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A COMPARATIVE ANALYSIS OF PRE-TRAINED DEEP NEURAL NETWORKS FOR MANGO LEAVES PESTS AND DISEASES IDENTIFICATION

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Abstract. *Mango is one of the critical agricultural sectors in Indonesia. However, various pests and diseases arise in cultivating the mango crop, becoming the primary problem for the farmers, as their identification requires a time-consuming process. To escalate the identification process of mango leaves pest and disease, this study explores several state-of-the-art and popular pre-trained deep neural networks, namely ConvNeXtTiny, ConvNeXtSmall, ConvNeXtBase, EfficientNetV2B0, EfficientNetV2B3, EfficientNetV2M, EfficientNetV2S, InceptionV3, InceptionResNetV2, ResNet50V2, ResNet101V2, and ResNet152V2. The performance of each model was compared based on several evaluation metrics, specifically Accuracy, Precision, Recall, and F1 score. EfficientNetV2M gave a superior performance with an Accuracy of 91.75%, Precision of 0.8849, Recall of 0.8841, and F1 score of 0.8732.*
Keywords: Comparative analysis, Deep neural networks, Mango leaves pests and diseases identification

1. **Introduction.** Indonesia's mango fruit production in 2021 reached up to 2.8 million tons and contributed USD 4.56 million to Indonesia's export value [1]. They are one of the most popular fruits consumed in Indonesia, with an average household consumption of 140.3 thousand tons [1-3]. Mango farming is considered one of Indonesia's crucial agriculture sectors, affecting the nation's GDP. However, cultivating mangos is prone to various pests and diseases which impact the mango's quality. In taking control of mango pests and disease, it is crucial to immediately identify and analyze the infected plants to optimize crop production.

Mango pest and disease identification can be performed by visual observation from the leaf. The unusual physical symptom on the leaf characterizes infected mango plants. Identifying specific pests and diseases is vital to handle the infected plants properly. Current mitigation techniques are performed manually by the farmers. However, it is no longer practical for the farmers to observe mango pests and diseases extensively as the mango plantation lands have expanded in Indonesia. Therefore, a semi-automatic, fast, and reliable system is required for mango pest and disease identification.

Machine learning has drawn attention due to the rapidly expanding demand for systems that could learn to solve various complex problems [4,5]. The implementation of machine learning-based techniques in the agriculture sector has also grown in the past few years as it is giving satisfactory results in solving agriculture's problems. Several studies have successfully implemented machine learning methods to identify pests and plant diseases [6-10]. In recent years, deep neural network models have also begun to be widely implemented in identifying pests and plant diseases [11-14]. [15-25] showed that Convolutional

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Neural Networks (CNN), a deep neural networks-based method gave promising results in disease classification for several crops such as apples, melons, maize, rice, wheat, potatoes, grape, guava, tomatoes, and strawberries.

Several deep-learning implementations in mango pest and disease identification were introduced in previous studies. [26] applied CNN with AlexNet architecture to classifying mango infected by Anthracnose Disease with around 70% accuracy. The same method was also demonstrated in [27] to detect mango leaf disease using a combination of the PlantVilllage dataset [28] and the self-acquired dataset taken in India. The developed system achieved an accuracy of up to 89%. The previous methods may be impractical to be adopted in Indonesia, as the types of mango pests and diseases are diverse. The development of Indonesian mango pest and disease identification was pioneered by [29]. The research created a multi-pest Indonesian mango leaves image dataset and trained a VGG 16 model with data augmentation. The proposed solution resulted in 73% and 76% accuracy on validation and testing accuracy, respectively.

The previous study only focuses on one pre-trained model for identifying mango pests and diseases. This research will apply various leading deep neural network models implemented using transfer learning methods for Indonesian mango pest and disease identification. The pre-trained model, namely ConvNeXtTiny, ConvNeXtSmall, ConvNeXtBase, EfficientNetV2B0, EfficientNetV2B3, EfficientNetV2M, EfficientNetV2S, InceptionV3, InceptionResNetV2, ResNet50V2, ResNet101V2, and ResNet152V2 was evaluated on mango leaves pests and diseases images dataset with augmentation provided by [30]. Performance comparison will be conducted between those twelve models to determine the best model for classifying mango leaves pests and diseases. The results show that EfficientNetV2M had the best performance with an Accuracy of 91.75%, Precision of 0.8849, Recall of 0.8841, and F1 score of 0.8732. These findings demonstrated that deep neural networks could perform well in identifying mango leaves pests and diseases.

The paper is organized as follows. Section 2 describes research methods, starting with the datasets and then describing implemented pre-trained deep neural network models. The performance results of each deep neural network model and comparative analysis of each model will be presented in Section 3. Finally, Section 4 concludes with this study's result and the outline for future work.

2. **Methodology.**

The overall research workflow is depicted in Figure 1. Initially, the image dataset of mango leaves pests and diseases, which represents the actual condition in Indonesia [30], was selected. The image dataset was trained using the deep neural network models via the transfer learning method. Test accuracy, precision, recall, and F1 score were used as performance metrics to assess the model's results.

2.1. **Datasets.**

The datasets were collected from [30]. The datasets represent mango leaves pests and diseases frequently found across the Indonesian archipelago. There are 16 classes of mango leaves pests and diseases, including the uninfected mango leaf, labelled as the normal leaf. The other classes are *Mictis Longicornis*, *Apoderus Javanicus*, *Valanga Nigricornis*, *Dappula Tertia*, *Neomelicharia Sparsa*, *Dialeuropora Decempuncta*, *Icerya Seychellarum*, *Procontarinia Matteiana*, *Procontarinia Rubus*, *Orthaga Euadrusalis*, *Cisaberoptus Kenyae*, *Aulacaspis Tubercularis*, *Erosomyia Sp*, *Ceroplastes Rubens*, and *Ischnaspis Longirostris*.

This study used the version1 dataset, which applied several augmentation techniques to the training data, such as blur and affine transformation, contrast and affine transformation, and noise and affine transformation. Based on the previous research [29], the version1 dataset was divided into 46,500 images, 103 images, and 97 images as training, validation, and testing data, respectively. The class distribution on the dataset is given in Table 1. The images collected from the dataset are in a variety of sizes. The image sizes

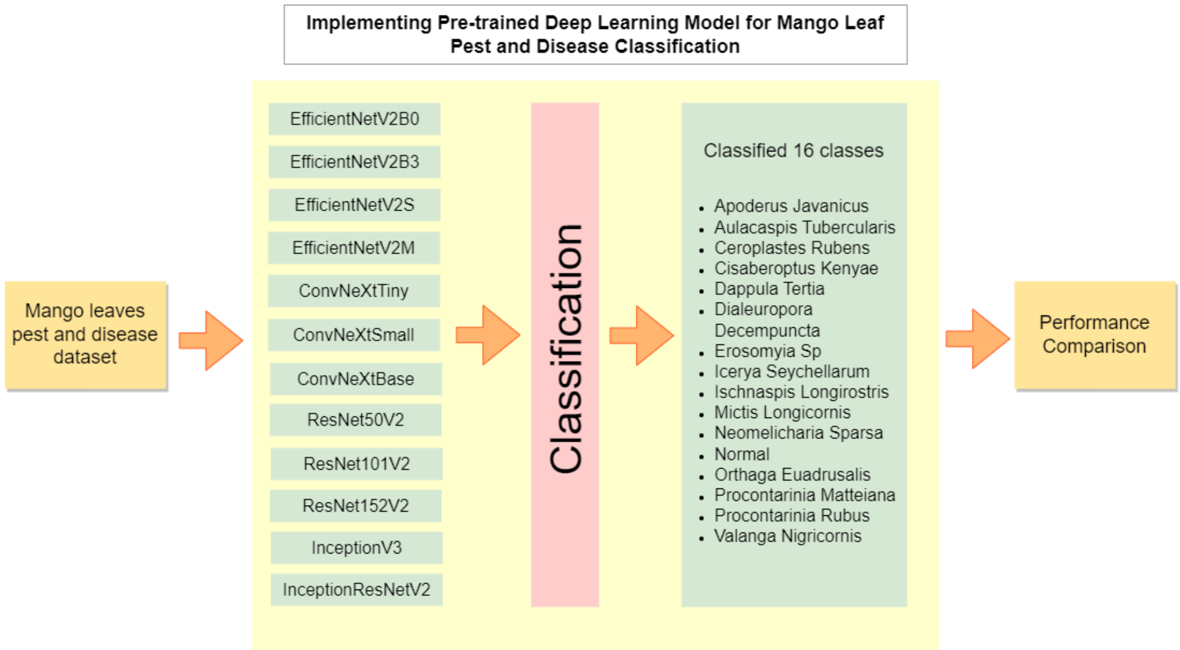


FIGURE 1. Research workflow for mango leaves pests and diseases identification

TABLE 1. Class distribution in the dataset [30]

Class	No. of images
Mictis Longicornis	7685
Apoderus Javanicus	5725
Valanga Nigricornis	5122
Dappula Tertia	3465
Neomelicharia Sparsa	3314
Normal	3314
Dialeuropora Decempuncta	2712
Icerya Seychellarum	2560
Procontarinia Matteiana	2560
Procontarinia Rubus	2410
Orthaga Euadrusalis	2108
Cisaberoptus Kenyae	1807
Aulacaspis Tubercularis	1205
Erosomyia Sp	1205
Ceroplastes Rubens	1054
Ischnaspis Longirostris	454

were then reduced to a smaller size to meet the input size requirement of the deep neural network models.

2.2. **Deep neural networks classifier.** This present study implemented various leading and high-potential pre-trained deep neural network models, namely ConvNeXtTiny, ConvNeXtSmall, ConvNeXtBase, EfficientNetV2B0, EfficientNetV2B3, EfficientNetV2M, EfficientNetV2S, InceptionV3, InceptionResNetV2, ResNet50V2, ResNet101V2, and ResNet152V2. The model was selected based on its performance on the ImageNet dataset [31,32]. Table 2 presents the main characteristics of each model implemented in this study.

The model was implemented using pre-trained weights of ImageNet via the transfer learning method. Transfer learning redistributes knowledge throughout many other deep

TABLE 2. Characteristics of deep neural network models evaluated in this study

Model	Size	Parameters	Depth	Image size
ConvNeXtTiny	109.42 MB	28,589,128	–	224×224
ConvNeXtSmall	192.29 MB	50,223,688	–	224×224
ConvNeXtBase	338.58 MB	88,591,464	–	224×224
EfficientNetV2B0	29 MB	7,200,312	–	224×224
EfficientNetV2B3	59 MB	14,467,622	–	300×300
EfficientNetV2M	220 MB	54,431,388	–	480×480
EfficientNetV2S	88 MB	48,312,243	–	384×384
InceptionV3	92 MB	24,080,020	189	299×299
InceptionResNetV2	215 MB	55,875,273	449	299×299
ResNet50V2	98 MB	23,561,152	103	224×224
ResNet101V2	171 MB	44,677,609	205	224×224
ResNet152V2	232 MB	60,382,697	307	224×224

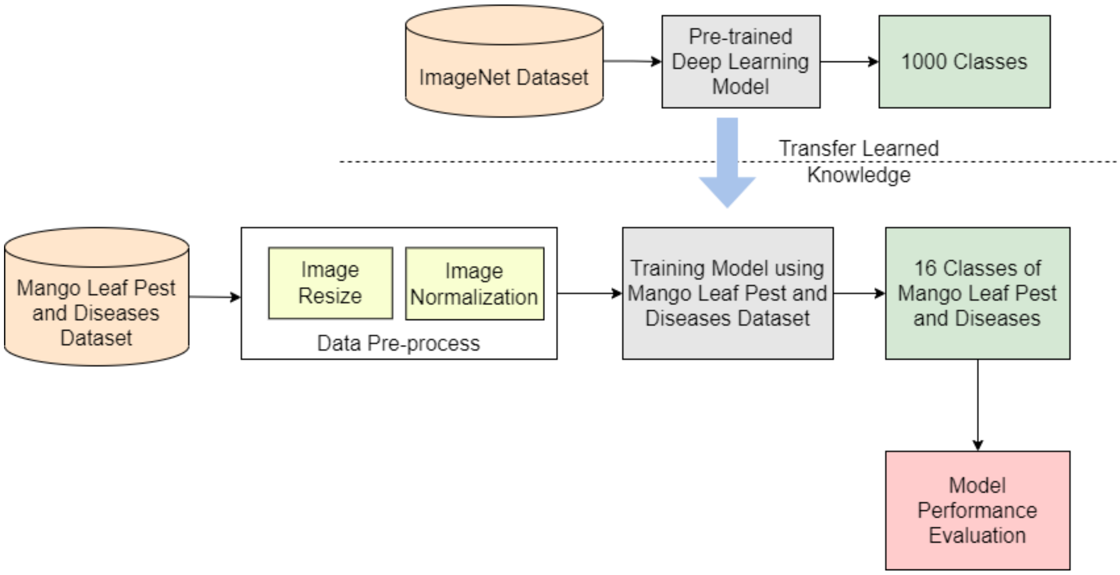


FIGURE 2. Training the pre-trained deep neural networks on mango leaves pest and disease dataset

neural network models using a pre-trained model tailored for a single task. Transfer learning adopts a model trained on a general dataset to enable the model to specialize in smaller datasets [33]. This approach can speed up model training and enhance overall performance. The steps involved in training the deep neural networks on the mango leaves pest and disease are given in Figure 2. The same hyperparameters value is applied to all pre-trained deep neural network models, including the batch size of 32 and Adam Optimizer [34] with a learning rate of 0.001, a beta value of 0.9-0.999, and an epsilon of 10^{-7}. Categorical cross entropy for multi-class classification and SoftMax activation for the dense layer was also implemented in the model. To prevent overfitting, callbacks.Earlystopping function was also applied.

2.2.1. *ConvNeXt.* The state-of-the-art convolutional Network (ConvNeXt) [35] is a family of pure Convolutional Networks which redesign a conventional ResNet toward the vision Transformer [36] architecture. ConvNeXt replaces ResNet-style blocks with a patchify strategy, a large kernel size of 14-16 and a non-overlapping convolution. This patchify strategy is implemented using 4×4, stride four convolutional layers, resulting in higher accuracy. ConvNeXtTiny, ConvNeXtSmall, ConvNeXtBase, ConvNeXtLarge, and ConvNeXtXLarge are the versions of this model, which differentiate by the number of parameters and size. The first three models, ConvNeXtTiny, ConvNeXtSmall, and ConvNeXtBase, which have smaller parameters, were implemented in this research.

2.2.2. *EfficientNet.* The EfficientNet model is a new scaling technique that uses a straightforward compound coefficient to scale the model's width, depth, and resolution to increase the model capacity [37]. The new model, called EfficientNetV2, has a significantly smaller model and convergence speed. This model also performs better on the ImageNet dataset [37]. Compared to the first version, the EfficientNetV2 model can achieve a 5× to 11× faster-converging rate [38]. The versions of EfficientNetV2 that were employed in this study were B0, B3, M, and S.

2.2.3. *Inception.* The inception model is based on scaling up the networks. The model applies properly factorized convolutions and aggressive regularization, which make the computing process more efficient [39]. The popular Inception versions are InceptionV1, InceptionV2, InceptioV3, InceptionV4, and InceptionResNet. InceptionV3 and InceptionResNet were applied in this study. InceptionV3 incorporates all arrangements in the previous version while upgrading the network using factorized 7×7 convolutions and BatchNorm in the auxiliary classifier. The loss formula has included a regularizing element to stop the network from overfitting [39]. The InceptionResNet model is a hybrid Inception model inspired by the performance of ResNet. This model integrates residual connection to replace the filter concatenation stage of the Inception. This technique preserves Inception's processing efficiency while enabling it to gain all the advantages of the residual network [40].

2.2.4. *ResNet.* The Residual Network (ResNet) architecture is proposed by [41] to accommodate the previous CNN model, which is substantially deeper and hard to train. ResNet offers a residual learning framework to simplify the training process. The vanishing gradient issue in the previous model is addressed by skipping connections and providing shortcuts. The identity and convolutional blocks are the two fundamentals of ResNet blocks. By stacking these blocks, deep residual networks can be created. The newest version of this model, called ResNetV2, improved the first version by implementing identity mapping on the skip connections. This technique can elevate the data transmission speed in each residual block [42]. The variation of the second version of the model is based on the number of layers, which are ResNet50V2, ResNet101V2, and ResNet152V2. All versions of ResNetV2 were implemented in this study.

2.3. **Evaluation metrics.** This study implements four evaluation metrics to evaluate the model's performance. Test Accuracy is used to assess the model's overall average accuracy across all mango leaves pest and disease images in the test set. Precision was used to determine the percentage of observations accurately representing the model's positive predictions. The Recall was implemented to evaluate the model due to the unbalanced distribution in the mango leaves pest and diseases dataset. The F1 score metric, which incorporates Precision and Recall into a single metric, was also carried out. Equation (1) to Equation (4), respectively, provide the formulas for test Accuracy, Precision, Recall and F1 score. TP, FP, TN, and FN refer to True Positive, False Positive, True Negative, and False Negative, respectively.

$$Test\ Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1\ score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

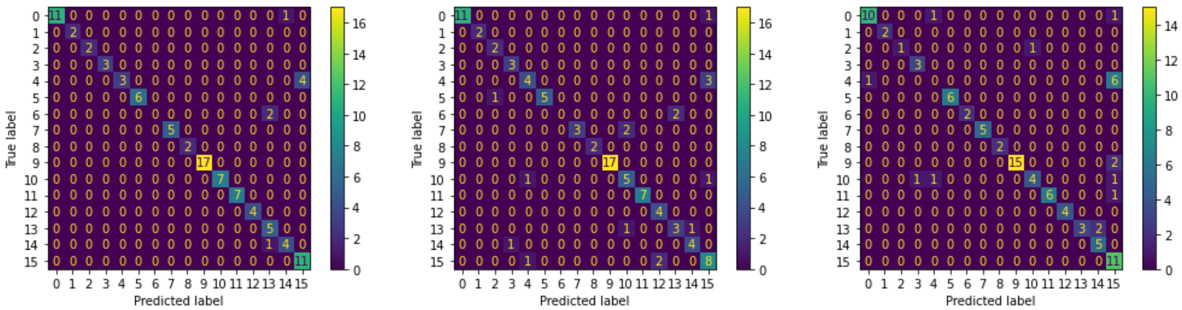
3. **Results and Discussion.** The identification of mango leaves pests and diseases using deep neural networks was implemented with Keras and TensorFlow Library. The selected pre-trained deep neural network model, which trains on the ImageNet dataset [32], was imported via the transfer learning method. The final layers were then modified to fit the desired output. The Google Colab Pro Platform [43] with the specification of NVIDIA P100 or T4 as GPU, CPU Xeon Processor @2.3GHz, and available memory of up to 25GB used to execute the code. The performance evaluation metric demonstrated using Accuracy, Precision, Recall, and F1 score derived from the confusion matrix is presented in Table 3.

Table 3. Metric evaluation result for each deep neural network model

Deep neural network model	Test Accuracy	Precision	Recall	F1 score
ConvNeXtTiny	81.44%	0.8546	0.8278	0.8232
ConvNeXtSmall	80.41%	0.8711	0.8331	0.8336
ConvNeXtBase	82.47%	0.7744	0.7977	0.7763
EfficientNetV2B0	80.41%	0.8247	0.7855	0.7835
EfficientNetV2B3	71.13%	0.7964	0.7289	0.7262
EfficientNetV2M	91.75%	0.8849	0.8841	0.8732
EfficientNetV2S	73.20%	0.5682	0.6204	0.5838
InceptionV3	78.35%	0.8708	0.8062	0.8146
InceptionResNetV2	72.16%	0.7891	0.6783	0.7022
ResNet50V2	80.41%	0.8061	0.8089	0.7982
ResNet101V2	71.13%	0.7398	0.6396	0.6489
ResNet152V2	70.10%	0.7345	0.7275	0.7072

Among the twelve pre-trained deep neural network models implemented in this study, EfficientNetV2M had the best performance with an Accuracy of up to 91.75%, Precision of 0.8849, Recall of 0.8841, and F1 score of 0.8732. The least performed model in terms of test Accuracy and Precision was ResNet152V2, with an Accuracy of only 70.10%. EfficientNetV2S was also the least performed model in terms of Precision, Recall and F1 Score, with the value of only 0.5682, 0.6204, and 0.5838, respectively.

The top three models ranked by test Accuracy are EfficientNetV2M, ConvNeXtBase, and ConvNeXtTiny, with an accuracy of 91.75%, 82.47%, and 81.44%, respectively. EfficientNetV2M and ConvNeXtTiny have similar performance in all metrics, with values for all metrics above 80%. While for ConvNeXtBase, although it had the second-best test Accuracy, the performance for other metrics was below two other deep neural network models, which is below 80%. Figure 3 provides the confusion matrix for the top three models ranked by test Accuracy, which was evaluated using the test dataset. The diagonal values for each deep neural network model show the actual predictions. In those figures, each label is represented by a number from 1 to 16, labelled as *Apoderus Javanicus*, *Aulacaspis Tubercularis*, *Ceroplastes Rubens*, *Cisaberoptus Kenyae*, *Dappula Tertia*, *Dialeuropora Decempuncta*, *Erosomyia Sp*, *Icerya Seychellarum*, *Ischnaspis Longirostris*, *Mictis Longicornis*, *Neomelicharia Sparsa*, Normal (leaf with no pest), *Orthaga Euadrusalis*, *Procontarinia Matteiana*, *Procontarinia Rubus*, and *Valanga Nigricornis*, respectively.



(a) EfficientNetV2M (b) ConvNeXtBase (c) ConvNeXtTiny

FIGURE 3. Confusion matrix for top three deep neural network model ranked by test Accuracy

4. **Conclusions.** The effectiveness of the deep neural network models for identifying mango leaves pests and diseases is explored in this study. This study evaluated some state-of-the-art and well-known pre-trained deep neural networks models such as ConvNeXt-Tiny, ConvNeXtSmall, ConvNeXtBase, EfficientNetV2B0, EfficientNetV2B3, Efficient-NetV2M, EfficientNetV2S, InceptionV3, InceptionResNetV2, ResNet50V2, ResNet101V2, and ResNet152V2. All selected models show promising results when trained using the transfer learning method. EfficientNetV2M results in the best performance with accuracy reaching 91.75%, Precision of 0.8849, Recall of 0.8841, and F1 score of 0.8732. This result could accelerate the identification of mango leaves pests and diseases and increase mango fruit production. ResNet152V2 is the least performed model in this implementation, with an accuracy of only 70.10%. EfficientNetV2S also gave unsatisfactory results with Precision, Recall and F1 score values of only 0.5682, 0.6204, and 0.5838, respectively. Further work is still needed to explore other augmentation techniques and compare them with the augmentation provided by the original dataset. In addition, future research can also investigate other parameter settings in training the deep neural network model.

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