Table 3, the proposed model has the lowest loss value compared to CNN transfer learning. The proposed model has 4 CNN architectures, and the third model has the best performance, with an evaluation loss value of 1.431 and an accuracy of 0.55. The highest accuracy is the third CNN architectural model with the number of parameters 1245989.

CONCLUSIONS AND RECOMMENDATIONS

Based on the evaluation test results of the proposed CNN architectural model, the best architectural model is the third. The number of third CNN architecture parameters is 1245989, with the loss and accuracy values when evaluating is 1.431 and 0.55. The parameter number is learning transfer InceptionV3 21,802,784, but the transfer of learning shows the lowest accuracy and highest lossy, namely, 0.2 and 1.61. It can conclude that the third architectural model has the best performance compared to the other four models.

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