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Enhancing Pest Classification in Oil Palm Farming: A Deep Learning Approach with GoogleNet Architecture and Fine-Tuning Strategies

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Abstract: Recent developments in the field of deep learning models for agricultural pest classification, particularly in relation to oil palm cultivation, highlight the possibility of accurate and effective pest identification. The goal of this study is to use deep learning computation to classify pests in oil palm. The main goal is to evaluate this method's effectiveness in identifying pests. The GoogleNet architecture, GoogleNet with fine-tuned grid search, and GoogleNet with fine-tuned random search are all used in the study. A thorough examination of the performance of the three models is carried out using a variety of assessment metrics, including accuracy, precision, recall, and F1-Score. Photographs of pests on oil palm plants are included in the dataset. While models improved by grid search and random search show significant performance improvement, approaching nearly perfect evaluation metrics, the default GoogleNet model exhibits high accuracy. These results imply that customization improves the model's precision and effectiveness. The study's findings highlight the efficiency of GoogleNet -based models in oil palm farms for classifying pests, with fine-tuning considerably improving their output. In order to advance pest monitoring and management in oil palm cultivation, future research avenues should prioritize dataset expansion, additional model optimization, and the integration of drone-based automatic control and Internet of Things (IoT) technologies.

Keywords: Classification; GoogleNet; Grid Search; Random Search, Pets Oil Palm

1. INTRODUCTION (HEADING 1)

Favorable circumstances are found for oil palm, a growing agricultural crop, in tropical nations including Thailand, Papua New Guinea, Malaysia, and Indonesia. The plantation business in Indonesia is a prime example of oil palm's prominence [1]. With oil palm plantations expanding at a rapid pace, Indonesia is now the world's largest producer of palm oil, accounting for more than 44% of total palm oil production. Known for its exceptional productivity, oil palm produces more oil per hectare than other crops that produce oil. Indonesia has an important role in the worldwide economy as a key supplier of crude palm oil (CPO) [2].

The cultivation of oil palm faces many difficulties these days, and infestations by pests and diseases are a major danger to the health of oil palm plants. Even with their innate resilience, oil palm plants are susceptible to the negative effects of pests and diseases, which may reduce their overall yield [3]. Attacks by insects on oil palms are especially dangerous since they can stunt plant growth and reduce yield. In a larger perspective, productivity losses from pest infestations alone could amount to as much as 70%, and the cumulative harm could be as high as 100% when combined with disease attacks [4].

Pest detection is one of the biggest challenges in agricultural production, accounting for 20% of global crop losses every year [5], [6]. Nearly 400 million hectares of land were impacted by plant diseases and pests in China alone in 2021. For this reason, prompt and accurate identification of pests and diseases in crops is crucial to agricultural output. This affects crop yields in addition to advancing the agricultural industry as a whole and raising farmers' incomes [7]. Creating artificial intelligence models based on agricultural image processing is a very successful tactic. These models are useful for identifying

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pests and grouping them into different categories [8], which makes it possible to respond and intervene against pests in agricultural production more effectively. Thus, losses in agricultural productivity are reduced and pest detection effectiveness is improved.

In order to overcome these obstacles, scientists have developed more potent pest detection systems by utilizing both conventional machine learning (ML) methods and deep learning-based models [9], [10]. Limitations are introduced by the fact that traditional methods of insect detection based on morphological traits frequently depend on qualified taxonomists for proper identification [11]. It is critical to recognize the limitations of conventional approaches. Numerous automated methods that employ traditional machine learning for pest detection have been proposed recently [12]. For instance, a K-means clustering technique for pest detection was presented by Faithpraise and associates [13]. Nevertheless, this approach necessitates laborious procedures due to its manual feature extraction and filter application—especially when dealing with large datasets. Based on vegetation spectra, Rumpf and colleagues [14] proposed the use of support vector machines and disease recognition in sugar beet crops. Traditional machine learning-based models are useful for detecting pests, but their limitations limit their overall efficiency. The manual feature extraction and classification processes used in traditional ML-based methods are laborious, time-consuming, prone to error, and require a high level of computer expertise. In order to get around these limitations and produce more effective pest detection, it is therefore becoming more and more important to integrate deep learning-based techniques with machine learning [15].

Technology has a great deal of promise to help farmers prevent diseases at an early stage and identify harmful insects effectively [16]. Notably, computer vision and imaging technologies have become highly effective instruments with a wide range of uses, especially in modern agriculture. A number of detection techniques that combine automation and image processing have begun to satisfy the basic needs for controlling pest infestations. For example, Kasinathan and colleagues [17] used machine learning techniques to categorize insect pests according to their physical characteristics. Similarly, using supervised machine learning techniques, Chiwamba and Nkunika [18] pioneered the development of an automated system that could identify moths in the field. Tageldin and his colleagues [19] used machine learning algorithms in a different setting to forecast leafworm infestations in greenhouse settings. Machine learning models are usually built to work on their own; when attributes and data change, they need to be rebuilt. In contrast, the transfer learning approach seeks to reduce the time and effort needed to develop new models by making use of pre-existing knowledge and existing models. When compared to a stand-alone learning model, this method can improve the performance of the model.

A concept found in transfer learning called fine-tuning has proven to be effective because it is quicker and more accurate than building models from the ground up [20]. A convolutional neural network (CNN) is fine-tuned by first training it for a comparable task, and then modifying the final layer of the model to accommodate the new data [21]. CNN-based transfer learning models have been widely used in numerous agricultural challenges, including plant disease recognition [22], fruit classification [23], weed identification [24], and crop pest classification [25], [26], as noted by Kamilaris and Prenafeta-Boldú [27]. These models have shown to be reliable resources for classifying images in an agricultural setting. Farmers have benefited from their use as it has made it easier to identify practical and efficient pest management techniques, which has reduced large financial losses.

Understanding the different types of pests, their attack patterns, and the extent of damage they cause is greatly aided by knowing how oil palm plants are classified [28]–[30]. Farmers can choose the most practical and successful pest management techniques with the help of this knowledge. Research on developing pest recognition technology for oil palm cultivation has focused on deep learning [31]–[34]. Using deep learning to create pest recognition technology is a novel way to address the automatic classification of pests in oil palm. Computer algorithms are trained using deep learning techniques to identify patterns and features [35], [36] found in photos of insect pests that damage oil palm plants [37], [38].

Within the framework of this study, the following specific goals are set forth:

1- Using visual images, classify pest cases on oil palm plants, such as Metisa plana, Setora nitens, and Setothosea asigna, using the Convolutional Neural Network (CNN) architecture, specifically GoogleNet.

2- Evaluate how well the GoogleNet -based classification method performs in identifying pests on oil palms by introducing model fine-tuning through grid search and random search with the goal of improving the model's accuracy and efficacy.

3- By examining relevant visual cues, we can help with the continuous efforts to identify and manage pests on oil palm plants. The purpose of this contribution is to help farmers and other agricultural professionals make more intelligent and effective pest management decisions.

2. Research Methods

A. Research Framework

Figure 1 depicts the research framework created for this study.

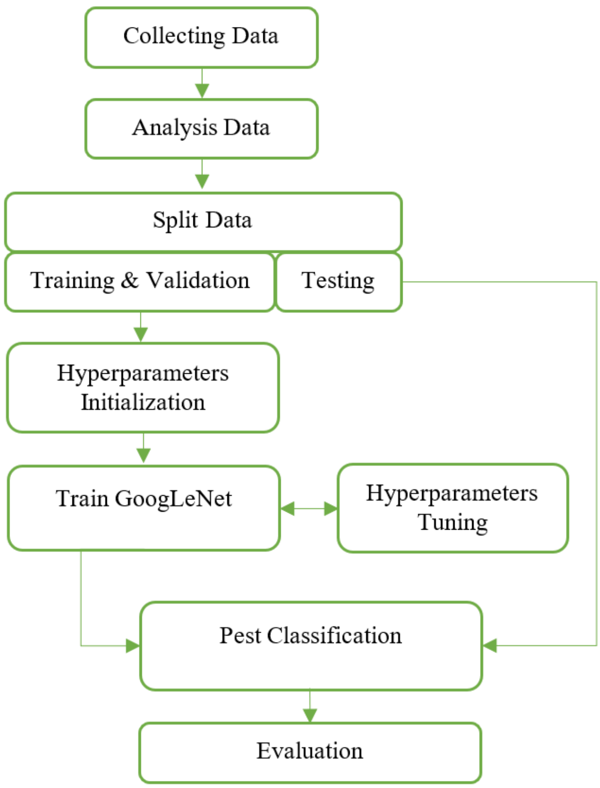

Figure 1. Confusion matrix (Top) GoogleNet (Middle) GoogleNet with Grid Search (Bottom) GoogleNet with Random Search

The research architectural model used in this study to categorize pests in oil palm plantations is shown in Figure 1. The first step in the research process is gathering data, which is then pre-processed to produce a dataset of appropriate and inappropriate photos that represent pest samples. After that, the dataset is split up into three subsets: testing, validation, and training. The training dataset is used to train the deep learning model, which makes use of the GoogleNet architecture. After training, the validation dataset is used to evaluate the accuracy and performance of the model. This includes calculating pertinent metrics like accuracy, precision, recall, and F1-score (Equations 1-4). In the end, testing the model on the independent testing set determines its effectiveness. This all-encompassing method ensures that the developed pest classification model for oil palm plantations is reliable and robust

B. Data collection and Pre-Processing data

Data on pests in the oil palm plantation of the Siantar Oil Palm Research Center were gathered for this study using a meticulous technical methodology. The primary pests that are the subject of our research, Metisa plana, Setora nitens, and Setothosea asigna, were depicted in the data as photographs. Every bug was meticulously captured on camera to record its unique attributes. We kept the shot distance between 15 and 20 cm in order to get precise and pertinent information.

One of the primary pests, Metisa plana, is distinguished by its unique patterned wings and body color, which frequently alternates between brown and green. On the other hand, Setora nitens has a unique morphology, with longer wings and more vibrant body colors. The primary distinguishing feature of Setothosea asigna is its transparent wings with distinct pattern marks. The methodical and comprehensive shooting procedure results in very accurate data that is pertinent to our study goals on the oil palm farm.

Important measures are made to preserve the quality of the data that is ready for use during the data preparation stage. Data cleaning is the first step in preparing the subject data, which involves finding and fixing any noise or anomalies that may exist in the dataset. Before starting the analysis, this stage tries to guarantee the data's integrity. After that, the image data is processed by resizing the pictures to uniform sizes so that they can be processed further. In the context of picture recognition or image analysis tasks, resizing guarantees that all images have the same proportions.

Finally, data augmentation techniques are applied to enhance the diversity of the image dataset. Operations like rotation, shearing, zooming, width shift, height shift, and vertical flip are examples of data augmentation. As a result, the training data varies, which can aid machine learning models in comprehending various image variations that they might come across in the real world. In image recognition and processing, data augmentation is a very helpful technique that can enhance model performance and avoid overfitting. Once the cleaning, resizing, and augmentation processes are combined, the data is prepared for additional analysis or deep learning model training.

C. Split Data

The dataset has 3000 photos divided into three pest categories, each comprising 1000 images, in order to prepare the data for analysis and training of the GoogleNet deep learning network. Setora nitens, Setothosea asigna, and Metisa plana are some of these classifications. After that, this dataset was split up into three different sets. The training data is the first set and is used to train the model so that it can recognize patterns in the data. The validation data, which makes up the second set, is used to assess how well the model performs during training, choose the ideal parameters, and avoid overfitting. In order to test the trained model with data that has never been seen before, the third batch of data is called test data. This allows for a more precise estimation of how much the model can be applied to real-world data. Before being employed in real-world applications, the 80:10:10 split guarantees that models are thoroughly tested, impartially assessed, and trained using an adequate amount of datasets.

D. Performance Measure

An effective method for evaluating an object estimation model's accuracy is the confusion matrix. It provides a thorough understanding of the model's performance by contrasting the predicted classification results with the actual class labels. The degree to which the model's predictions match the actual values is indicated by this method's accuracy. On the other hand, precision measures the accuracy of a prediction or its proportion. The model's recall quantifies its capacity to recognize accurate affirmative answers. Combining recall and precision yields the f1-score, which offers a fair and comprehensive evaluation of the model's performance. The following formulas can be used to compute these metrics, where TP, TN, FP, and FN stand for true positive, false negative, false positive, and false negative, respectively[39].

$$Accuracy = \frac{TN+TP}{TN+FP+TP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 = \frac{2*Presicion*Recall}{Presicion+Recall} \quad (4)$$

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E. GoogleNet Framework

GoogleNet, also known as InceptionV1, is a deep convolutional neural network (CNN) architecture that was introduced by researchers at Googl. It was designed to address challenges such as computational efficiency and the vanishing gradient problem. One of the distinctive features of GoogleNet is the use of inception modules, which incorporate multiple filter sizes (1x1, 3x3, 5x5) in parallel within the same layer. This allows the network to capture both fine and coarse-grained features, enhancing its ability to learn hierarchical representations. GoogleNet is known for its depth and complexity, utilizing 22 layers, yet it avoids the computational burden associated with traditional deep networks by using global average pooling and 1x1 convolutions to reduce the number of parameters. This architecture achieved notable success in the ImageNet Large Scale Visual Recognition Challenge, showcasing its effectiveness in image classification tasks. The inception modules and efficient use of parameters make GoogleNet a notable choice for applications requiring deep learning with computational efficiency.

F. Fine-tune GoogleNet Framework

Fine-tuning the selected GoogleNet model to optimize its performance in the context of palm oil pest classification was achieved through meticulous parameter adjustments. Employing grid search and random search techniques, The hyperparameters and their values that will be used in the tuning process are Epoch {10, 20 30}, Batch Size {16, 32, 64}, Learning Rate {0.001, 0.01, 0.1, 0.2, 0.3} and Optimizer {SGD, RMSProp, Adagrad, Adadelta, Adam, Adamax, Nadam} to determine the most effective combination. Through a comprehensive evaluation using grid search, we scrutinized each predefined parameter set in param_grid. Subsequently, with random search, we conducted experiments using diverse parameter combinations. These dual parameter search methodologies allowed us to pinpoint the optimal parameters, resulting in a model that demonstrated superior accuracy in identifying pests in oil palm.

3. RESULT AND DISCUSSION

A. Oil Palm Pest Samples

Three major pest species Metisa plana, Setora nitens, and Setothosea asigna are included in the sample data of pests on oil palm plants in this study. This dataset includes a range of photos that depict different field conditions and circumstances.

Figure 2. Oil Palm Pest (Top) Metisa plana (Middle) Setora nitens (Bottom) Setothosea asigna

B. Training GoogleNet

We ran the GoogleNet model on our preprocessed dataset in order to train it for pest classification on oil palms. Three different pest types on oil palms were identified using GoogleNet, which is well-known for its efficiency in image classification tasks: Metisa plana, Setora nitens, and Setothosea asigna. Using the Adam optimizer, the model was trained for 20 epochs with a batch size of 16. Over the course of the 20 epochs, the GoogleNet model's training results showed a noticeable improvement. On the training data, the model's accuracy was roughly 94.07% at first, and by the end of the training, it had increased to 99.46%. Interestingly, the model achieved 100% accuracy on the validation data in the final epochs, demonstrating its remarkable ability to identify pests on oil palm plants. On the other hand, possible overfitting should be avoided as it could jeopardize the model's ability to generalize to the validation data.

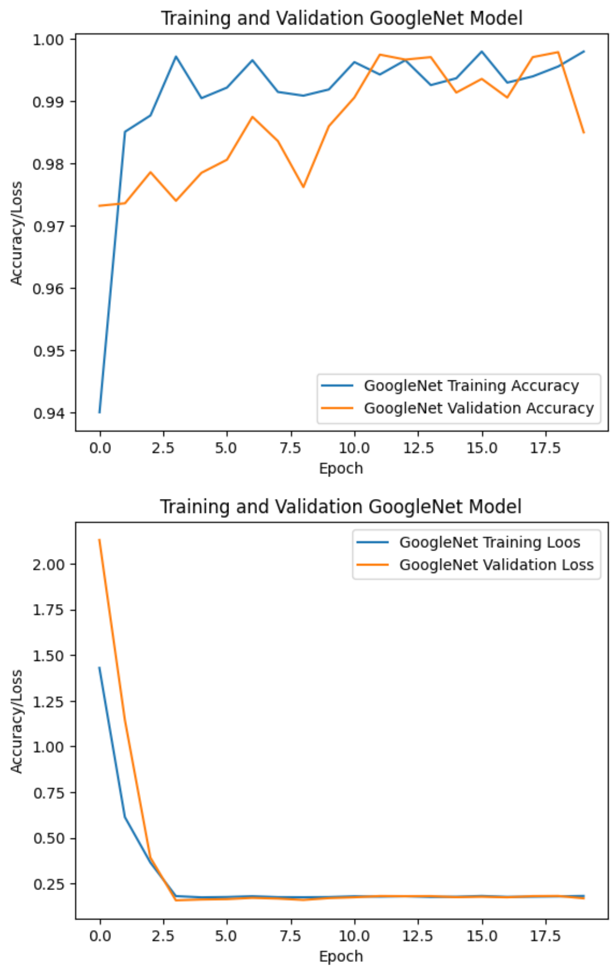


Figure 3. Training GoogleNet

C. *Fine-Tuning GoogleNet with Grid Search*

To get the best results, a number of experiments were carried out during the GoogleNet model's training phase using grid search for classifying pests on oil palms. The notable increase in model accuracy in these experiments can be attributed to the fine-tuning procedure. Grid search was used to investigate different parameter combinations in an effort to determine which one would produce the best accuracy. The experimental findings highlight how crucial precise parameter tuning is to enhancing the GoogleNet model's capacity to recognize pests in oil palm plants. The results of using grid search to find the optimal hyperparameter are displayed in Table I.

TABLE I. BEST HYPERPARAMTER USING GRID SEARCH

Hyperparameter	***Fine Tune Grid Search***
Epochs & Batch Size	Best: 0.953433 using {'batch_size': 32, 'epochs': 50}
Optimizer	Best: 0.968667 using {'optimizer': 'Adam'}
Learning Rate	Best: 0.9500 using {'optimizer__learning_rate': 0.001}

Over the 30 training epochs, the trained model demonstrated remarkable advancement. The model started training with an accuracy of roughly 66.47% on the training set, and it got better and better until the end of training, when it was about 100% accurate. One noteworthy accomplishment is that in the last few epochs, the model was able to achieve perfect accuracy (100%) on the validation data. This shows how accurately the model can classify images related to pests on oil palm plants. This model's training is classified as good fitting since it can effectively generalize the patterns in the training and validation data due to its high degree of accuracy.

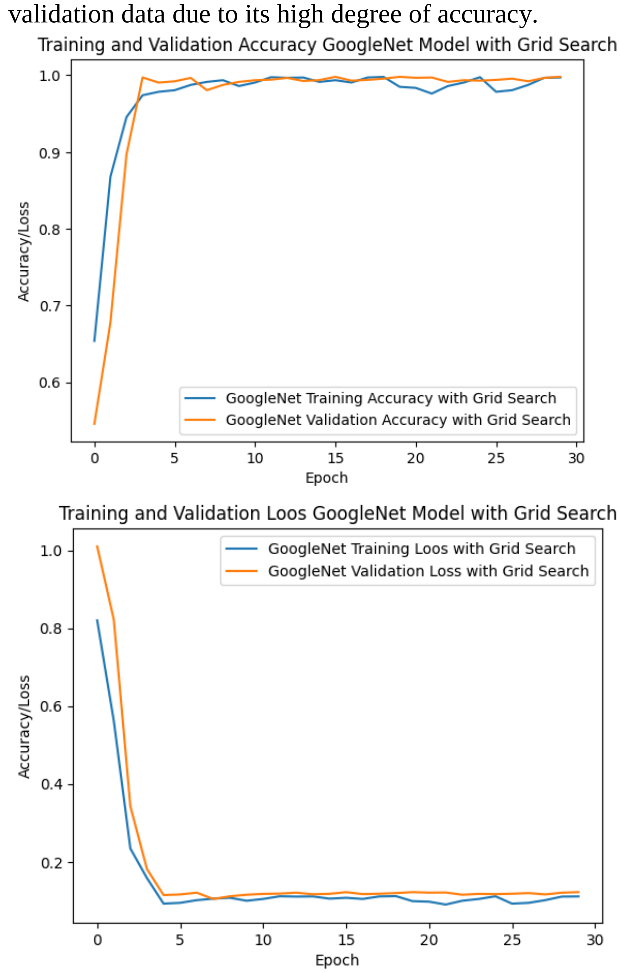


Figure 4. Training GoogleNet with Grid Search

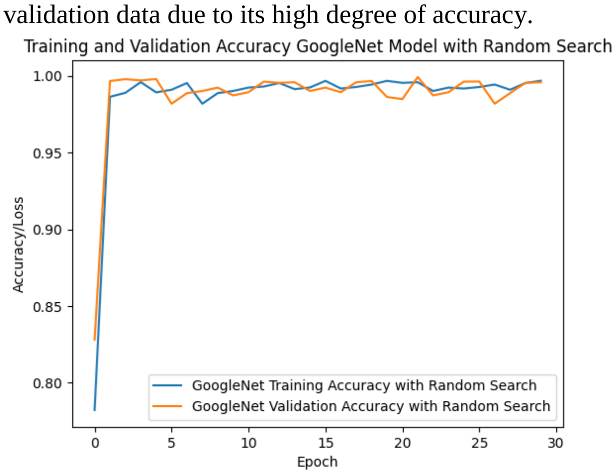
D. Fine-Tuning GoogleNet with Random Search

To get the best results, a number of experiments were carried out during the training phase of the GoogleNet model with random search for classifying pests in oil palms. The notable increase in model accuracy in these experiments can be attributed to the fine-tuning procedure. Through random search, different parameter combinations were investigated in order to determine which one could produce the highest accuracy. The outcomes of the experiment highlight how crucial precise parameter tuning is to enhancing the GoogleNet model's capacity to recognize pests in oil palm plants. Table II displays the outcomes of using random search to identify the optimal hyperparameter.

TABLE II. BEST HYPERPARAMTER USING RANDOM SEARCH

Hyperparameter	***Fine Tune Grid Search***
Epochs & Batch Size	Best: {'epochs': 30, 'batch_size': 64}
Optimizer	Best: {'optimizer: 'SGD'}
Learning Rate	Best: {'optimizer_learning_rate': 0.001}

Over the 30 training epochs, the trained model demonstrated remarkable advancement. The model started training with an accuracy of roughly 77.92% on the training set, and it got better over time, finishing with an accuracy of roughly 99.71%. One noteworthy accomplishment is that in the last few epochs, the model was able to achieve perfect accuracy (100%) on the validation data. This shows how accurately the model can classify images related to pests on oil palm plants. This model's training is classified as good fitting since it can effectively generalize the patterns in the training and validation data due to its high degree of accuracy.



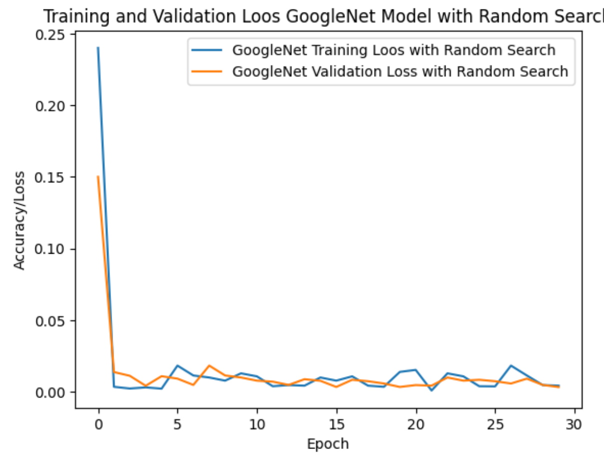


Figure 5. Training GoogleNet with Random Search

E. Evaluation

The evaluation phase includes a thorough examination of the GoogleNet -based models that have been developed, providing insight into how well they perform in the task of classifying pests in oil palm plants. A variety of metrics, such as accuracy, precision, and recall, are used in the thorough evaluation to provide a detailed picture of the models' performance in the assigned task. This assessment is essential to determining each model's effectiveness. A direct comparison between the GoogleNet model, the improved model via grid search, and the optimized model using a random search strategy is carried out. The debate that follows explores whether fine-tuning produces appreciable gains in model performance and determines which model is best suited for classifying pests in oil palms. Figures 6 visually represent the classification results for the three pest categories (Metisa plana, Setora nitens, and Setothosea asigna) using the three GoogleNet training models.

In addition, Tables III-V provide an extensive analysis of the performance metrics of the three GoogleNet models, providing a thorough assessment of their classification abilities. These tables provide metrics for accuracy, gain, precision, and F1 Score for every scenario, which are essential for assessing how well the models work. Table V corresponds to GoogleNet with fine-tuned grid search, Table IV to GoogleNet with fine-tuned random search, and Table III to the default GoogleNet. Analyzing these metrics in detail makes it easier to comprehend how well the model performs in various situations and helps determine which strategy is best for the palm oil pest classification model. These tables play a pivotal role in interpreting the advantages and disadvantages of every scenario, directing data-driven choices to maximize and improve the model's classification efficacy. The performance metrics and confusion matrix analysis provide insightful information that can be used to improve the model and get better classification results.

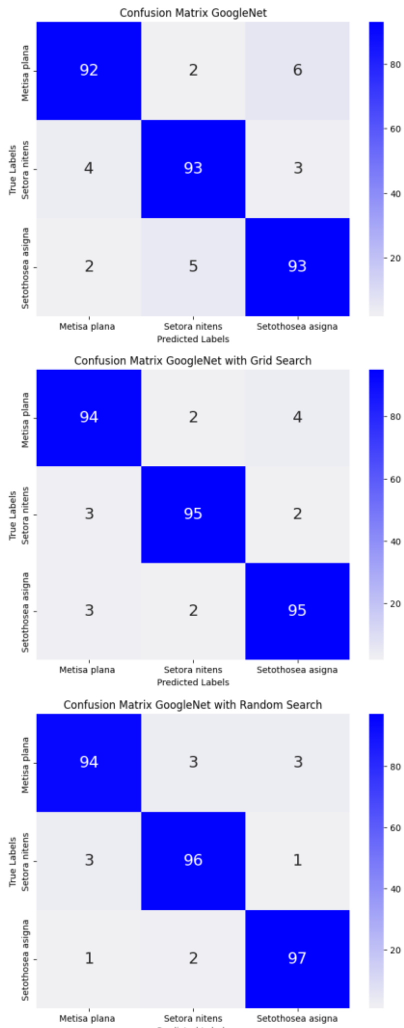


Figure 6. Confusion matrix (Top) GoogleNet (Middle) GoogleNet with Grid Search (Bottom) GoogleNet with Random Search

TABLE III. PERFORMANCE OF GOOGLENET FOR PALM OIL PEST CLASSIFICATION

Class	Precision	Recall	F1-Score	Support
Metisa plana	0.9388	0.9200	0.9293	100
Setora nitens	0.9300	0.9300	0.9300	100
Setothosea asigna	0.9118	0.9300	0.9208	100
Accuracy	**0.9267**			300
Macro Average	**0. 9268**	**0. 9267**	**0. 9267**	300

TABLE IV. PERFORMANCE OF GOOGLENET FOR PALM OIL PEST CLASSIFICATION

Class	Precision	Recall	F1-Score	Support
Metisa plana	0.9400	0.9400	0.9400	100
Setora nitens	0.9596	0.9500	0.9548	100
Setothosea asigna	0.9406	0.9500	0.9453	100
Accuracy	**0.9467**			300
Macro Average	**0. 9467**	**0. 9467**	**0. 9467**	300

TABLE V. PERFORMANCE OF GOOGLENET FOR PALM OIL PEST CLASSIFICATION

Class	Precision	Recall	F1-Score	Support
Metisa plana	0.9592	0.9400	0.9495	100
Setora nitens	0.9505	0.9600	0.9552	100
Setothosea asigna	0.9604	0.9700	0.9652	100
Accuracy	**0.9567**			300
Macro Average	**0. 9567**	**0. 9567**	**0.9566**	300

With great accuracy, the GoogleNet model classifies pests in oil palm. Evaluation metrics demonstrated strong performance, including precision, recall, and F1-Score. The model's precison for Metisa plana is approximately 93.88%, recall is approximately 92%, and F1-Score is approximately 92.93%. The F1-Score is approximately 93%, recall is approximately 93%, and precision is approximately 93% for Setora nitens. In contrast, Setothosea asigna has an approximate 92.08% F1-Score, a recall of 93%, and a precision of 91.18%. The overall correct prediction ratio indicates that the model is approximately 92.67% accurate. These findings demonstrate that the GoogleNet model performed well in accurately classifying pests on oil palm, with the majority of evaluation metrics falling into the excellent range.

Excellent performance is shown in the results of pest classification in oil palm using the GoogleNet model that was fine-tuned using a grid search technique. The model achieved perfect precision of 94%, recall of approximately 94%, and F1-Score of approximately 94% for the Metisa plana category. The model's precision in the Setora nitens category is approximately 95.96%, recall is approximately 95%, and F1-Score is approximately 95.48%. Regarding Setothosea asigna, the model exhibits approximately 94.06% precision, 95% perfect recall, and roughly 94.53% F1-Score. The model's overall accuracy of 94.67% indicates that it performed exceptionally well in classifying pests on oil palm. These results show that fine-tuning the model with grid search has produced a highly accurate and effective model, with evaluation metrics that are almost perfect.

Excellent performance is demonstrated by the pest classification results in oil palm using the GoogleNet model that was fine-tuned using a random search technique. The model achieved perfect precision of 95.92%, recall of approximately 94%, and F1-Score of approximately 94.95% for the Metisa plana category. The model has an approximate precision of 95.05%, an approximate recall of 96%, and an approximate F1-Score of 95.52% in the Setora nitens category. Regarding Setothosea asigna, the model exhibits approximately 96.04% precision, 97% perfect recall, and approximately 96.52% F1-Score.The model's overall accuracy of 95.67% indicates that it performed exceptionally well in classifying pests on oil palms. These results demonstrate that using random search to fine-tune the model has resulted in a highly accurate and effective model when compared to the first two models, with evaluation metrics that are almost perfect.

F. Discussion

When it came to classifying pests on oil palms, the three models this study evaluated—the default GoogleNet, GoogleNet with resets using a grid search approach, and GoogleNet with resets using a random search approach—performed remarkably well. The GoogleNet model by default showed good precision, recall, and high accuracy. On the other hand, performance was significantly improved by fine-tuning using grid search and random search, with metric evaluations nearly perfect. The utilisation of these two refinement techniques yielded an incredibly efficacious and precise GoogleNet model for pest identification in oil palm, indicating noteworthy prospects for augmenting pest observation and control methodologies in oil palm cultivation.

The study carried out by Liu et al.[41] produced an accuracy of roughly 95.1% in identifying bothersome insects in rice fields when compared to related research. This effectively backs both higher agricultural yields and crop protection initiatives. Similar to this, Wang et al.'s study effectively classified crop pests with an accuracy of roughly 91%, which can help farmers increase agricultural productivity.

Though more accuracy improvements are required, Barbedo and Castro's [42]study's 70% accuracy rate in identifying psilids suggests the potential application of convolutional neural network techniques for pest identification. In the meantime, a study by Alves et al.[43]classified cotton pests in the field with an accuracy of roughly 97.8%, offering strong support for pest monitoring and management in cotton farming.

The research findings represent a noteworthy addition to the domain of agricultural pest classification, specifically in relation to oil palm cultivation. This study validates the model's effectiveness in precisely categorizing pests in oil palm by applying the refined GoogleNet model. These findings provide important new information for the efficient control of pests and the preservation of oil palm plants, with practical implications for farmers and agricultural researchers alike. There are certain restrictions, even though this study's classification of pests in oil palm plants is deemed successful. The size of the dataset is one of them; it can be increased to boost sample diversity. Furthermore, there exists the possibility to enhance the model's optimization to attain an elevated degree of precision.

It is advised to increase the dataset size in the future by including more diverse pest species on oil palm. Furthermore, incorporating attention mechanisms and applying techniques like Bayesian optimization to the model's fine-tuning could lead to an even higher accuracy gain. It would also be beneficial to combine Internet of Things (IoT) with drone-based automated control technology. Real-time information on the presence of pests in oil palms can be obtained by utilizing drones that are fitted with cameras and sensors. An efficient response to pest infestations is made possible by the automatic transmission of this data over the Internet of Things network

4. CONCLUSION

The results of this study show that three evaluated models—the default GoogleNet, the GoogleNet with grid search fine-tuning, and the GoogleNet with random search fine-tuning perform remarkably well in the classification of pests in oil palm. The GoogleNet model that was used by default produced excellent recall and precision at a high accuracy level. On the other hand, significant performance gains were achieved through fine-tuning using grid search and random search, nearly reaching perfection in metric evaluations. This study effectively used the GoogleNet model for oil palm pest identification when compared to related research. In order to improve accuracy and efficacy in monitoring and managing pests in oil palm, future research endeavors may take into account increasing the dataset size, further optimizing the model, and integrating drone-based automatic control technology and the Internet of Things (IoT).

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significant contribution to the advancement of knowledge in this field.

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