Res-DSCBAM: A Comprehensive Framework for Efficient Oil Palm Pest Classification Using Integrated ResNet50, Depthwise Separable Convolution, and Convolutional Block Attention Module

Muhathir*, Andre Hasudungan Lubis, Dwika Karima Wardani, Mahardika Gama Pradana

***Abstract*— In this study, we provide a revised insight into the performance of the ResNet50 model in identifying pests affecting oil palm plants. This issue is particularly critical due to the significance of monitoring and early detection of pests to enhance oil palm productivity. This study aims to assess and enhance the performance of the ResNet50 model in identifying pests that affect oil palm plants. We aim to explore how the integration of Depthwise Separable Convolution and the Convolutional Block Attention Module (CBAM) techniques can enhance the model's accuracy and capability in effectively identifying pest classes. This study employed an experimental approach utilizing ResNet50 as the foundational model. The impact of incorporating Depthwise Separable Convolution and the CBAM was assessed to evaluate its effect on model performance. The experiments were conducted using a dataset that featured a diverse array of images depicting oil palm pests. The assessment of model performance involved a detailed examination of the Confusion Matrix and the classification report. The results surprisingly showed significant improvements in accuracy, precision, recall, and F1-score. The improvement was observed in each pest class, with the best final result achieved by combining both techniques, resulting in an average accuracy of 99.07%. This study demonstrated that the addition of Depthwise Separable Convolution and CBAM techniques significantly enhanced the ResNet50 model's ability to classify pests in oil palm. The results are noteworthy. However, additional analysis is required to identify the factors contributing to specific misclassifications. Future recommendations include exploring additional model architectures and further evaluating the factors that influence model decisions.**

***Index Terms*— Classification, ResNet50, Depthwise Separable, CBAM, Palm Oil Pests**

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Muhathir is a lecturer at the Department of Informatic Engineering, Faculty of Engineering, Universitas Medan Area, Medan, 20223, Indonesia (e-mail: muhathir@staff.uma.ac.id).

Andre Hasudungan Lubis is a lecturer at the Department of Informatic Engineering, Faculty of Engineering, Universitas Medan Area, Medan, 20223, Indonesia. (e-mail: andrehasudunganlubis@uma.ac.id).

Dwika Karima Wardani is a lecturer at the Department of Agrotechnology, Faculty of Agriculture, Universitas Medan Area, Medan, 20223, Indonesia. (e-mail: dwika@staff.uma.ac.id).

Mahardika Gama Pradana is a researcher at Palm Oil Research Center, Medan, 20158, Indonesia. (e-mail: mahardikagama@gmail.com).

I. INTRODUCTION

Oil palm is an product that thrives in tropical regions, like Indonesia and Malaysia along with other countries such as Papua New Guinea and Thailand where it plays a significant role, in the plantation sector of Indonesia [1]. Indonesia has seen an increase, in the growth of oil palm plantations lately. Has become the top global producer of palm oil with a contribution of more than 44% to the total palm oil production worldwide. Oil palm is known for being highly productive as it yields oil per hectare compared to oil producing plants. Indonesia plays a role, in the crude palm oil (CPO) market [2].

Currently, oil palm production encounters several challenges, including pest attacks and diseases that can damage oil palm plants. Despite their inherent resistance, these plants are not immune to pests and diseases that can potentially reduce productivity [3]. Oil palms are also sensitive to insect attacks that can inhibit plant growth and reduce production. Typically, pest-related damage can lead to a production decrease of as much as 70%, and when coupled with disease outbreaks, total losses may escalate to 100% [4].

In the context of agricultural production, pest detection has become a serious concern, resulting in crop losses of up to 20% annually worldwide [5], [6]. In 2021, China faced a challenge with plant pests and diseases affecting 400 million hectares of land about a quarter of the country’s total area. This underscores the need to promptly and precisely detect crop diseases and pests for maintaining productivity and sustainability. Beyond crop damage this issue plays a role, in advancing agriculture growth and boosting farmers’ incomes. [7]. Apart from that, developing artificial intelligence models via agricultural image processing is regarded as one of the most effective approaches. These models are capable of detecting pests and categorizing them into various classifications. [8]. This enables a more efficient response and intervention strategy against pests in agricultural production, leading to improved efficacy in pest detection and mitigation. Consequently, it helps minimize the losses incurred in agricultural production.

Many researchers have embraced both traditional machine learning (ML) techniques and deep learning models to create more effective pest detection systems [9], [10]. However, the traditional methods of detecting insects based on morphological characteristics may requires some trained taxonomists to perform accurate identification. Hence, it can be restrictive. [7], [11]. It is important to note that traditional methods have some constraints that must be addressed. Recently, a number of automated methods for pest detection using traditional machine learning have been proposed [12]. For example, Faithpraise et al. [13] proposed a K-means clustering algorithm for pest detection. However, this method requires manual feature extraction and the application of filters, which can be time-consuming, especially when dealing with large datasets. Moreover, Rumpf et al. [14] proposed the use of Support Vector Machines for disease recognition in sugar beet crops based on vegetation spectra. The method is effective for detecting pests. Nevertheless, the efficiency of traditional machine learning-based models can be affected by various limitations. In traditional ML-based methods, the processes of manual feature extraction and classification are time-consuming, monotonous, prone to errors, and require a high level of computer proficiency. Therefore, the use of deep learning-based approaches with machine learning is becoming increasingly important to overcome these constraints and achieve more efficient pest detection [15].

Technology has great potential in helping farmers efficiently detect destructive insects and prevent diseases at an early stage [16]. Imaging and computer vision technologies have emerged as pivotal tools with wide-ranging applications, particularly in contemporary agriculture. Various detection techniques that combine mechanization with image processing, are currently meeting the initial demands for effectively managing pest infestations. For example, Kasinathan et al. [17] harnessed machine learning methodologies for the classification of insect pests, focusing on their morphological attributes. Similarly, Chiwamba and Nkunika [18] proposed the development of an automated system proficient in on-field moth identification by leveraging supervised machine learning techniques. On a different note, Tageldin et al. [19] employed machine-learning algorithms to forecast leafworm infestations in greenhouse environments. In general, machine learning models are designed to operate autonomously, requiring redevelopment when attributes and data change. On the other hand, the Transfer Learning approach aims to re-utilize existing models and gain existing knowledge, which can ultimately reduce the time and effort to develop new models. It can also improve the model's performance compared to a stand-alone learning model.

Fine-tuning, a concept in Transfer Learning, has been shown to be a faster and more accurate method of building models when compared to building models from scratch [20]. In the process of fine-tuning, a Convolutional Neural Network (CNN) undergoes initial training for a related task. Subsequently, the last layer of the model is modified to better align with the characteristics of the new dataset [21]. According to Kamilaris and Prenafeta-Boldú [22], a CNN Transfer Learning-based models is acceptable to be employed in various agricultural problems such as plant disease recognition [23], fruit classification [24], weed identification [25], and crop pest classification [26], [27]. Hence, it can be argued as the powerful tools for classifying images in an agricultural context. The use of these models has positively impacted farmers by helping them identify effective and efficient pest control strategies, as well as reducing significant economic losses.

The classification of pests in oil palm plants plays an important role in determining the types of pests that infest them, the patterns of their attacks, and the level of the damage caused [28]–[30]. This information helps farmers in choosing the most effective and efficient pest control strategy. Hence, research on deep learning techniques is currently underway to enhance pest recognition technology in oil palm crops [31]–[34]. An approach to address the challenge of automatic classification of pests in oil palm involves the development of deep learning-based oil palm pest recognition technology. Deep learning methods are used to train computer algorithms to recognize patterns and features [35] that appear in images of insect pests that attack oil palm plants [36]–[38].

Authors should consider the following points:

1) Classify pest cases on oil palm plants, including *Metisa plana, Setora nitens, Parasa lepida, Pteromas pendula,* and *Setothosea asigna,* based on visual images using Convolutional Neural Network (CNN) architecture, specifically ResNet50.
2) Evaluate the performance of the ResNet50-based classification method in identifying pests in oil palm with improvements through the addition of Depthwise Separable Convolution and Convolutional Block Attention Module (CBAM) in the ResNet50 architecture.
3) Contribute to efforts to identify and control pests in oil palm plants through the analysis of relevant visual features. This analysis is expected to help farmers and agricultural practitioners in making more informed and efficient decisions.

II. Methodology

A. Research Framework

The research framework developed in this study is illustrated in Figure 1.

Figure 1 shows the research architecture model used in this study to classify pests in oil palm plantations. The initial step in the research process involves gathering data, which is subsequently preprocessed to construct a dataset comprising images that match or do not match pest samples. The dataset is then divided into three subsets: training, validation, and testing. In the training stage, the neural network model uses the ResNet50 architecture and is trained using the training dataset. Then, the model’s performance is evaluated using the validation dataset to confirm its ability to generalize well. This evaluation includes some metrics such as accuracy, precision, recall, and F1-score (Equations 1-4). Ultimately, to test the effectiveness of the model, the model is tested using an independent testing dataset. This approach ensures that the developed model is reliable and has good performance in classifying pests in oil palm plantations.

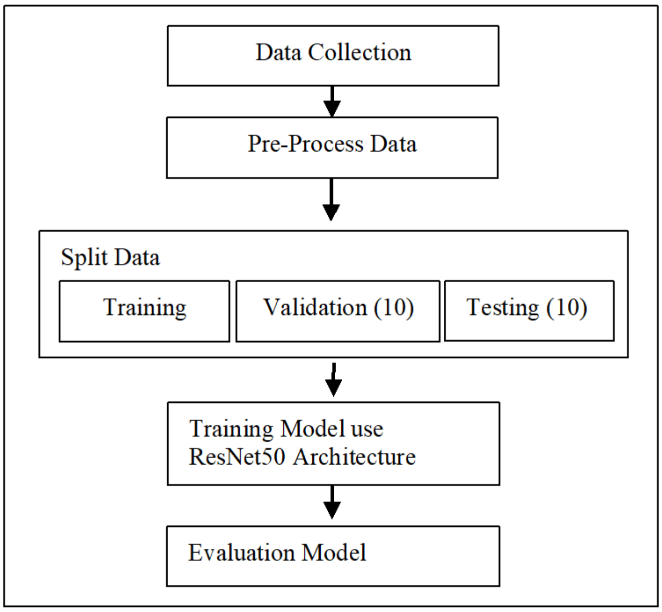


Fig. 1. Research framework model utilized in this study for oil palm pests classification.

B. *Data collection and Pre-Processing data*

In this study, pest-related data in the oil palm plantation of the Siantar Oil Palm Research Center was collected through a detailed technical approach. The data included images of the pests *Metisa plana*, *Setora nitens*, *Parasa lepida*, *Pteromas pendula*, and *Setothosea asigna*, which are the main pests that are the focus of our research. Each pest was carefully photographed to document its distinctive characteristics. The shooting distance was maintained at about 15-20 cm to allow us to obtain accurate and relevant details.

During the data preprocessing phase, maintaining the data quality is quite important to go through the process. Firstly, the subject data is prepared by performing data cleaning and identifying and addressing noise or anomalies that may be present in the dataset. This step aims to ensure the integrity of the data before proceeding with the analysis. Next, the image data is treated by resizing the images to consistent dimensions, allowing further processing with a uniform size. Resizing ensures that all images have the same dimensions, which is important in the context of image recognition or image analysis tasks.

Ultimately, data augmentation techniques are employed to enhance the diversity within the image dataset. Data augmentation includes operations such as rotation, width shift, height shift, shearing, zoom, and vertical flip. This generates variations in the training data that can help machine learning models understand different variations of images that may be encountered in the real world. Data augmentation is a very useful method in image recognition and image processing, which can improve model performance and prevent overfitting. Through the integration of cleaning, resizing, and augmentation steps, the data is prepared for further analysis or training of deep learning models.

C. *Split Data*

To prepare the data for analysis and training of the ResNet deep learning model, the dataset consists of 7500 images including three pest categories, with each category covering 1500 images. These categories include *Metisa plana*, *Setora nitens*, *Parasa lepida*, *Pteromas pendula*, and *Setothosea asigna*. This dataset was then divided into three separate sets. The first dataset is the training data, which is utilized to train the model and help it understand the patterns in the data. The second dataset is the validation data, which is used to assess the model's performance during training, determine the best parameters, and prevent overfitting. Ultimately, the test data is employed to validate the trained model's effectiveness on unfamiliar data, thereby providing a more accurate gauge of the model's capacity to generalize to real-world data. The 80:10:10 split ensures that models are trained with sufficient datasets, objectively evaluated, and carefully tested before being used in practical applications.

D. *Performance Measure*

The Confusion Matrix utilized as an effective tool for evaluating the accuracy of an object estimation model. It provides a comprehensive elaboration into the model's performance by comparing predicted classification outcomes against the actual class labels [39]. The accuracy of the model, indicating the extent to which its predictions align with the actual values, is a key metric provided by this method. Accuracy, as represented by Equation 1, calculates the ratio of correctly predicted instances (TP + TN) to the total instances (TP + TN + FP + FN), offering a fundamental measure of overall correctness. Precision, on the other hand, measures the accuracy of a prediction or its proportion, offering a valuable perspective on the model's capability to make accurate positive predictions. Precision, as indicated by Equation 2, assesses the ratio of true positive instances (TP) to the total predicted positive instances (TP + FP), emphasizing the model's ability to avoid false positives. The model's recall quantifies its ability to recognize true positive instances. Recall, as defined by Equation 3, calculates the ratio of true positive instances (TP) to the total actual positive instances (TP + FN), providing insights into the model's capacity to capture all relevant instances. The combination of recall and precision yields the F1-Score, a metric that provides a balanced and comprehensive evaluation of the model's overall performance. The F1-Score, as depicted by Equation 4, is the harmonic mean of precision and recall, offering a holistic measure of a model's effectiveness in both positive and negative predictions. The calculation of these metrics involves the use of specific formulas, where TP (true positive), TN (true negative), FP (false positive), and FN (false negative) are essential components in the assessment process. These metrics contribute to a nuanced understanding of the model's strengths and areas for improvement in object estimation tasks.

E. *ResNet*

ResNet, or Residual Network, is one of the most influential Convolutional Neural Network (CNN) architectures in the world of deep learning. It firstly emerged by Kaiming He and his team in 2015, ResNet presents a breakthrough that overcomes training problems in very deep neural networks. ResNet's main advantage lies in the use of residual blocks, which allow information to flow more smoothly through the layers of the network. This overcomes the gradient constraints that often arise in very deep networks [40]. ResNet is often used in various image recognition tasks, including image classification, object detection, and image segmentation, and has become one of the basic architectures in deep learning that is often used in various applications [41]. The capability of ResNet to tackle deep network training challenges solidifies its significance as a key milestone in the evolution of Convolutional Neural Networks [42].

F. Depthwise Separable Convolution

Depthwise separable convolution is a technique in image processing used to reduce the number of parameters required in Convolutional Neural Networks (CNNs). This technique replaces standard convolution with two separate operations: Depthwise Convolution and Pointwise Convolution. Depthwise Convolution: In this stage, each input channel is handled separately with a small filter kernel. This means each input channel is connected to one filter of a small size. This operation aims to extract spatial features from each input channel separately. Pointwise Convolution: After depthwise convolution, the results are then fed into pointwise convolution. In this stage, convolution is performed on the entire output channels from the depthwise convolution using filter kernels with a size of 1x1. This operation aims to perform linear adjustments to the spatial features extracted earlier [43].

The depthwise separable convolution technique has several significant advantages. Firstly, its use results in a reduction of the parameters required in the network, compared to standard convolution. This reduces the overall model complexity and computational requirements. Secondly, by reducing the number of parameters, the technique also improves computational efficiency, thus making it more suitable for devices with limited resources such as mobile phones or IoT devices. Finally, this technique enables better feature-representation learning by neural networks. This occurs due to the utilization of the depthwise separable convolution approach, which enables the independent processing of each input channel before carrying out advanced spatial transformations through pointwise convolution. As such, this technique is an efficient and effective approach to strengthen convolutional neural networks in learning important features from images, while reducing the overall complexity and computational requirements of the model [44].

G. Convolutional Block Attention Module

CBAM (Convolutional Block Attention Module) is an attention module used in Convolutional Neural Networks (CNNs) to improve performance in computer vision tasks. It is designed to assisting CNN networks to focus on the most relevant features for decision-making by dynamically assigning attention weights to different parts of the input image [45]. CBAM consists of two main components: a spatial attention module and a channel attention module. The spatial attention module allows the network to focus on important areas in the image, while the channel attention module helps in adjusting the weights of each feature channel to improve the overall feature representation [46]. By using CBAM, CNN networks can learn to allocate resources more efficiently and strengthen the features that are most relevant for object recognition or image classification tasks [47].

H. Combination of ResNet50 with Depthwise Separable CBAM

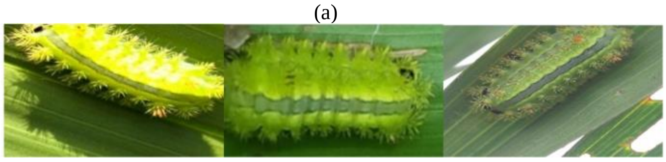
CBAM is a powerful approach in improving the performance of convolutional neural networks (CNNs) for computer vision tasks such as image classification. ResNet50 is a deep CNN architecture, which is well known for its ability to address deep training problems with the introduction of shortcut connections or skip connections. Depthwise Separable Convolution reduces the number of parameters and improves computational efficiency by separating the convolution process into two stages: spatial convolution and channel convolution. Meanwhile, CBAM provides an attention module that helps CNN networks focus on the features that are most relevant in decision making, by paying attention to both the spatial and channel of the features. The combination of these three components allows the network to learn better feature-representations, improve classification accuracy, and reduce model complexity, making it suitable for a variety of computer vision applications, including pest classification in oil palm crops.

III. Results and Discussion

A. Oil Palm Pest Samples

The sample data of pests on oil palm plants in this study includes five main pest species, namely *Metisa plana*, *Setora nitens*, *Parasa lepida*, *Pteromas pendula*, and *Setothosea asigna*. This dataset contains a variety of images that reflect various situations and conditions in the field.

(a)



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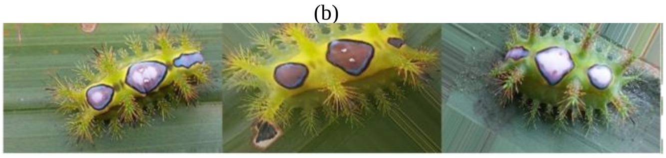

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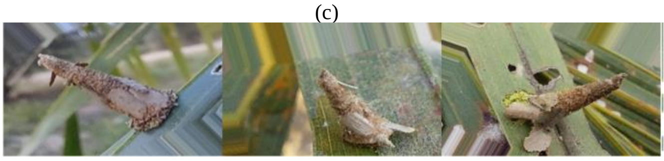

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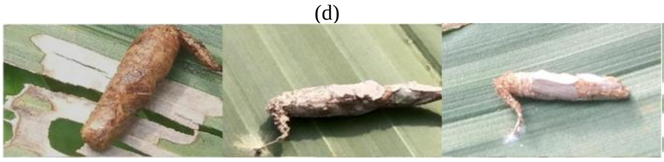

(e)

Fig. 2. Oil Palm Pest (a) *Setora nitens* (b) *Parasa lepida* (c) *Setothosea asigna* (d) *Metisa plana* (e) *Pteromas pendula*.

B. Training and Evaluation ResNet50

As part of the analysis of the use of ResNet50 models for oil palm plant pest categorization, the Training ResNet50 (Figure 3) offers a graphic representation of the model's development throughout training. By displaying the variations in accuracy and loss values over iterations, it provides information on the learning dynamics of the model. The model's classification results for each class are shown graphically in the Confusion Matrix ResNet50 (Figure 4). Furthermore, Table I shows the classification report of ResNet50, which including critical performance measures for assessing the efficacy of the model, such as F1-Score, recall, and precision, broken down for each class. From Figure 4, it can be seen that the model has high performance in most cases. For example, the *Metisa plana* class shows 140 True Positives, which means that the model accurately identified *Metisa plana* 140 times.

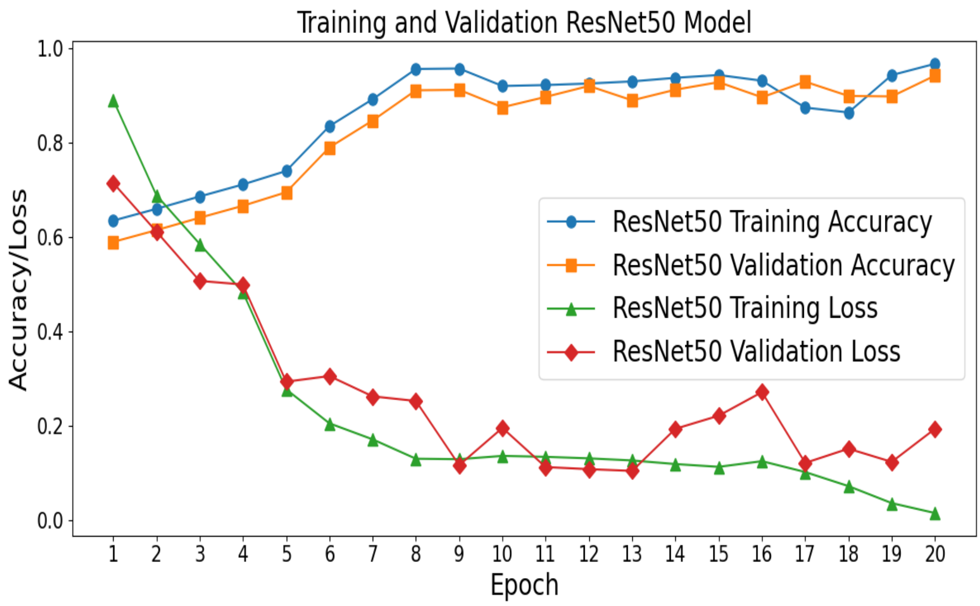

Fig. 3. Training ResNet50

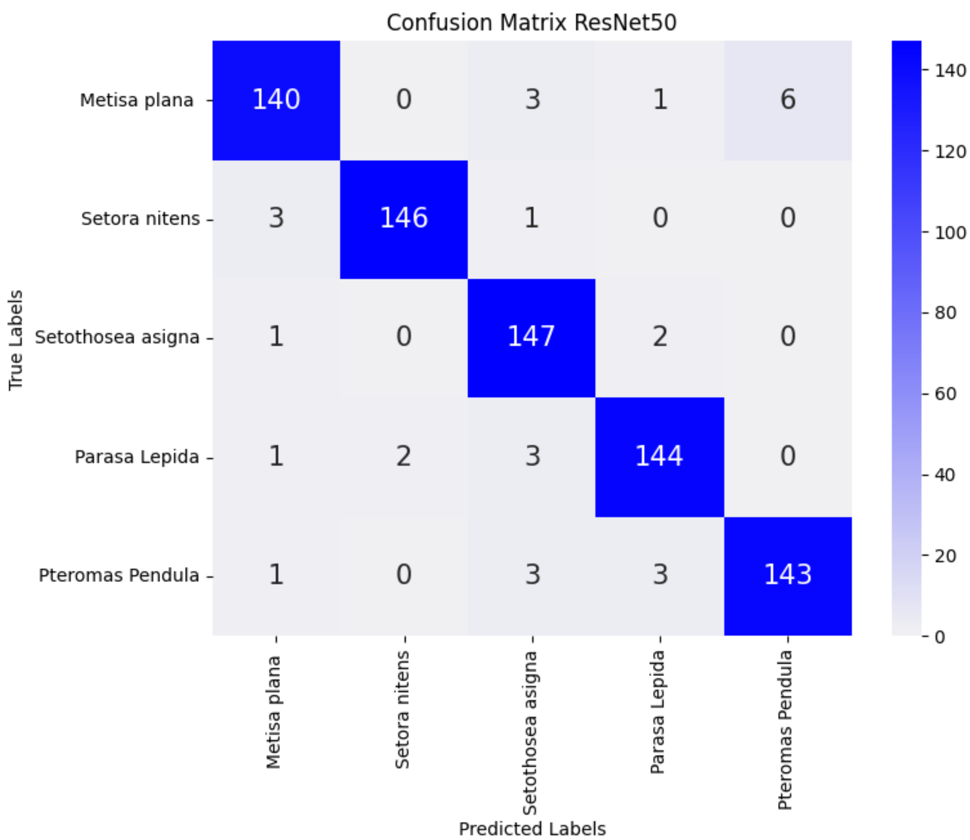

Fig. 4. Confusion Matrix ResNet50

However, there were some errors, such as 3 cases where the model classified *Metisa plana* as *Parasa lepida*, 1 as *Pteromas pendula*, and 6 as *Setothosea asigna*. The *Setora nitens* class also showed excellent results with 146 True Positives and only 4 misclassifications. *Parasa lepida* had 147 True Positives, with 3 misclassifications. *Pteromas pendula* had 144 True Positives, but 6 misclassifications. *Setothosea asigna* also had good results with 143 True Positives and only 7 misclassifications. However, there were 3 errors where the model classified *Setothosea asigna* as *Parasa lepida* 3 as *Pteromas pendula* and 2 as *Metisa plana*. Overall, the ResNet50 model performed well in classifying oil palm pests, but it is worth noting some misclassifications, especially between *Metisa plana* and *Pteromas pendula*. Further analysis may be needed to understand the factors causing these errors and improve the model's performance in certain cases.

In the ResNet50 scenario of classifying oil palm pests, the model showed excellent results with an average accuracy of 96.00%. For each class, precision was high, reaching above 93.63%, demonstrating the model's ability to correctly identify positive instances. Recall, or sensitivity, was also high for each class, above 95.33%, indicating that the model could find most of the positive instances. The high F1-Score, above 94.59%, indicates a good balance between precision and recall. Overall, the ResNet50 model showed excellent ability in classifying oil palm pests, with consistent performance across classes.

TABLE I
CLASSIFICATION REPORT RESNET50

Class	Precision	Recall	F1-Score	Support
Setora nitens	0.9589	0.9933	0.9459	150
Parasa lepida	0.9865	0.9733	0.9799	150
Sethosea Asigna	0.9363	0.9800	0.9577	150
Metisa plana	0.9600	0.9600	0.9600	150
Pteromas pendula	0.9597	0.9533	0.9565	150
Accuracy	0.9600			
Average	0.9603	0.9600	0.9600	750

C. Training and Evaluation ResNet50 with Depthwise Separable Convolution

In the examination of the application of ResNet50 with Depthwise Separable Convolution models for the classification of pests on oil palm plants, the Training ResNet50 with Depthwise Separable Convolution (Figure 5) provides a visual depiction of the model's progression during the training process. It illustrates the fluctuations in loss and accuracy values across iterations, offering insights into the model's learning dynamics.

The Confusion Matrix ResNet50 with Depthwise Separable Convolution (Figure 6) serves as a graphical representation of the model's classification outcomes for each class. Additionally, Table II, Classification Report ResNet50, encompasses crucial metrics for model performance evaluation, including precision, recall, and F1-Score, delineated for each individual class.

From Figure 6, it can be seen that the model managed to improve performance in most classes. For example, the *Metisa plana* class shows 143 True Positives, indicating that the model accurately identified *Metisa plana* 143 times. Although there were some errors, such as 3 cases where the model classified *Metisa plana* as *Parasa lepida* and 1 as *Pteromas pendula*, the increase in the number of True Positives illustrates that the addition of Depthwise Separable Convolution has helped in improving the classification of *Metisa plana*. The *Setora nitens* class also showed good results with 146 True Positives and only 4 misclassifications, illustrating the improved model performance for this class. *Setothosea asigna* had 147 True Positives with 3 misclassifications, showing that the model can identify *Setothosea asigna* with a high degree of accuracy. *Parasa lepida* showed significant improvement with 145 True Positives and only 5 misclassifications, compared to the ResNet50 model without Depthwise Separable Convolution which had 144 True Positives and 6 misclassifications. This shows that the addition of this technique helped improve the model's ability to better classify *Parasa lepida*. *Pteromas pendula* also showed good results with 144 True Positives and 6 misclassifications. There were some errors, such as 2 cases where the model classified *Pteromas pendula* as *Setothosea asigna* 3 as *Parasa lepida* and 1 as *Metisa plana*, however, the increase in the number of True Positives indicates an improvement in classification.

Overall, the ResNet50 model with Depthwise Separable Convolution showed significant improvement in classifying oil palm pests, especially for the *Pteromas pendula* class. Further analysis of specific classification errors may provide further insights for future improvements to this model.

In palm oil pest classification, the standard ResNet50 model showed high performance with an average accuracy of 96.00%, precision above 93.63%, recall above 95.33%, and F1-Score above 94.59%, indicating the model's ability to identify and classify pests with consistent accuracy. However, with the addition of Depthwise Separable Convolution (DSC), the model performance improved significantly.The ResNet50 model with DSC achieved an average accuracy of 96.67%, precision above 95.39%, recall above 96.67%, and F1-Score above 95.97%. The DSC technique helps the model to be more efficient by reducing computational complexity and overfitting, as well as allowing better focus on relevant features in the image, which contributes to the improved ability in detecting and classifying pests. Overall, the ResNet50 model with Depthwise Separable Convolution showed significant performance improvement, indicating that the addition of Depthwise Separable Convolution positively contributed to the model's ability to classify oil palm pests.

TABLE II
CLASSIFICATION REPORT RESNET50 WITH DEPTHWISE SEPARABLE CONVOLUTION

Class	Precision	Recall	F1-Score	Support
Setora nitens	0.9662	0.9933	0.9597	150
Parasa lepida	0.9865	0.9733	0.9799	150
Sethosea Asigna	0.9608	0.9800	0.9703	150
Metisa plana	0.9539	0.9667	0.9603	150
Pteromas pendula	0.9664	0.9600	0.9632	150
Accuracy	0.9667			
Average	0.9668	0.9667	0.9667	750

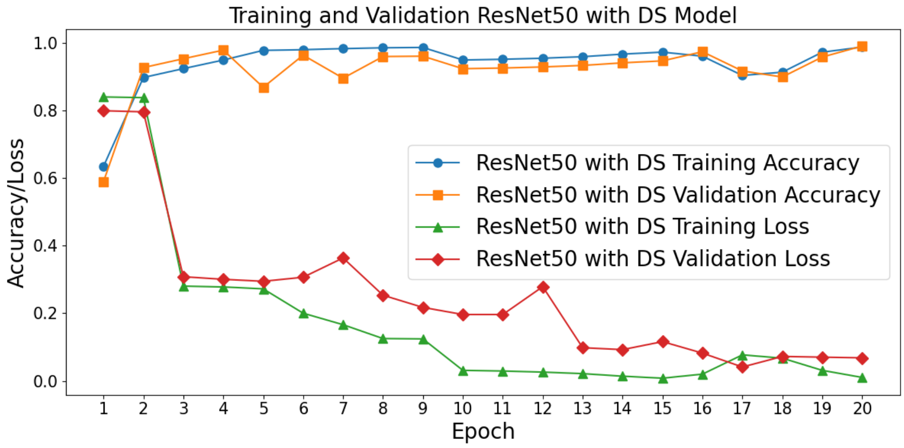

Fig. 5. Training ResNet50 with Depthwise Separable Convolution

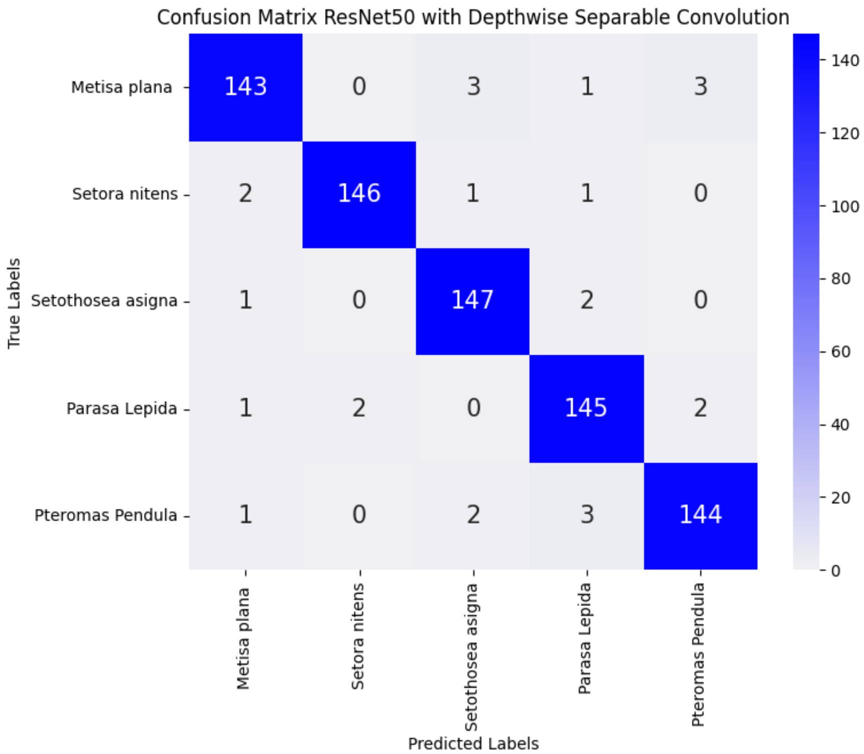

Fig. 6. Confusion Matrix ResNet50 with Depthwise Separable Convolution

D. Training and Evaluation ResNet50 with Convolutional Block Attention Module

In the exploration of the application of ResNet50 models with Convolutional Block Attention Module for classifying pests on oil palm plants, the Training ResNet50 with Convolutional Block Attention Module (Figure 7) visually portrays the model's journey throughout the training process. This depiction illustrates the fluctuations in loss and accuracy values across iterations, providing valuable insights into the learning dynamics of the model. The Confusion Matrix ResNet50 with Convolutional Block Attention Module (Figure 8) acts as a graphical representation of the model's classification outcomes for each class. Furthermore, Table 3, Classification Report ResNet50 with Convolutional Block Attention Module, comprehensively presents key metrics for evaluating model performance, including precision, recall, and F1-Score, individually detailed for each class.

From Figure 8, it can be seen that the ResNet50 model with CBAM has achieved excellent results in classifying all classes. For example, the *Metisa plana* class shows 145 True Positives, which indicates that the model can identify *Metisa plana* with high accuracy. With only a few errors, such as 3 cases where the model classified *Metisa plana* as *Setothosea asigna* 1 as *Parasa lepida* and 1 as *Pteromas pendula*, the CBAM attention module made a positive contribution in improving classification accuracy. In summary, while minor errors in classification remain, the CBAM module's inclusion contributed significantly to the model's capacity to correctly classify the majority of samples, showcasing its value in handling complex and closely related categories in insect species identification.

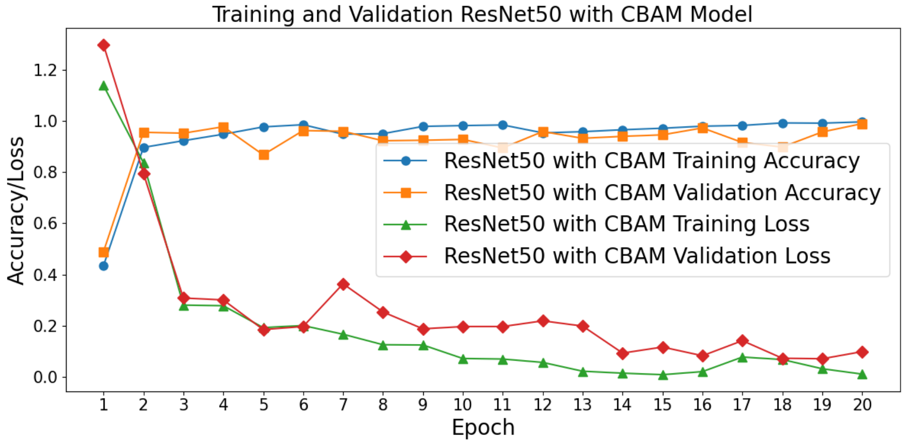

Fig. 7. Training ResNet50 with Convolutional Block Attention Module

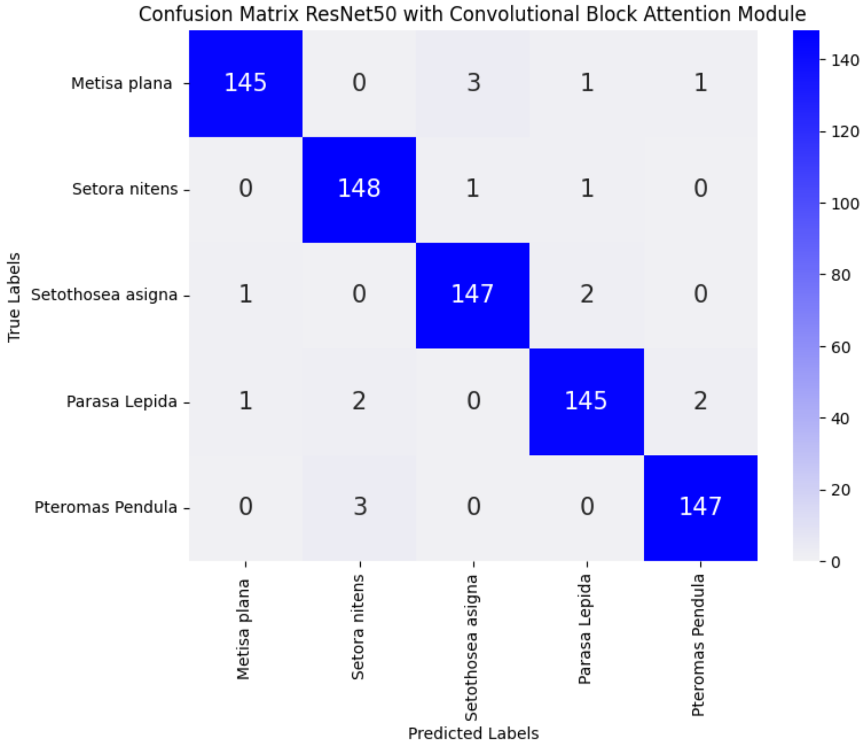

Fig. 8. Confusion Matrix ResNet50 with Convolutional Block Attention Module

The *Setora nitens* class showed excellent results with 148 True Positives and only 2 misclassifications. This reflects the model's ability to identify *Setora nitens* with a high degree of accuracy. *Setothosea asigna* had 147 True Positives with only 3 misclassifications, showing that the model with CBAM can classify *Setothosea asigna* very well. This class showed high accuracy and few errors. *Parasa lepida* also showed excellent results with 145 True Positives and only 5 misclassifications. The model with CBAM provided an improvement in classifying Pendula Pteromas compared to the ResNet50 model without this attention module. Pendula Pteromas showed excellent results with 147 True Positives and only 3 misclassifications.

This class reflects the model's ability to identify Pendula Pteromas with a high degree of accuracy. Overall, the ResNet50 model with CBAM showed significant improvement in classifying oil palm pests, with excellent performance for each class.

In comparing the performance of the standard ResNet50 model and ResNet50 enriched with Convolutional Block Attention Module (CBAM) in palm oil pest classification, there is a significant difference in the results achieved. The standard ResNet50 model showed excellent results with an average accuracy of 96.00%. Precision for each class reached over 93.63%, demonstrating the model's ability to correctly identify positive instances. Recall, or sensitivity, was also high for each class, exceeding 95.33%, indicating that the model could find most of the positive instances. The high F1-Score, above 94.59%, indicates a good balance between precision and recall. This confirms that the standard ResNet50 has an excellent ability to classify oil palm pests with high consistency across classes.

However, with the implementation of the Convolutional Block Attention Module (CBAM), the performance of the model improved substantially. ResNet50 with CBAM achieved an average accuracy of 97.60%, showing a significant improvement compared to the standard model. Precision for each class increased to over 96.73%, indicating a better ability to correctly identify positive instances. Recall also improved, reaching over 96.67% for each class, indicating a higher ability of the model to detect most positive instances. The high F1-Score, above 97.64%, reflects a better balance between precision and recall. This improvement indicates that the use of CBAM effectively helps the model to focus on more relevant features in the image, reduce noise, and improve the model's ability to classify oil palm pests. Overall, the addition of CBAM provides significant gains, making the model more accurate and efficient, outperforming the performance of standard ResNet50.

TABLE III
CLASSIFICATION REPORT RESNET50 WITH CONVOLUTIONAL BLOCK ATTENTION MODULE

Class	Precision	Recall	F1-Score	Support
Setora nitens	0.9864	0.9667	0.9764	150
Parasa lepida	0.9673	0.9867	0.9769	150
Sethosea Asigna	0.9735	0.9800	0.9767	150
Metisa plana	0.9732	0.9667	0.9699	150
Pteromas pendula	0.9800	0.9800	0.9800	150
Accuracy	0.9760			
Average	0.9761	0.9760	0.9760	750

E. Training and Evaluation ResNet50 with Depthwise Separable Convolution and Convolutional Block Attention Module

In the exploration of the application of ResNet50 models with Depthwise Separable Convolution and Convolutional Block Attention Module for classifying pests on oil palm plants, the Training ResNet50 with Depthwise Separable Convolution and Convolutional Block Attention Module (Figure 9) vividly depicts the model's progression throughout the training process. This visualization captures the fluctuations in loss and accuracy values across iterations, offering valuable insights into the dynamic learning patterns of the model. The Confusion Matrix ResNet50 with Depthwise Separable Convolution and Convolutional Block Attention Module (Figure 10) serves as a graphical representation of the model's classification outcomes for each class. Moreover, Table IV, Classification Report ResNet50 with Depthwise Separable Convolution and Convolutional Block Attention Module, provides a comprehensive overview of key metrics for evaluating model performance, including precision, recall, and F1-Score, meticulously detailed for each class.

The *Metisa plana* and *Setothosea asigna* classes showed excellent results with 150 True Positives, indicating that the model can identify with perfect accuracy. No misclassification was detected for these classes, indicating the superiority of the model in classifying. *Setora nitens* also showed excellent results with 149 True Positives and only 1 misclassification. Although there was one case where the model classified *Setora nitens* as *Setothosea asigna*, this error remained low and reflects the high accuracy in identifying *Setora nitens*. *Parasa lepida* showed excellent results with 148 True Positives and only 2 misclassifications. These two errors indicate that the model had some difficulty in classifying *Pteromas pendula*, but still achieved high accuracy. *Pteromas pendula* also achieved excellent results with 146 True Positives and only 4 misclassifications.

Overall, the ResNet50 model with Depthwise Separable Convolution and CBAM showed excellent performance in classifying oil palm pests, with high accuracy and minimal misclassification. The combination of Depthwise Separable Convolution and CBAM provides a significant improvement in the accuracy of this model, and the results are very promising for application to similar classification tasks in the future.

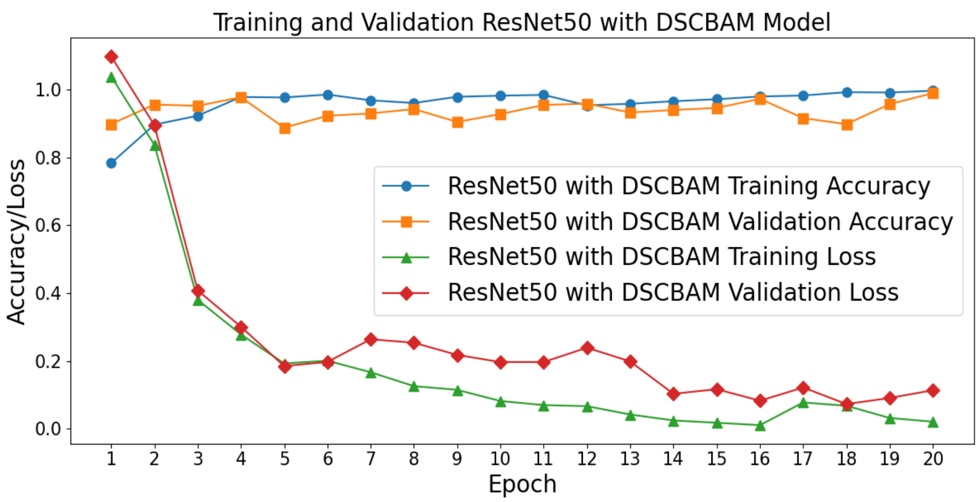

Fig. 9. Training ResNet50 with Depthwise Separable Convolution and Convolutional Block Attention Module

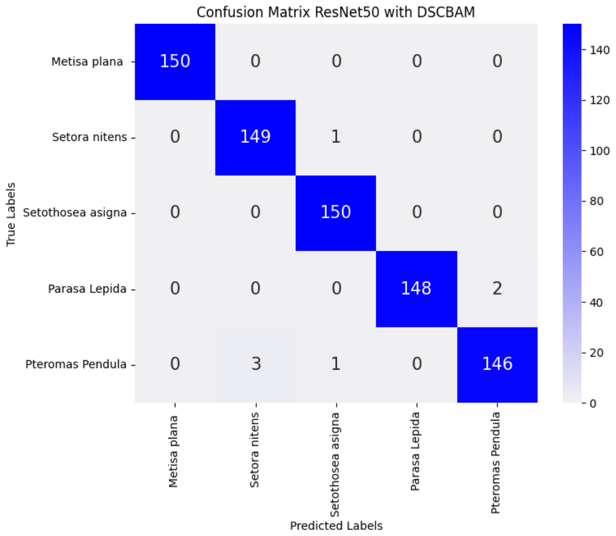

Fig. 10. Confusion Matrix ResNet50 with Depthwise Separable Convolution and Convolutional Block Attention Module

In contrast, when Depthwise Separable Convolution and Convolutional Block Attention Module are applied to the ResNet50 model, there is a substantial performance improvement. The modified model achieved a very high average accuracy of 99.07%, showing a significant jump in classification capability. Precision and recall for each class reached very high levels of over 97.33% each, reflecting the model's superior ability to accurately identify positive instances and detect most positive instances. The high F1-Score, exceeding 98.07%, indicates that the model successfully achieved an optimal balance between precision and recall.

These results show that the combination of Depthwise Separable Convolution and CBAM significantly improves ResNet50's ability to classify oil palm pests. Depthwise Separable Convolution allows the model to focus more on important features while reducing computational complexity, while CBAM gives the model the ability to effectively highlight important features in the image, reducing irrelevant noise. The combination of these techniques not only improves the accuracy and sensitivity of the model but also optimizes the balance between the two, resulting in outstanding performance in this complex classification task.

TABLE IV
CLASSIFICATION REPORT RESNET50 WITH DEPTHWISE SEPARABLE CONVOLUTION AND CONVOLUTIONAL BLOCK ATTENTION MODULE

Class	Precision	Recall	F1-Score	Support
Setora nitens	1.0000	1.0000	1.0000	150
Parasa lepida	0.9803	0.9933	0.9868	150
Sethosea Asigna	0.9868	1.0000	0.9934	150
Metisa plana	1.0000	0.9867	0.9933	150
Pteromas pendula	0.9907	0.9733	0.9799	150
Accuracy	0.9907			
Average	0.9907	0.9907	0.9907	750

F. Discussion

The research findings based on Table V comparison of research results show the improvement of ResNet50 model performance with the addition of Depthwise Separable Convolution and Convolutional Block Attention Module techniques:

TABLE V
COMPARISON CLASSIFICATION REPORT RESNET50 WITH THE ADD DEPTHWISE SEPARABLE CONVOLUTION AND CONVOLUTIONAL BLOCK ATTENTION MODULE

Scenario	Precision	Recall	F1-Score	Accuracy
ResNet50	0.9603	0.9600	0.9600	0.9600
ResNet50 with Depthwise Separable Convolution	0.9668	0.9667	0.9667	0.9667
ResNet50 with Convolutional Block Attention Module	0.9761	0.9760	0.9760	0.9760
ResNet50 with Depthwise Separable Convolution and Convolutional Block Attention Module	0.9907	0.9907	0.9907	0.9907

The ResNet50 base model has good performance with accuracy, precision, recall, and F1-Score around 96%. However, there is potential to improve the performance of the model. The addition of Depthwise Separable Convolution improved the model performance, especially in terms of accuracy, precision, recall, and F1-Score which reached around 96.67%. This shows that the Depthwise Separable Convolution technique makes a positive contribution to the performance of the ResNet50 model. The use of the Convolutional Block Attention Module provided further improvements in model performance, with accuracy, precision, recall, and F1-Score reaching approximately 97.61%. These results show that the Attention Module technique makes a positive contribution in improving the model's ability to classify oil palm pests. The combination of Depthwise Separable Convolution and Convolutional Block Attention Module provides a significant performance improvement, with accuracy, precision, recall, and F1-Score around 99.07%. These results indicate that combining the two techniques provides a strong synergy in improving the model's capabilities.

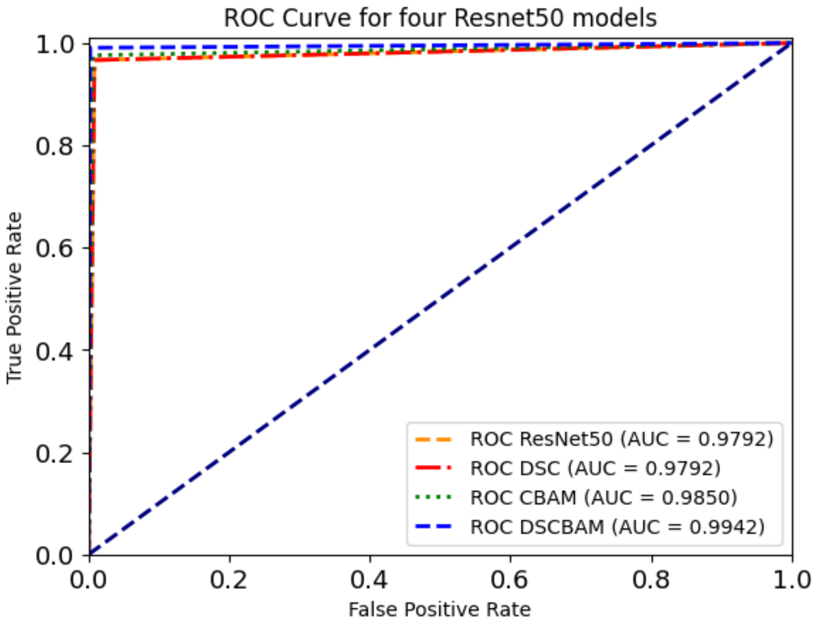

Fig. 11. ROC Curve of all Scenarios

Furthermore, the study also utilizes the ROC curve to illustrates the performance comparison of four scenarios of ResNet50 as depicted in Figure 11. The standard ResNet50 model, represented by the orange line, achieves an AUC of 0.9792, indicating strong discriminative ability between positive and negative classes. A similar performance is observed with the ResNet50 model enhanced with Depthwise Separable Convolution (DSC), shown by the blue line, also attaining an AUC of 0.9792. This suggests that while DSC may improve computational efficiency, it does not significantly alter the model's overall performance. In contrast, the ResNet50 model integrated with the Convolutional Block Attention Module, depicted by the green line, shows a slight improvement with an AUC of 0.9850, highlighting the benefits of enhanced feature focus through attention mechanisms. The most significant improvement is seen in the ResNet50 model that combines both DSC and CBAM, represented by the red line, which achieves the highest AUC of 0.9942. To sum up, the result of ROC curve pointed out that the combination of Depthwise Separable Convolution and Convolutional Block Attention Module significantly boosts the ResNet50 model's ability to distinguish between classes and delivers the best performance. Figure 12 presents a detailed and zoomed-in view of the Receiver Operating Characteristic (ROC) Curve for all scenarios analyzed in the study. This enhanced visualization allows a closer examine the performance of each model.

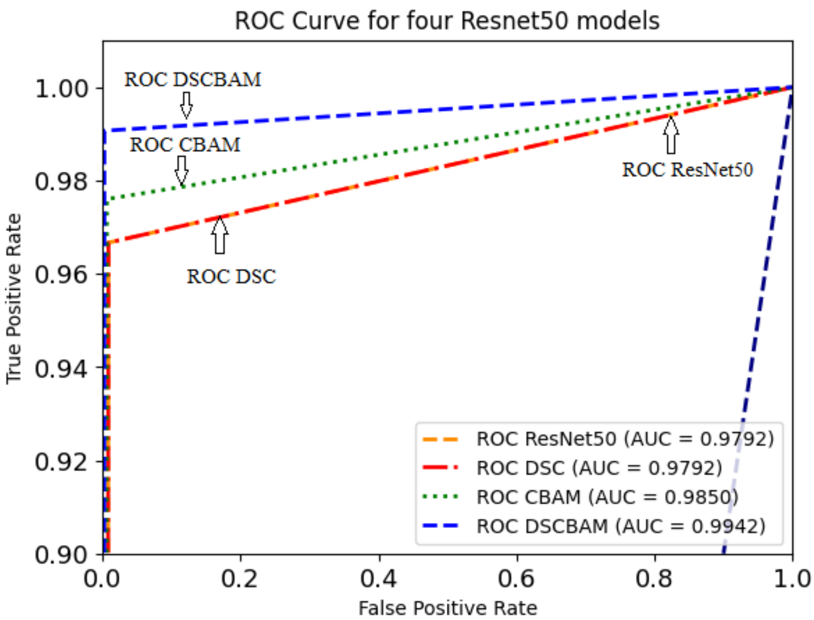

Fig. 12. Zoomed in ROC Curve of all Scenarios

The study also employs ANOVA to statistically evaluate whether there are significant differences in performance metrics—namely Precision, Recall, F1-Score, and Accuracy—across the proposed models. By analyzing the variability in these metrics, ANOVA helps determine if the observed differences in the confusion matrix results of the four models are statistically significant. Table VI shows the ANOVA test result.

TABLE VI
ANOVA RESULT

Class (average ± standard deviation)	Precision	Recall	F1-Score	Accuracy
ResNet50	96.03±0.02	96.04±0.03	96.02±0.02	96.10±0.05
ResNet50 with Depthwise Separable Convolution	97.60±0.03	97.60±0.03	97.60±0.02	97.61±0.04
ResNet50 with Convolutional Block Attention Module	96.67±0.02	96.66±0.02	96.68±0.02	96.68±0.03
ResNet50 with Depthwise Separable Convolution and Convolutional Block Attention Module	99.06±0.02	99.06±0.03	99.06±0.03	99.06±0.04
F-Value	15672.190	11727.753	16454.101	6007.326
P-Value	0.000**	0.000**	0.000**	0.000**

Table VI shows the low of standard deviation scores (in the range of ±0.02 to ±0.05), which it indicates that the model is consistent in performance across all metrics. Then, the table also presents the extremely high F-values (ranging from 6007.326 to 16454.101). Hence, there is a large difference between the means of the performance metrics for the different classes or models. Moreover, the p-values are all reported as 0.000 (with a significance level typically denoted by **), meaning the p-values are less than 0.001. Therefore, the observed differences in accuracy, recall, precision, and F1 scores between the models are not due to random chance, but are indeed significant.

Improved performance is often accompanied by increased model complexity. Complex models can require more computational resources, and this can be a constraint in resource-constrained environments. The more complex the model, the more difficult it is to interpret the resulting decisions. In the context of oil palm pest classification, understanding what factors influence model decisions may be more difficult. Improving model performance often depends on the quality and representativeness of the training data. A model that is highly optimized for a particular training data may not be as good when faced with different data.

In an effort to improve the ability to classify oil palm pests, it is necessary to explore and test innovative model architectures. One promising approach is to combine Vision Transformer with other deep learning architectures, such as EfficientNet, DenseNet, or recent models. Engaging these models can provide additional insights into the performance and reliability of the models in handling the visual complexity of oil palm pest images. In addition, evaluating the effect of combining the Depthwise Separable and Convolutional Block Attention Module with other layers or modules, such as Squeeze-and-Excitation, is key in optimizing model features. Combining these techniques has the potential to produce a more robust model, with enhanced capabilities in recognizing and classifying different types of oil palm pests.

The study conducted by Liu et al. [48] achieved an accuracy of approximately 95.1% in identifying troublesome insects in rice fields, outperforming related research. This significantly supports both higher agricultural yields and crop protection initiatives. Similarly, Wang et al.'s research effectively classified crop pests with an accuracy of around 91%, which can assist farmers in increasing agricultural productivity.

Despite the need for further accuracy improvements, Barbedo and Castro's [49] study demonstrated a 70% accuracy rate in identifying psyllids, suggesting the potential application of convolutional neural network techniques for pest identification. Meanwhile, Alves et al.'s [50] research classified cotton pests in the field with an accuracy of approximately 97.8%, providing robust support for pest monitoring and management in cotton farming.

Furthermore, Johari et al. [36] reported a high accuracy in the classification of bagworm infestations in oil palm plantations through various vegetation indices and machine learning techniques. The study achieved the highest performance in classification with more than 98% of the F1-score from all models proposed. Moreover, Johari et al. [37] also investigate the similar object, but with different method. Through the utilization of five different deep CNN architectures, the models come out the highest classification accuracy of 96.18%.

This research introduces a new and unprecedented approach to oil palm pest classification, making a very significant contribution to the field of agricultural pest classification. By using the ResNet50 model which has been refined through the application of the Depthwise Separable Convolution and Convolutional Block Attention Module techniques, this research opens up new avenues in efforts to accurately categorize oil palm pests. The model proposed in this study is the first to be applied specifically for oil palm pest classification, an innovation that not only shows effectiveness in identifying pests, but also provides a much-needed practical solution for farmers and researchers in the field of agriculture. The results of this research offer valuable insights and have great potential for more efficient pest control and conservation of oil palm crops. Although this research brings new breakthroughs, there are several limitations that need to be considered. One of the main limitations is the size of the dataset used. Using larger and more diverse datasets can improve model performance and generalization. Additionally, there is potential to further optimize the model to achieve higher levels of precision and provide more robust solutions for oil palm pest classification in the future. Overall, this research introduces a new approach to classifying oil palm pests that has not previously existed. These findings not only fill a gap in the literature but also provide a strong basis for further development in the field of agricultural pest classification.

IV. CONCLUSION

The ResNet50 model showed high performance in classifying oil palm pests, with impressive results especially after the addition of Depthwise Separable Convolution and Convolutional Block Attention Module (CBAM) techniques. Although there were some misclassifications, especially between *Metisa plana* and *Pteromas pendula*, the model overall provided consistent and impressive results. The complexity of the model needs further consideration, given the potential increase in computational resource requirements and the complexity of interpreting model decisions. Factors causing misclassification, especially between the *Metisa plana* and *Pteromas pendula* classes, need to be further analyzed to improve model performance. The improved model has great potential to be applied in automated monitoring of oil palm pests, contributing to efficiency and accuracy in the identification of pest problems. Despite the high performance of the model, it is important to remember that these results depend on the quality and representativeness of the training data. Special attention should be paid to the characteristics of the dataset. Recommendations for future research include exploring additional model architectures, such as Vision Transformer, and testing the combination of Depthwise Separable and CBAM techniques with other modules such as Squeeze-and-Excitation for further optimization. Further evaluation on the factors causing misclassification may provide additional insights for further improvements.

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