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OIL PALM LEAF DAMAGE CLASSIFICATION USING HYPERPARAMETER TUNING OF XCEPTION MODEL

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ABSTRACT

The oil palm industry, vital to tropical economies, faces significant challenges from leaf damage. Despite advancements in leaf damage detection, accuracy and efficiency still need improvement. This study implements the Xception model for classifying oil palm leaf damage. We evaluated the model's performance using a dataset of healthy and infested leaf images, optimising parameters such as epochs, batch size, learning rate and optimiser. The best results were achieved with 15 epochs, a batch size of 64, the RMSProp optimiser and a learning rate of 0.001. The Xception model demonstrated exceptional performance, achieving an accuracy, precision, recall and F1-score of 99.73%, with a computational time of 272 s. Despite the promising results, challenges due to environmental variations and limited data remain. Future study should focus on further optimising hyperparameters, expanding the dataset and applying the model in field settings with a decision support system. This study provides a solid foundation for developing practical solutions to support the palm oil industry in addressing leaf damage.

Keywords: classification, hyperparameter, leaf damage, oil palm leaf, Xception.

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INTRODUCTION

Oil palm plays a very important role in tropical countries such as Indonesia, Malaysia, Papua New Guinea and Thailand (Sukiyono et al., 2021; Widians et al., 2019). Oil palm is a highly productive crop, producing higher oil per hectar compared to other oil-producing crops (Hayata et al., 2018). Oil palm plays a vital role in meeting global oils and fats requirements.

However, despite oil palm's resilience, oil palm production currently faces a number of major challenges, particularly those related to pest and disease attacks. These pests and diseases can reduce crop productivity and reduce yields, which directly impacts smallholders' profits (Saragih & Afrianti, 2021). Pest attacks on oil palms can result in a reduction in yield of up to 70%, and when combined with disease attacks, the damage can reach 100% (Harahap et al., 2018). Common pests include the rhinoceros beetle (*Oryctes rhinoceros*) and caterpillars from the orders Lepidoptera and Coleoptera (Nurhasnita et al., 2020). Attacks by pests such as *O. rhinoceros* can delay plant growth and, if infestations reach a critical level, may cause plant death (Aidoo et al., 2022; Bedford, 2014).

Diseases in oil palm can also cause a decrease in productivity. Oil palm diseases can be categorised based on the location of the symptoms, namely root, stem and leaf diseases. Among the three, leaf diseases are the most common and are often prioritised for detection, as they are easier to see and can be an indicator of the overall health of the plant (Hamdani et al., 2021; Ong

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et al., 2022; Septiarini et al., 2021). Oil palm plants rely heavily on their leaves for photosynthesis, so disease infestation of the leaves can lead to reduced yields and affect overall plant growth (Azmi et al., 2020; Faizah et al., 2022; Rebitanim et al., 2020).

One of the major challenges in oil palm management is the limited knowledge of smallholders on the type of diseases and how to control them. In many areas, disease detection is still done visually by agricultural experts, which requires expertise and time. This slows down the response to diseases and can lead to a wider spread (Harahap et al., 2018; Kamal et al., 2018; Olajide et al., 2021). Therefore, there is a need for a faster and more practical method to detect foliar diseases in oil palm, which can be used by smallholders in the field.

Along with the development of technology, the utilisation of image processing and machine learning has shown great potential in plant disease detection, including oil palm. The study on plant disease classification through leaf image analysis has grown rapidly in recent years. Various crops, both food and commodity, have been the subject of this study, such as apple leaves (Si et al., 2024; Wang et al., 2024a), chilli (Azwan et al., 2023), mango (Suprayoga et al., 2023), tomato (Radočaj et al., 2024), peanut (Chapu et al., 2024), as well as other food crops such as potato (Xu et al., 2024) and cucumber (Yao et al., 2024). These approaches utilise image processing technology and machine learning algorithms to detect and classify various crop diseases, enabling smallholders to take faster and more effective preventive measures in the management of their crops. *Table 1* provides an overview of the multiple models that have been used in this study and the accuracy achieved.

A study on disease and pest classification in oil palm leaves using machine learning has shown significant progress. For instance, Rasywir et al. (2020) achieved 96.00% accuracy by applying the convolutional neural network (CNN) method to diagnose diseases on oil palm leaves. Similarly, Indrawati et al. (2023) utilised the GoogLeNet architecture with optimal hyperparameter configuration and attained 93.22% accuracy in classifying healthy leaves and those infested with pests such as caterpillars and bagworms. Furthermore, Ahmad et al. (2021) employed faster regional-based convolutional neural network (Faster R-CNN) to detect bagworm larvae, achieving accuracy ranging from 73.00% to 100.00%. Additionally, Johari et al. (2023a, 2023b) reported classification accuracies exceeding 98.00% for bagworm infestations using machine learning techniques.

This study aims to develop a faster, more accurate and efficient disease detection system by utilising Xception architecture. Although previous studies have used various machine learning methods with good results, there are still opportunities to

TABLE 1. SUMMARY OF EXISTING SYSTEM FOR LEAF DAMAGE CLASSIFICATION

Model	Type of leaf damage	Accuracy (%)	Reference
RegNet	Apple (7 Class)	99.23	Wang et al. (2024a)
ResNet	Red pepper (3 Class)	42.14	Azwan et al. (2023)
XGBoost + HoG	Mango (3 Class)	93.00	Suprayoga et al. (2023)
InceptionV3 with incMB	Tomato (6 Class)	97.78	Radočaj et al. (2024)
ANN	Peanut (4 Class)	74.45	Chapu et al. (2024)
DVT	Tomato (10 Class)	99.45	Chen et al. (2024)
Coformer	Potato (3 Class)	97.86	Xu et al. (2024)
Dual-branch model (DBCoST)	Apple (5 Class)	98.06	Si et al. (2024)
TRNet and U-Net	Cucumber (5 Class)	94.43	Yao et al. (2024)
VGG16	Corn (4 Class)	95.00	Mohanty et al. (2023)
SE-VIT	Sugarcane (5 Class)	89.57	Sun et al. (2023)
Integration of clustering and deep learning	Olive (3 Class)	98.30	Alsaeedi et al. (2023)
GLD-Det	Guava (5 Class)	98.06	Mustak Un Nobi et al. (2023)
EfficientNet + RegNet	Strawberry (5 Class)	85.60	Kim and Kim (2023)

Note: RegNet - regularised evolutionary network; ResNet - residual neural network; XGBoost - extreme gradient boosting; HoG - histogram of oriented gradients; InceptionV3 with incMB - inception version 3 with inception mobile blocks; ANN - artificial neural network; DVT - dual vision transformer; Coformer - collaborative transformer; Dual-branch model (DBCoST) - integrating CNN and Swin Transformer; TRNet and U-Net - Transformer network and U-Net for segmentation; VGG16 - visual geometry group network 16 layer version; SE-VIT - squeeze-and-excitation vision transformer; GLD-Det - guava leaf disease detection; Class - number of categories or types of leaf damage that can be recognised or classified by the model for each type of plant tested.

improve detection performance, especially in terms of accuracy and speed. Therefore, this study focuses on exploring the best hyperparameter configuration for oil palm leaf damage classification, with the aim of achieving higher accuracy based on leaf photographic image analysis.

MATERIALS AND METHODS

Experimental Framework

The study employs a research framework model as illustrated in *Figure 1*. First, this study begins with an important step, namely data collection. We collected a dataset consisting of images of healthy and infested oil palm leaves with various leaf damage. This dataset is an important foundation for training and testing classification models. Next, the collected data undergoes pre-processing. This includes steps such as resizing images to a consistent size, normalising pixel values and other processing to ensure the quality and consistency of the dataset. After that, the dataset is divided into three main subsets: Training, validation and testing. Good data sharing is key to avoiding overfitting and validating model performance. Then, we trained the Xception model with 16 different scenarios. Each scenario is a combination of parameters such as number of epochs (15 and 25), batch size (32 and 64), learning rate (0.001 and 0.009) and optimiser (Adam and RMSprop). This is an important step to identify the best combination of parameters that produces a model that has the highest performance in classifying leaf damage on oil palm leaves. Finally, the evaluation is conducted using classification reports, which include key performance metrics such as accuracy, precision, recall and F1-score. These metrics are used to assess the model's ability to recognise leaf damage in oil palm leaves. The mathematical formulations for these metrics are provided and explained in more detail in the Performance Measure subsection. The results of this evaluation offer insight into the model's effectiveness and assist in selecting the optimal parameters for the Xception model.

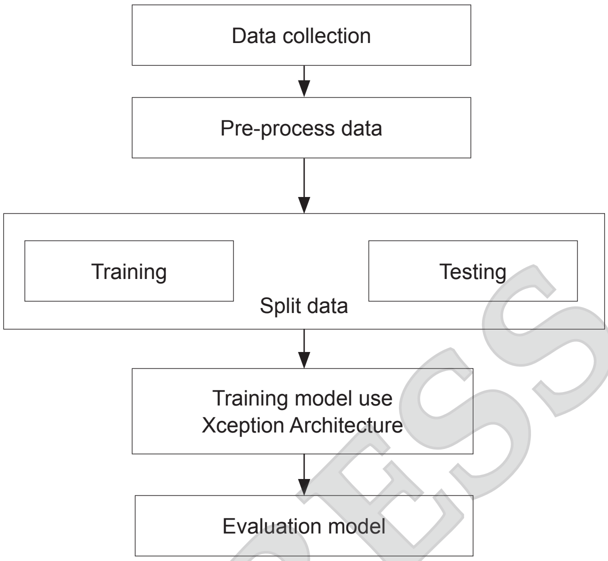


Figure 1. *Research architecture.*

Data Gathering Approach

In this study, image data were acquired using the rear camera of an Oppo F5 smartphone, which is equipped with a 16-megapixel sensor and an f/1.8 aperture lens. Images were captured at a fixed distance of 30 cm under controlled lighting conditions to ensure consistent illumination. The primary data collection site was the main oil palm plantations in Dolok Baja, North Sumatra Province, Indonesia. Direct observations were conducted on the oil palm leaves in these plantations. Additionally, conversations with experts from the Pusat Penelitian Kelapa Sawit (PPKS) provided valuable insights into plant protection. Three categories of oil palm leaves were collected: Healthy oil palm leaves, leaves infested with bagworms and leaves infested with nettle caterpillars. Each leaf sample was placed on a sheet of Houtvrij Schrijfpapier, wood-free writing paper (HVS) and photographed using the mobile camera to ensure consistent and clear imaging for further analysis.

Oil palm plantations are susceptible to damage from various caterpillar species. A notable example is the bagworm (*Cremastopsyche pendula*), a polyphagous species often found alongside *Metisa plana*. These caterpillars infest not only oil palms but also a wide range of other plants, including *acacia*, cocoa, coffee, tea, sago and *albizia*. Bagworms create protective sacs from plant material, which they use for cover and damage the surface of the leaves they infest, leading to significant foliage loss and impaired plant health (Anggraini & Berutu, 2022; Priwiratama et al., 2019).

Another serious threat to oil palm crops is the nettle caterpillar, which can cause considerable damage, especially on young oil palm plantations. These caterpillars feed voraciously on oil palm leaves, leading to severe defoliation and stunted growth in young plants. Notable species posing this threat include *Setothosea asigna*, *Darna trima*, *Setora nitens*, *Darna diducta*, *Susia malayana*, *Darna bradleyi*, *Birthosea bisura*, *Olona gater* and *Thosea vetusta*. These species are especially destructive during their larval stages, making them a significant concern for oil palm growers (Pangaribuan et al., 2017).

Data Analysis

For this study, data gathering focused on three categories of oil palm leaves: Healthy leaves, leaves affected by bagworms and leaves affected by nettle caterpillars. The process yielded a total of 1,230 sample images, with 410 images representing each leaf type. The dataset was subsequently divided into training and testing subsets using a 70:30 split ratio. This means 861 images were allocated for training, and 369 images were reserved for testing. Detailed information on the distribution and comparison of these subsets is provided in *Table 2*.

TABLE 2. DISTRIBUTION OF TRAINING AND TESTING DATASETS

Leave types	Training (70%)	Testing (30%)
Healthy leaves	287	123
Leaf affected by bagworms	287	123
Leaf affected by nettle caterpillar	287	123

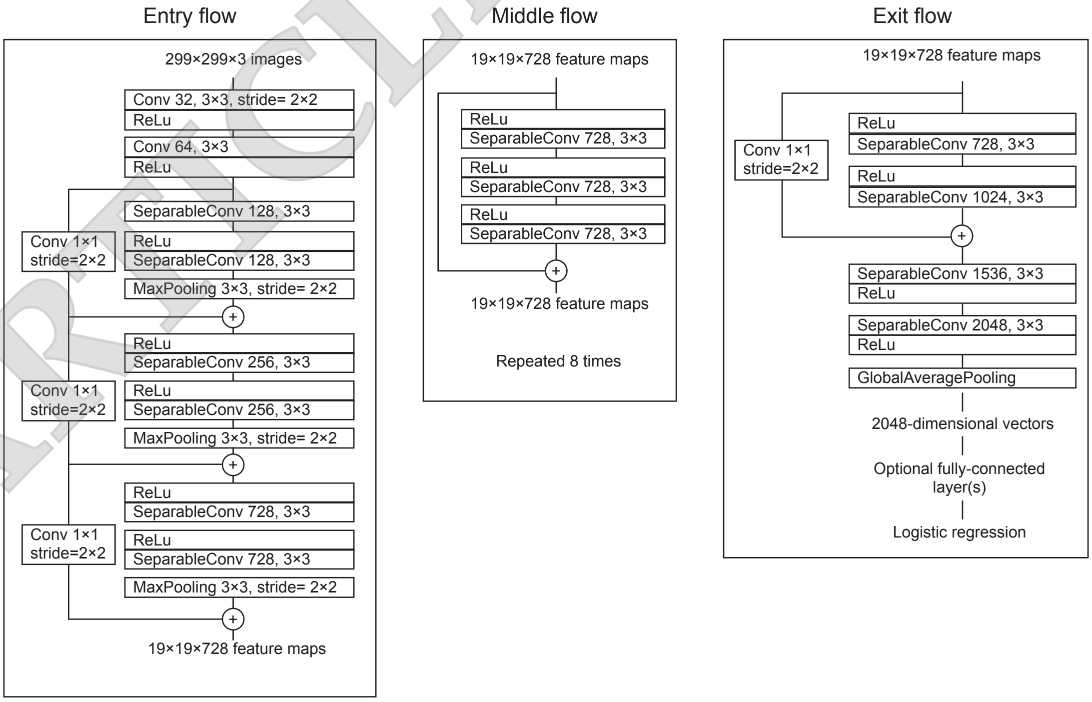
Xception Network

Xception is a convolutional neural network architecture developed by François Chollet in 2016. Its name, "Xception," is derived from "Extreme Inception," indicating its evolution from the Inception Architecture introduced in 2014. The core innovation of Xception lies in replacing the conventional convolutional layers within Inception modules with depthwise separable convolutions. This technique involves two main operations: Depthwise convolution, which applies a single filter per input channel and pointwise convolution, which uses a 1x1 filter to combine outputs from the depthwise step. By adopting depthwise separable convolutions, Xception reduces network parameters and enhances computational efficiency while maintaining or even improving accuracy (Chollet, 2017; Gülmez, 2022; Muhammad et al., 2021).

Xception incorporates additional architectural advancements, including linear bottleneck modules and residual connections, aimed at enhancing network training stability and performance. Demonstrating its efficacy, Xception has achieved top-tier performance across various image classification benchmarks such as ImageNet, CIFAR-10 and CIFAR-100. Moreover, it has proven effective in diverse computer vision applications, including but not limited to object detection and semantic segmentation. *Figure 2* illustrates the Xception Architecture.

Hyperparameter Initialisation

In this study, these parameters were carefully selected to optimise the performance of the model. The number of epochs chosen ranged between 15 and 25, ensuring sufficient iterations over the entire training dataset to facilitate proper learning and



Source: Chollet (2017).

Figure 2. Xception architecture.

convergence. The batch size was varied between 32 and 64, balancing between computational efficiency and accuracy of gradient descent during weight updates (Wang et al., 2024b). The learning rate was explored with values of 0.001 and 0.009, affecting the speed of adjusting the model weights to minimise the loss function. The choice between the Adam and RMSprop optimisers significantly influenced the training dynamics of the model. Adam, which combines momentum and adaptive learning rate techniques, is generally preferred for problems involving sparse gradients or when faster convergence is needed. In contrast, RMSprop adjusts learning rates based on a moving average of recent squared gradients and is particularly effective in dealing with non-stationary objectives or when training recurrent models. Each optimiser affects how gradients are computed and how model weights are updated during training, thereby impacting convergence speed and final model performance (Karakan, 2024). This systematic selection and adjustment of hyperparameters aims to maximise training effectiveness, increase convergence speed and improve the overall accuracy of the model for the specific tasks addressed.

Performance Measure

One approach to evaluate the precision of an object estimation model is by utilising a confusion matrix. This matrix displays information about the predicted and actual classification outcomes by comparing the prediction matrix with the initial input class.

The accuracy of a technique reflects the correctness of the estimated values [Equation (1)]. Precision is the repeatability of the measurement or the proportion of accurate predictions [Equation (2)]. Recall measures the number of accurate positive responses [Equation (3)]. By combining precision and recall, we can calculate the f1-score [Equation (4)], which provides a balanced average outcome. The following equations can be used to calculate these metrics, where TP_PalmLeaves, TN_PalmLeaves, FP_PalmLeaves and FN_PalmLeaves represent true positive, true negative, false positive, and false negative, respectively (Jiang et al., 2024).

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

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

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

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

RESULTS AND DISCUSSION

Sample of Palm Leaves

The symptoms of oil palm leaves attacked by bagworms are holes or cut parts on the leaves caused by bagworms feeding on certain parts of the leaves. In addition, cylindrical or cone-shaped bags made of leaf fibres by bagworms can be seen around the oil palm leaves, which serve as shelters and homes for the bagworms. When oil palm leaves are attacked by this caterpillar, they will show signs of burning or being on fire. This is caused by the caterpillar eating the leaf tissue and leaving burn-like marks on certain parts of the leaf. The leaves will become severely damaged and brittle, with parts of the leaf drying out and changing colour to yellow or brown. Healthy oil palm leaves are usually greenish-grey in colour and have a symmetrical and upright shape. Healthy leaves also have a stiff texture and do not easily tear when blown by the wind or touched. In addition, healthy oil palm leaves do not have spots or other signs of damage such as bite marks from pests or fungi. Healthy leaves are essential for maximising oil palm fruit production. *Figure 3* represents healthy palm leaf samples versus damaged.

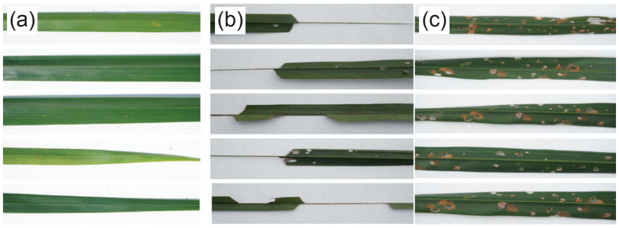


Figure 3. Examples of palm leaves: (a) Healthy palm leaves, (b) leaves attacked by bagworms, and (c) leaves attacked by nettle caterpillar.

Training Scenarios in Oil Palm Leaf Damage Classification

In an effort to optimise the performance of the model for leaf damage classification of oil palm leaves, a series of experiments were conducted with various configurations of training parameters. The objective was to understand how different parameter combinations affect the accuracy and effectiveness of the model in recognising leaf health conditions, whether they are healthy, infested by nettle caterpillar or bagworms. The study involved 16 different training scenarios, each with varying parameters such as number of epochs, batch size, learning rate and optimiser type. The combination of these parameters resulted in 16 different scenarios, which are detailed in *Table 3*.

TABLE 3. THE COMBINATION OF THESE PARAMETERS RESULTED IN 16 DIFFERENT SCENARIOS

Scenario	Epoch	Batch size	Optimiser	Learning rate
1	15	32	Adam	0.001
2	15	32	RMSProp	0.001
3	15	32	Adam	0.009
4	15	32	RMSProp	0.009
5	15	64	Adam	0.001
6	15	64	RMSProp	0.001
7	15	64	Adam	0.009
8	15	64	RMSProp	0.009
9	25	32	Adam	0.001
10	25	32	RMSProp	0.001
11	25	32	Adam	0.009
12	25	32	RMSProp	0.009
13	25	64	Adam	0.001
14	25	64	RMSProp	0.001
15	25	64	Adam	0.009
16	25	64	RMSProp	0.009

Training Xception with 15 Epoch

Xception training was conducted for 15 epochs, resulting in eight training models according to *Table 3*. Visualisation of training with 15 epochs can be seen in *Figure 4*, which presents the performance of various deep learning models along with their respective accuracies achieved across different training epochs. Scenario 1 has an accuracy of 90% during the 1st epoch, which increases to 99% during the 12th epoch. Scenario 2 has an accuracy of 93% during the 1st epoch and increases to 99% during the 7th and 14th epochs. Scenario 3 has an accuracy of 89% during the 1st epoch and reaches a peak accuracy of 98% during the 7th epoch. Scenario 4 has an accuracy of 89% during the 1st epoch and achieves a significant increase in accuracy during the 5th and 11th epochs, reaching a peak accuracy of 98% during the 13th epoch. Scenario 5 has an accuracy of 90% during the 1st epoch and significantly increases during the 6th and 13th epochs, achieving a peak accuracy of 99% during the 12th and 13th epochs. Scenario 6 has an accuracy of 89% during the first epoch and achieves a significant increase during the 2nd and 12th epochs, reaching a peak accuracy of 99% during the 13th and 14th epochs. Scenario 7 has an accuracy of 86% during the 1st epoch and significantly increases during the 6th and 11th epochs, achieving a peak accuracy of 98% during the 12th epoch. Lastly, Scenario 8 has an accuracy of 85% during the 1st epoch and achieves a significant increase during the 1st and 11th epochs, reaching a peak accuracy of 98% during the 11th and 13th epochs.

The loss accuracy plots for the Xception architecture across eight different scenarios provide valuable insights into the model's training dynamics. In Scenario 1, despite starting with a relatively high loss accuracy, the model demonstrates a consistent reduction in loss, indicating its capacity to learn and adapt. Scenario 2 follows a similar trend, starting with lower initial loss accuracy and gradually improving over epochs, highlighting the model's ability to optimise its performance. In Scenario 3, the model faces a challenging start with high initial loss accuracy but eventually manages to significantly reduce it, showcasing its resilience in training. Scenario 4 starts with a high loss accuracy but quickly converges to a much lower value, indicating rapid learning. Scenarios 5 and 6 both exhibit steady improvements, while Scenario 7 shows how the model can overcome an initial high loss accuracy to achieve better results. Finally, Scenario 8, with an exceptionally high initial loss accuracy, demonstrates the model's robustness in dealing with extreme challenges, ultimately achieving a substantial reduction in loss. These scenarios collectively illustrate the versatility and adaptability of the Xception Architecture in various training conditions.

Training Xception with 25 Epoch

Xception training was conducted for 25 epochs, resulting in eight training models according to *Table 3*. Visualisation of training with 25 epochs can be seen in *Figure 5*. The training accuracy plots for the Xception architecture over 25 epochs in eight different scenarios reveal intriguing patterns of the model's learning process. In Scenario 9, the model starts with a high accuracy and consistently maintains it, reflecting the model's strong and stable learning capability. Scenario 10, on the other hand, begins with a lower accuracy but gradually improves over epochs, indicating that the model requires more training to achieve optimal performance. Scenario 11 exhibits fluctuations in accuracy but converges to a relatively high value, showcasing the model's adaptability. Scenario 12 shows initial instability but eventually reaches a satisfactory level of accuracy. In Scenario 13, the model swiftly reaches a high accuracy and maintains it, indicating efficient learning. Scenario 14 demonstrates rapid convergence to a high accuracy, highlighting the model's ability to adapt quickly. In Scenario 15, the model starts with a moderate accuracy and shows

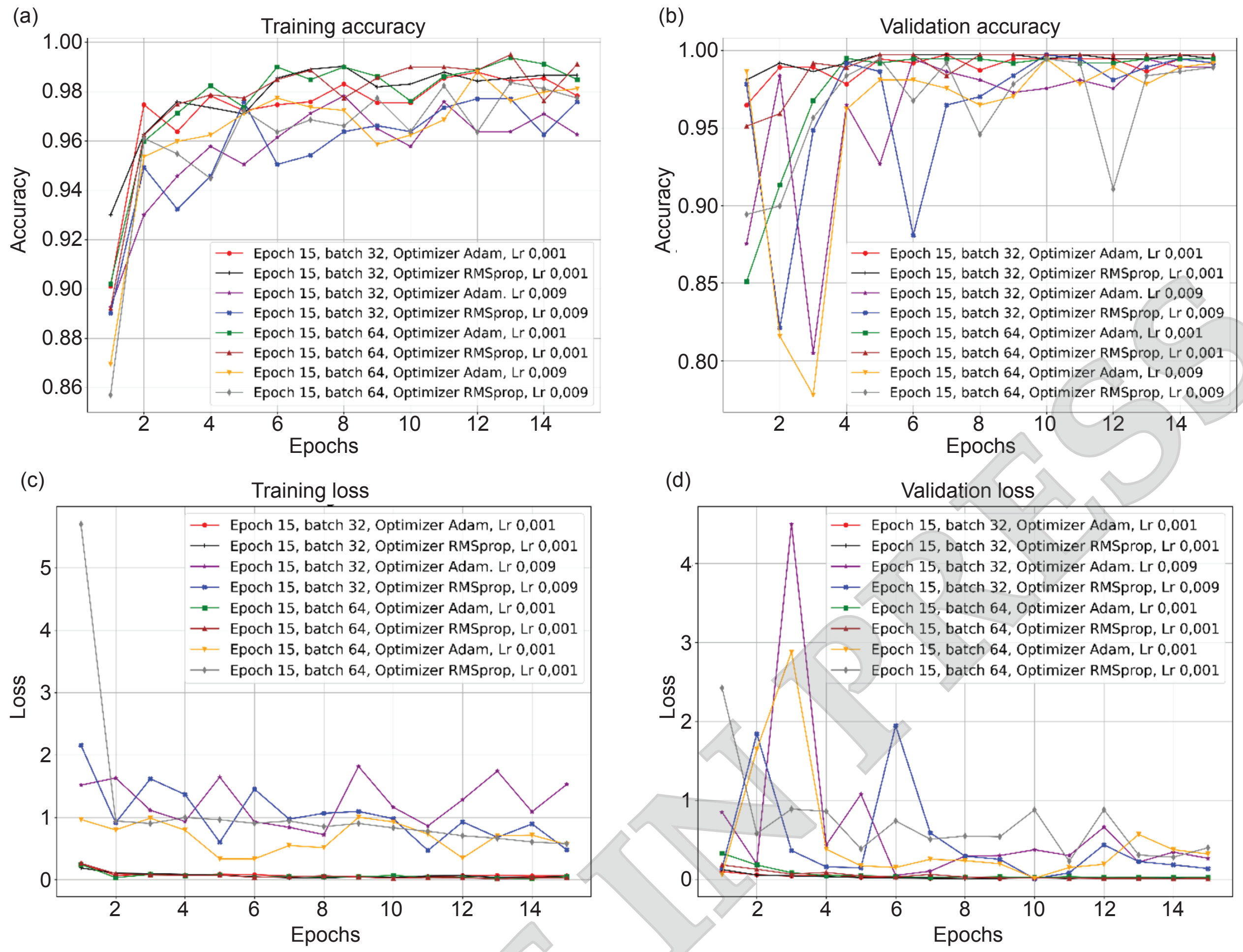


Figure 4. Training Xception with 15 epoch: (a) Training accuracy, (b) validation accuracy, (c) training loss, and (d) validation loss.

gradual improvement, indicating steady learning. Finally, Scenario 16 displays a challenging start but ultimately achieves a commendable level of accuracy, emphasising the model's robustness. These scenarios collectively illustrate the Xception Architecture's diverse learning trajectories under varying conditions, showcasing its ability to adapt and optimise training outcomes.

In the graphs of loss and validation accuracy for the Xception Architecture over 25 epochs using eight different scenarios, we can analyse the possibilities of overfitting, underfitting, or good fitting of the model. Scenario 9 shows a trend indicating underfitting, with high and fluctuating validation loss throughout training. This indicates that this model struggles to understand and model the data effectively. Scenario 10 performs very well, with low and stable validation loss throughout training. This suggests a good fit between the model and the data. Scenario 11 depicts overfitting, with validation loss initially decreasing but then starting to increase after several epochs. This suggests that this model might be too complex and overly adept at learning the training data but does not generalise well to validation data. Scenario 12 shows a stable trend, with validation loss continually decreasing throughout training. This suggests a good fit between the model and the data. Scenarios 13, 14 and 15 also show very good results, with low and stable validation loss throughout training. Scenario 16 displays good results, with low and stable validation loss throughout training, indicating a good fit. Overall, these results show variations in the quality of model fitting to the data. Scenarios 10, 12, 13, 14, 15 and 16 indicate good fitting, while Scenario 9 indicates underfitting and Scenario 11 indicates overfitting. In practice, model selection and hyperparameter tuning may be necessary to address issues of overfitting or underfitting.

Performa Xception

The 16 training models, shown in *Figure 4* and *5*, were used as the knowledge base for testing on 30% of the test data. The results of the confusion matrix, which maps model predictions against actual classes to determine model performance, are presented in *Figure 6*. Meanwhile, the classification report, which summarises the various evaluation metrics and provides a complete overview of model performance, is shown in *Table 4*.

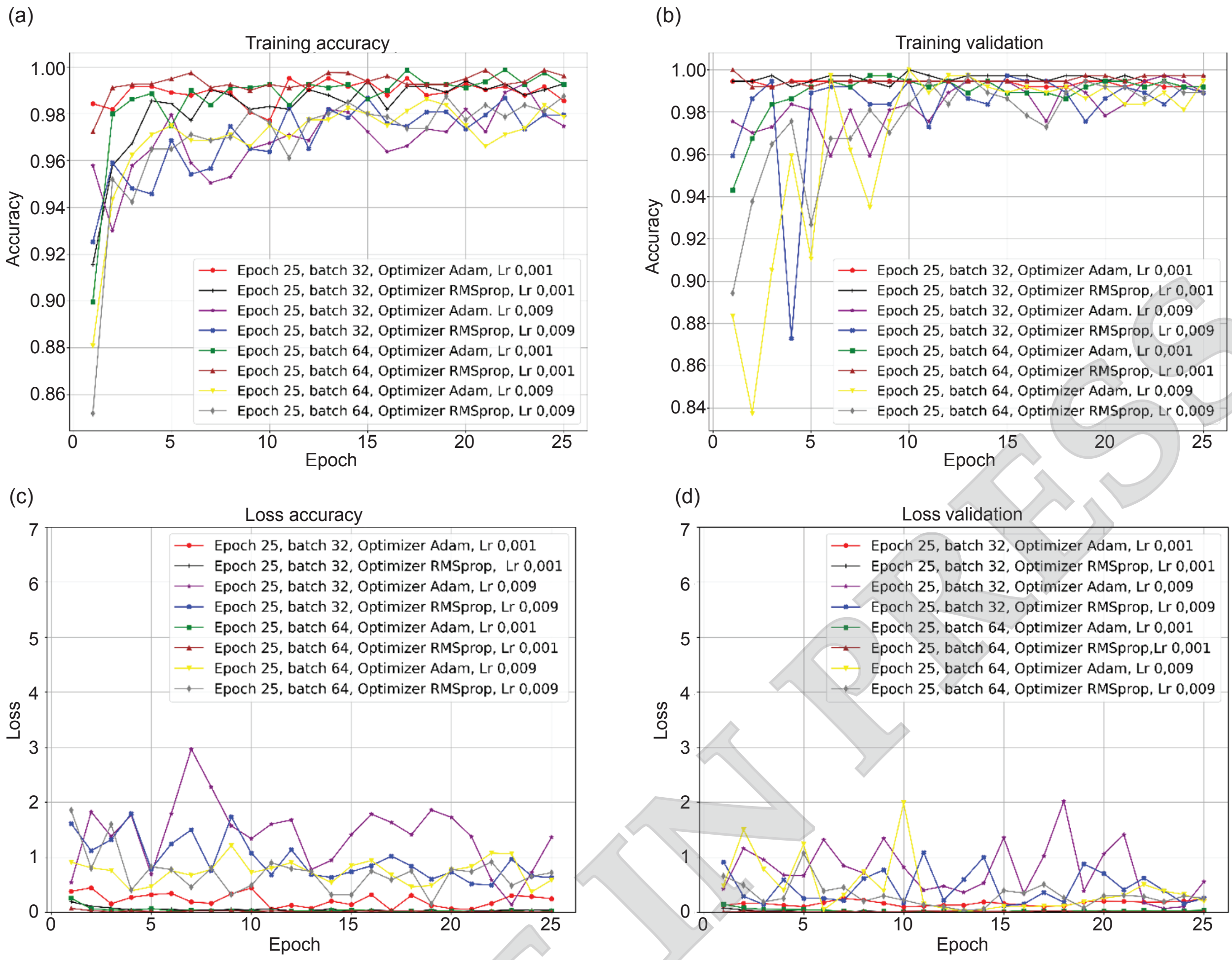


Figure 5. Training Xception with 25 epoch: (a) Training accuracy, (b) validation accuracy, (c) training loss and (d) validation loss.

In the analysis of leaf damage classification on oil palm leaf based on the experimental results using metrics such as accuracy, precision, recall and F1-score, it was found that the model used showed excellent performance. The experimental results revealed high consistency, with most scenarios providing metric values that are very close to or even reaching 0.9900 or 0.9973. This high level of consistency depicts the model's ability to deliver similar results under various conditions. Furthermore, there are scenarios where metric values, such as accuracy, precision, recall and F1-score, have the same values, indicating a high level of result uniformity in the experiments. Overall, the model's performance in classifying leaf damage on oil palm leaves is excellent, with metric values approaching perfection.

Additionally, the experimental results indicate that this model does not show significant signs of overfitting or underfitting, which is a positive outcome. The high consistency between metrics on the training and validation datasets suggests that the model is capable of providing reliable results across different scenarios. The elevated values of precision, recall and F1-score underscore the model's proficiency in accurately detecting and classifying leaf damage affecting oil palm leaves. These metrics indicate that the model can effectively differentiate between healthy and damaged leaves, which is crucial for early leaf damage detection and prevention. Therefore, this model holds promise for practical applications in identifying and managing leaf damage in oil palm plantations. However, further field testing is necessary to evaluate the model's performance in real-world environments before its broader deployment in agricultural practices.

In evaluating the performance of the Xception model across 16 different scenarios, the results demonstrate the model's success in classifying leaf damage in oil palm leaves. Certain scenarios, such as Scenario 6 (with 15 epochs), achieved the highest accuracy of 99.73%, precision of 99.73%, recall of 99.73% and F1-score of 99.73%, demonstrating the effectiveness of the model under specific conditions. This scenario also showed the best computational time, taking only 272 s. The optimal performance in this case was achieved with 15 epochs, a batch size of 64, a learning rate of 0.001 and the RMSProp optimiser. Although

Figure 6. Confusion matrix result.

TABLE 4. PERFORMANCE METRICS FOR LEAF DAMAGE CLASSIFICATION IN OIL PALM LEAVES SCENARIOS

Scenario	Accuracy	Precision	Recall	F1-score	Time computation (s)
1	0.9946	0.9946	0.9946	0.9946	372
2	0.9946	0.9947	0.9946	0.9946	315
3	0.9892	0.9893	0.9892	0.9892	313
4	0.9919	0.9921	0.9919	0.9919	316
5	0.9946	0.9946	0.9946	0.9946	323
6	0.9973	0.9973	0.9973	0.9973	272
7	0.9919	0.9921	0.9919	0.9919	321
8	0.9892	0.9893	0.9892	0.9892	256
9	0.9892	0.9893	0.9892	0.9892	503
10	0.9973	0.9973	0.9973	0.9973	494
11	0.9892	0.9892	0.9892	0.9892	616
12	0.9892	0.9893	0.9892	0.9891	502
13	0.9919	0.9919	0.9919	0.9919	494
14	0.9973	0.9973	0.9973	0.9973	614
15	0.9946	0.9947	0.9946	0.9946	615
16	0.9892	0.9894	0.9892	0.9892	499

Scenario 10 and 14 also achieved the same accuracy as Scenario 6 (99.73%), their computational times were much higher, reaching 494 s and 614 s, respectively. Some other scenarios exhibited variations in performance, likely due to different combinations of parameters such as epochs, batch size, learning rate and optimiser. To provide further context, our results are compared with previous studies. For example, a study by Asrianda et al. (2021) used CNN for disease classification in oil palm leaves and achieved an accuracy of 69.00%.

Additionally, a study by Indrawati et al. (2023) focused on classifying diseases in oil palm leaves, distinguishing between healthy leaves and leaves affected by conditions such as fungal infestations and leaf spot disease. The GoogLeNet method was employed for classification, with parameter configurations including a batch size of 32, RMSProp optimiser and a learning rate of 0.009. The experimental results indicated an accuracy rate of 93.22%, demonstrating the model's ability to effectively identify different disease conditions affecting oil palm leaves. These results emphasise the potential of the GoogLeNet approach in supporting accurate disease detection in oil palm cultivation.

In comparison, our Xception model significantly surpassed that performance with an average accuracy of approximately 99%, illustrating substantial progress in leaf damage detection. Our findings contribute to the existing knowledge on leaf damage detection in oil palm plants. The Xception model, optimised with specific parameters, has shown excellent capability in identifying leaf damage in palm leaves, laying a solid foundation for developing field systems that can assist smallholders in faster, more accurate leaf damage detection.

Future Recommendations and Limitations

While the Xception model's performance is promising, the study has some limitations. Variations in environmental conditions, limited data availability and potential non-optimal hyperparameter selection may influence the robustness and generalisability of the results. These factors should be considered when interpreting the findings. To further improve the model's performance and make the results more generalisable, we recommend the following steps: a) Hyperparameter tuning, b) attention mechanism, c) dataset expension and d) field implementation and integration.

Hypermeter tuning. Future study could explore advanced hyperparameter optimisation techniques such as grid search, random search and Bayesian optimisation. This would allow for a more systematic approach in finding the optimal configuration for the model. As stated by Muhathir et al. (2024), the selection and adjustment of appropriate hyperparameters greatly affect the performance of the model in classification tasks.

Attention mechanisms. The application of attention mechanisms has the potential to improve the model's ability in feature selection and interpretation of visual data. By focusing attention on important areas in the image, the model can produce more accurate classifications and provide better transparency to the decision-making process. The integration of the convolutional block attention module (CBAM) into the ResNet50 Architecture was demonstrated to significantly improve classification performance for oil palm pest detection (Muhathir et al., 2025). These findings confirm that attention modules can enhance feature representation and enable the model to prioritise critical visual information more effectively.

Expansion of the dataset. A more diverse and comprehensive dataset should be used to account for different environmental conditions and leaf damage severity levels. Including various levels of leaf damage progression (e.g., mild, medium, severe) would help the model learn to recognise different stages of disease attack more effectively.

Field implementation and integration. A key next step would be to deploy the model in real-world agricultural settings, possibly integrated with a decision support system. Such a system could help smallholders make timely, informed decisions about crop health. This could further be enhanced by using drones for real-time leaf damage detection and monitoring.

CONCLUSION

This study focuses on the classification of leaf damage in oil palm leaves using the Xception model. The model achieved a maximum accuracy of 99.7%, outperforming some previous studies (*Table 1*), while maintaining an average accuracy of around 99.0%, indicating significant success in the classification task. This achievement provides valuable insight into the potential of the model in supporting early leaf damage detection in oil palm. In future studies, several aspects can be further improved and enhanced. The hyperparameter search can be optimised by considering methods such as grid search, random search and Bayesian optimisation to find the best configuration. Additionally, expanding the dataset will introduce greater variation and enhance the model's generalisation. The integration of attention modules could also be explored to improve learning efficiency and accuracy. This study holds significant benefits for the palm oil industry. The implementation of the Xception model can assist smallholders in detecting leaf damage on oil palm leaves more quickly and accurately, enabling more effective preventive measures. The deployment of this solution can enhance productivity and sustainability in oil palm cultivation, contributing to better crop management and disease control strategies.

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