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Butterfly Classification Accuracy Analysis Using EfficientNet with Adam and AdamW Optimizer

Amanda Mutiara Bunga*
Universitas Muhammadiyah Kotabumi
INDONESIA

Risma
Universitas Muhammadiyah Kotabumi
INDONESIA

Fauzan Ulyadda Putra
Universitas Muhammadiyah Kotabumi
INDONESIA

*** Corresponding author:**
Amanda Mutiara Bunga, Universitas Muhammadiyah Kotabumi, INDONESIA. ✉ amandamutiara185@gmail.com

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Abstract

Background: Accurate butterfly species classification plays an important role in biodiversity monitoring and environmental conservation. However, image-based classification remains challenging due to similarities in wing color patterns and shapes among species.
Aims: This study aims to evaluate the performance of butterfly image classification using transfer learning based on the EfficientNet architecture with different optimization strategies.
Methods: EfficientNet-B2 and EfficientNet-B3 were implemented as the main models. Image preprocessing techniques, including resizing, normalization, and data augmentation, were applied to improve model performance. The models were optimized using Adam and AdamW optimizers with different learning rates. Performance evaluation was conducted using accuracy, precision, recall, and F1-score.
Results: The results show that EfficientNet-B2 optimized with the Adam optimizer (learning rate 5×10^{-4}) achieved the best performance, with a validation accuracy of 92.62% and an F1-score of 92.61%. In comparison, EfficientNet-B3 optimized using AdamW (learning rate 6×10^{-4}) produced slightly lower performance, indicating the influence of optimizer selection and learning rate configuration on model convergence and generalization.
Conclusion: EfficientNet-B2 combined with the Adam optimizer provides a stable and effective approach for butterfly species classification. These findings highlight the importance of optimization strategies in improving model performance and support the development of automated systems for biodiversity monitoring.

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INTRODUCTION

The Convolutional Neural Network (CNN) is able to extract visual features from images automatically making it effective in object recognition, where each layer of the network recognizes patterns ranging from edges and colors to complex shapes, and research shows that the VGG16 architecture with transfer learning can achieve up to 94% accuracy in the classification of animal imagery (Ardiansyah & Desyani, 2025). In addition, the color histogram method was used to extract the color of butterflies' wings to distinguish species, with a preprocessed dataset analyzed using Random Forest, resulting in an accuracy of 72%, although limited in distinguishing species with similar wing patterns, but transfer learning with EfficientNet-B0 can increase accuracy by up to 80% (Nadiyah Hidayati & Maulidah, 2023). Butterflies also act as bioindicators of the quality of urban habitats based on the distribution of their species, where RDA analysis shows a close relationship between butterfly species and environmental characteristics in different areas, and certain species mark natural habitats while adaptive ones indicate environmental disturbances (Azahra, 2021; Wang, Y., et al. 2021).

In Baning Nature Park, the presence of 15 species of butterflies from four main families demonstrates an important role as natural pollinators, with habitat conditions and feed availability influencing the activity and distribution of species, confirming the importance of this area for conservation and research (Kurniawan & Samani, 2023; Loshchilov et al.,2019). Time-constrained counts found 50 species from five families with habitat variation affecting the number of species, with agroforestry having the highest diversity while marginal land having the lowest, suggesting that vegetation and habitat conditions play an important role in the conservation of urban butterflies (Bibas et al., 2025; Xin, et al 2020). The Langsa City Protected Forest Area also has a high diversity of butterflies with 12 species from five families, where natural vegetation and microclimatic conditions affect the distribution of species, and this visual data can be used for the development of an image-based automatic classification system (Anggrela et al., 2023; Saedan et al.,2024).

The diversity of species in Ngesrepbal Village is related to the variety of host plants, where some species require special attention due to their conservation status, thus preserving host plants and minimizing environmental disturbances is important for butterfly conservation and ecosystem balance (Irsa et al., 2022; Rawat et al.,2017). Suranadi Nature Tourism Park has moderate diversity with an even distribution of individuals, influenced by flowering vegetation and open habitats, supporting the development of conservation-based ecology learning e-modules (Efendi et al., 2024; Kingma et al.,2015). The diversity of 45 species of butterflies from various habitats with the predominance of the Nymphalidae indicates that environmental factors such as temperature, humidity, and feed plants influence activity and distribution, where butterflies function as bioindicators and pollinators so that habitat preservation is important (Zulaikha & Bahri, 2021).

High diversity in the Sintuwu Maroso FMU area provides a visual dataset for automated image classification using CNN, which supports biodiversity monitoring and primary forest conservation (Toding et al., 2024). The use of the school environment with documentation of insect specimens such as butterflies helps in the identification and analysis of diversity, thereby increasing students' understanding and awareness of conservation (Tresnani et al., 2025). The EfficientNet-B7 model with transfer learning is able to classify arthropods with high accuracy of up to 93.67%, the data is trained with augmentation and early stopping to prevent overfitting, demonstrating the effectiveness of the CNN model in the automatic classification of biological images (Dalimunthe, 2025; Tan et al.,2019). CNN also effectively classified six Panthera species from a dataset of 6,290 images with an accuracy of 85.21%, where image pre-processing helped extract important features, proving the effectiveness of deep learning in wildlife image classification (Bismi & Qomaruddin, 2023).

The selection of activation functions affects the performance of the CNN model, where LeakyReLU proved to be the most superior while Sigmoid and Tanh failed to differentiate classes, so ReLU-based activation functions are recommended for multi-class image classification (Ray, n.d.). Invasive species threaten native habitats and therefore need monitoring, and machine learning is an efficient alternative to overcome cost and limited reach, supporting ecological conservation and loss mitigation (Irfan et al., 2022). Machine learning such as SVM and Random Forest effectively predict student academic performance with high accuracy, supporting early intervention for students at risk of failure (Azis, 2025; Castro et al.,2021). The application of AI in human resource management improves the efficiency, accuracy, and objectivity of the recruitment process, although supervision is needed to reduce bias, so that the quality of the workforce can be improved (Norman et al., 2024). Finally, K-Means clustering effectively groups elementary school students based on interests and talents, resulting in three main clusters, namely academic, arts, and social, leadership, so that educators can design more personalized and targeted learning strategies (Sonianto & Hartono, 2025).

METHOD

Here the stages of experiments carried out in the research on the classification of butterfly images are explained, starting from the selection of datasets, baseline models, modification processes, to system implementation. The dataset used is Kaggle's Butterfly Image Classification, consisting of

9,285 images divided into 6,499 images for training and 2,786 images for testing, for a total of 75 butterfly species classes. The data is processed through several pre-processing stages, including missing value checking, label conversion to numerical format, data division into 80% train and 20% validation, and image augmentation such as rotation, flip, and random resized crop to increase the variety of the training data. The baseline model uses EfficientNet-B2 with ImageNet pretrained weights, equipped with an additional fully connected layer along with batch normalization and dropout to prevent overfitting, as well as an Adam optimizer with a learning rate of 5×10^{-4}. The training process was carried out for 50 epoches with a batch size of 32, and evaluation was carried out using Accuracy metrics and monitoring loss on data train and validation. In the modification phase, the architecture was changed to EfficientNet-B3 with layer adjustments, hyperparameters, and the use of AdamW optimizer (learning rate = 6e-4) to improve model efficiency and performance. The evaluation was expanded with a classification report (Precision, Recall, F1-Score) and the visualization was updated to a Smoothed Trend Chart and a Heatmap Confusion Matrix to make it easier to interpret the results. The entire implementation process is done in Google Colab using a free GPU, with the flow including dataset loading, normalization, model architecture, training, evaluation, and performance visualization.

Tabel 1. A Review of Research Literature Related to CNN-Based Classification of Butterfly Images

No	Author & Year	Research Focus	Method	Datasets Used	Relevance to the Kaggle Butterfly Dataset
1	Anggrela et al., 2023	Identification of butterfly species	Morphological observations	Primary data of the butterfly field	As a visual biological reference
2	Ardiansyah & Desyani, 2025	Classification of animal images	Transfer Learning CNN (VGG16)	Animal imagery dataset	A similar CNN approach
3	Azahra, 2021	Butterflies as bioindicator	Survey ecology	Butterfly population data	Supporters of the ecological context
4	Bibas et al., 2025	Butterfly diversity	Biodiversity analysis	Habitat field data	Proponents of species classification
5	Bismi & Qomaruddin, 2023	Classification of wild animal images	CNN	Dataset citra Panthera	CNN method is relevant
6	Dalimunthe, 2025	Classification of Arthropods	CNN	Dataset citra arthropoda	Similar classification approach
7	Efendi et al., 2024	Butterfly diversity	Biodiversity survey	Field data	Species identification reference
8	Irfan et al., 2022	CNN Optimization	CNN (SGD, Adam, Adadelta)	Flower image dataset	Model optimization support
9	Irsa et al., 2022	Butterfly community structure	Ecological analysis	Field community data	Biological context support
10	Kurniawan & Samani, 2023	Butterfly identification	Butterfly field data	Butterfly field data	Manual vs image comparator
11	Nadiyah & Maulidah, 2023	Butterfly image feature extraction	Color Histogram + RF	Butterfly imagery dataset	Similar visual datasets

12	Norman et al., 2024	AI in MSDM	Conceptual study of AI	Data seconds	Similar visual datasets
13	Ray, n.d.	CNN activation function	CNN	Animal imagery dataset	Relevant to
14	Sonianto & Hartono, 2025	Education clustering	K-Means	Student data	Data mining method reference
15	Toding et al., 2024	Butterfly diversity	Field survey	Local species data	Supporters of species identification
16	Tresnani et al., 2025	Biodiversity education	Educational studies	Learning data	Supporters of the educational context
17	Zulaikha & Bahri, 2021	Butterfly diversity	Biodiversity survey	Field data	Proponents of species classification
18	Azis, 2025	ML Comparison	Literature Review	Data seconds	Algorithm evaluation support
19	Norman & Pahlawati, 2024	AI and accuracy	Conceptual studies	Data seconds	Supporters of accuracy discussion
20	Sonianto & Hartono, 2025	Talent interest clustering	K-Means	Student data	Data analysis method reference

Based on the mapping in the table above, the differences between journals can be seen from the focus of the study and the methods used, ranging from morphological observation-based research to image processing using deep learning techniques. Some previous research, such as (Ardiansyah & Desyani, 2025) And (Dalimunthe, 2025), shows that the Convolutional Neural Network (CNN) model with transfer learning is able to achieve high accuracy in the classification of animal images, even exceeding 90%. This is in line with the results of this study which shows that the EfficientNet-B2 model with the Adam optimizer (learning rate = 5×10^{-4}) produces a validation accuracy of 92.62% and an F1-score of 92.61%, being the best configuration compared to the EfficientNet-B3 variant with AdamW (90%) and EfficientNet-B0 (80%). In addition, conventional approaches such as those carried out by (Nadiyah Hidayati & Maulidah, 2023) using the Color Histogram and Random Forest methods was only able to achieve an accuracy of about 72–80%, indicating that the deep learning method has a significant advantage in recognizing complex patterns in butterfly images. Meanwhile, biological research such as (Bibas et al., 2025), (Anggrela et al., 2023), and (Toding et al., 2024) emphasizing the importance of butterfly species diversity as an indicator of ecosystems, so that an automatic classification system such as the one developed in this study has the potential to help the biodiversity conservation and monitoring process. Another study by (Irfan et al., 2022) also supports the results of this study, where the use of the Adam optimizer is proven to provide better stability and convergence rates than other methods such as SGD and Adadelta. These results are consistent with the performance of the EfficientNet-B2 + Adam model in this study which shows the most stable training trend based on the visualization of the Smoothed Trend Chart and Confusion Matrix. Thus, it can be concluded that the combination of the EfficientNet-B2 architecture and the Adam optimizer is the most optimal approach for the classification of butterfly imagery in the context of digital biodiversity, while reinforcing the results of previous studies with more specific quantitative proofs

Dataset

The dataset used in this study is Butterfly Image Classification obtained from the Kaggle platform. The dataset consists of 9,285 butterfly images, which are divided into 6,499 images for training data and 2,786 images for testing data, with a total of 75 different species of butterfly species. Each image on the dataset has label information that represents the name of the butterfly species, such as Monarch, Adonis, Brown Cyproeta, and other species. Before being used in the model training process, the dataset first goes through the data cleanup and preprocessing stages. Checking the missing values shows that all the data in the dataset is in a valid condition with no empty values. Next, the class labels are converted into numerical format using Label Encoder so that they can be processed by the deep learning model. The dataset was then divided into 80% training data and 20% validation data using the train_test_split method with stratified parameters to keep the class proportions balanced. The entire image was resized to 150×150 pixels to fit the model's architectural needs. In addition, data augmentation was carried out in the form of random rotation up to 20°, horizontal flip, and random resized crop to increase the diversity of training data and reduce the risk of overfitting. To overcome the imbalance in the amount of data between classes, class weight calculations were carried out during the training process. All stages of preprocessing and model training are carried out using Google Colab with the support of GPU CUDA:0, so that computing time can be significantly accelerated.

Baseline Model

The initial model used in this experiment is EfficientNet-B2, which is one of the Convolutional Neural Network (CNN) architectures designed to produce an optimal balance between accuracy and computational efficiency. This model uses pre-trained weights from the ImageNet dataset, so it can leverage the initial knowledge of the common imagery to speed up the training process on the new dataset. In the original notebook, the structure of the EfficientNet-B2 was modified by adding several new fully connected layers (FC) after the main layer of the model. This additional layer consists of 512 FCs and 256 neurons that are equipped with a Batch Normalization and Dropout of 0.5 respectively to reduce the risk of overfitting. The number of output classes used was 75 classes, according to the number of butterfly species in the dataset. The training process was carried out using the Adam optimizer with a learning rate of 5×10^{-4} and the Cross Entropy Loss function equipped with class weighting to handle data imbalances between species. The model was trained for 50 epochs with a batch size of 32, using a dataset split of 80% for training data and 20% for validation data. The main evaluation metric used in this baseline model is the accuracy of training and validation data. In addition, during the training process, the loss value was also monitored to assess the level of convergence of the model over time.

Development

This study uses an experimental quantitative approach with the aim of improving the training efficiency and performance quality of the deep learning-based image classification model. Development was carried out on the baseline notebook that was used as an initial reference, namely the EfficientNet-B2 model with an Adam optimizer and a learning rate of 5×10^{-4}. All experiments were carried out using the same dataset to maintain the consistency and validity of the results comparison. Major development was carried out through the replacement of the model architecture, where EfficientNet-B2 at baseline was modified to EfficientNet-B3. The selection of the EfficientNet-B3 architecture was based on its better ability to extract visual features in depth than EfficientNet-B2, while maintaining parameter efficiency. In addition, the model structure is modified with the addition of fully connected layers, batch normalization, and dropouts to improve the model's generalization capabilities and reduce the risk of overfitting during the training process. Furthermore, hyperparameter and optimizer adjustments are made to improve training efficiency. The number of epochs was reduced from 50 to 15 epochs to speed up training time without compromising the stability of the model convergence. This study compared two optimizers, namely Adam with a learning rate of 5×10^{-4} used in the EfficientNet-B2 model as a baseline, and AdamW with a learning rate of 6×10^{-4} applied to the modified EfficientNet-B3 model. Both experiments were run on separate files but using identical datasets to ensure the fairness of the performance evaluation. In addition, additional tests were conducted using EfficientNet-B0 with a learning rate of

1×10^{-4}, but this model showed lower performance with a validation accuracy of 0.8046 and an F1-score of 0.8009, so it was not the main focus of the analysis. To strengthen the model evaluation, this study added more comprehensive evaluation metrics, including precision, recall, and F1-score through classification reports. In addition, the visualization of training results was also developed by replacing conventional line charts with smoothed trend charts on accuracy and loss to show a smoother and easier to analyze training pattern. Performance evaluations per class are visualized using a heatmap confusion matrix to identify the level of accuracy and prediction errors in each class. All main visualizations and evaluations use the results of the EfficientNet-B2 model with the Adam optimizer as a comparative reference to the development results model.

Implementation

The model development and training process is carried out using Google Colab with free GPU support to speed up the computing process during deep learning training. This environment was chosen because of its ease of access, flexibility, and ability to handle intensive computing without the need for high-performance local hardware. In general, the stages of system implementation are depicted in the form of a flowchart that shows the sequence of processes sequentially and systematically. The implementation stage begins with the loading of the image dataset which is then reinforced through image augmentation to increase data variation and reduce the risk of overfitting. This stage is the first step in the implementation flowchart, which aims to ensure sufficient and representative data availability. Furthermore, all images are normalized to have a uniform value scale, then the dataset is divided into training and validation data to evaluate the model's generalization capabilities. This process of normalization and data sharing is shown as an advanced stage on the flowchart before the modeling process is carried out. In the next stage, the development of a model architecture is carried out, which includes the creation of EfficientNet-B2 as the baseline model and EfficientNet-B3 as the model of the development results. This stage corresponds to the modeling blocks on the implementation flowchart, which marks the start of the deep learning modeling process. These two architectures were trained using different optimizer configurations, namely Adam and AdamW, with predetermined learning rate variations to observe their effect on the stability and performance of the model training. This training process is represented as a core stage in flowcharts, as it plays a direct role in the formation of model classification capabilities. The evaluation of model performance is carried out comprehensively using several metrics, including Accuracy, Precision, Recall, and F1-Score, so that the results of the classification can be analyzed in more depth and not only depend on accuracy. This evaluation stage is explicitly depicted in the flowchart as the process of measuring the performance of the model after the training is completed. In addition, the training results were visualized using the Smoothed Trend Chart to display accuracy and loss trends in a more subtle and informative way, and the Heatmap Confusion Matrix to show the level of classification accuracy and prediction errors in each class. This visualization is shown as the final stage before the model comparison analysis process on the flowchart. The visualization of graphs and confusion matrix presented in this study is taken from the EfficientNet-B2 baseline model with an Adam optimizer and a learning rate of 5×10^{-4}, which is used as the main reference in comparing performance to the development result model. This stage is the final part of the implementation flowchart that emphasizes the analysis process.

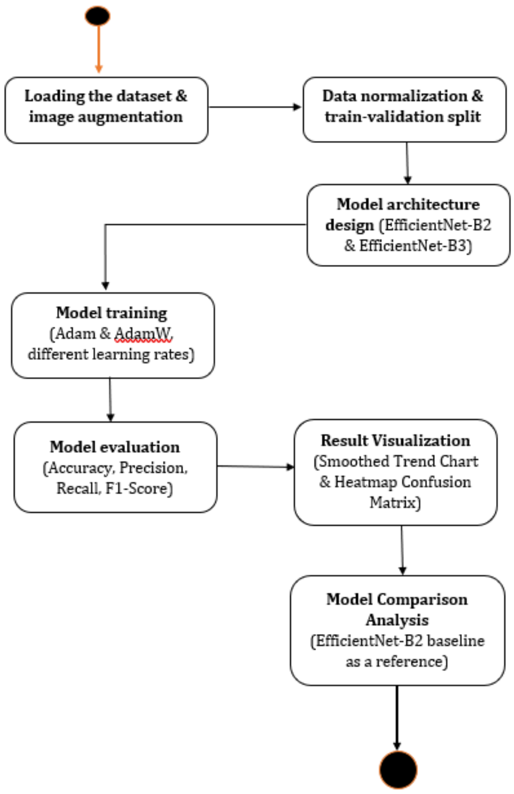

Figure 1. Flow Diagram of the Implementation of the Butterfly Image Classification System

RESULTS AND DISCUSSION

Result:

Experiments were conducted to compare the performance between the EfficientNet-B2 (baseline) and EfficientNet-B3 (modified) models with multiple optimizer configurations. The results of the model training are shown in Table 2. below.

Table 2. Comparison of Model Evaluation Results

Model	Optimizer	Epoch	Learning Rate	Validation Accuracy	Precision	Recall	F1-Score
EfficientNet-B2	Adam	15	5e-4	0.9262	0.9337	0.9262	0.9261
EfficientNet-B3	AdamW	15	6e-4	0.9000	0.9077	0.9000	0.8990

Based on table 2. above, the EfficientNet-B2 + Adam model (lr = 5e-4) produces the highest validation performance with Validation Accuracy = 0.9262 and F1-Score = 0.9261. Meanwhile, the EfficientNet-B3 + AdamW model (lr = 6e-4) has slightly lower performance (Accuracy = 0.9000), which is likely due to the learning rate being too large for the configuration. In addition, EfficientNet-B0 (lr = 1e-4) tests were also conducted which resulted in a Validation Accuracy = 0.8046 and F1-Score = 0.8009, indicating that performance increases with the architectural complexity of B0→B2 →B3.

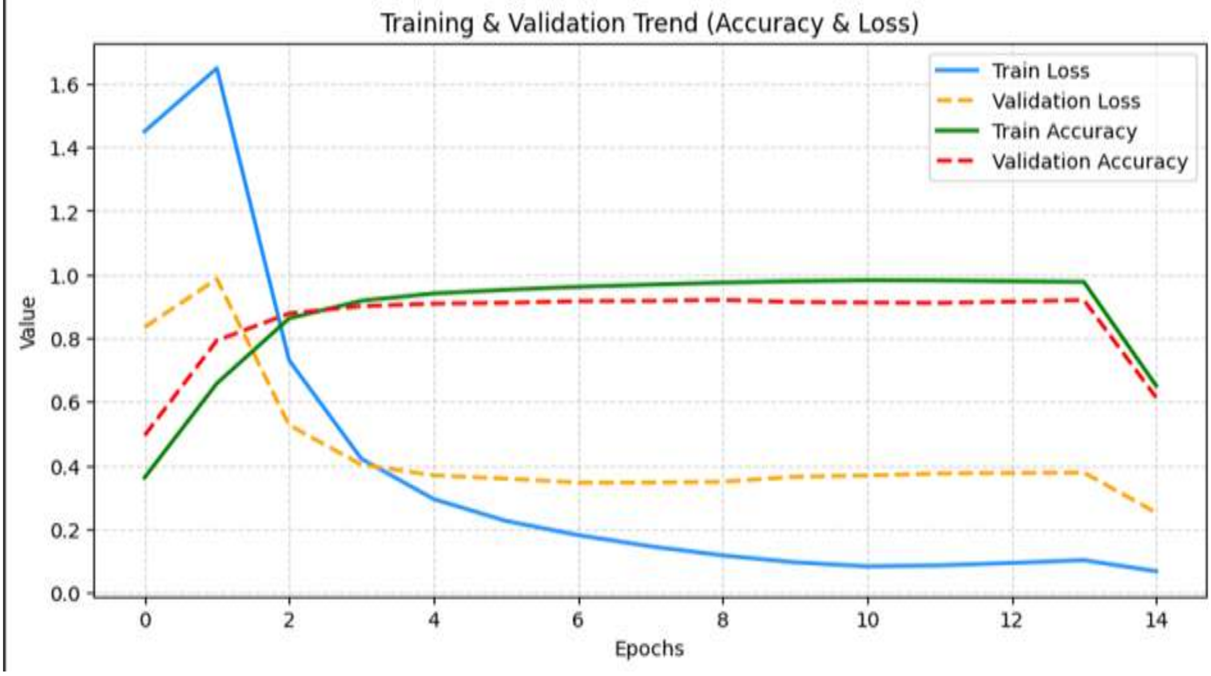

Figure 2. Training & Validation Trend (Accuracy & Loss) – EfficientNet-B2 (Adam lr = 5e-4)

The graph in figure 4.1 shows changes in training loss, validation loss, and training and validation accuracy over 15 epochs. This visualization previously used a regular line chart, then modified into a Smoothed Line Trend Chart so that the pattern of increasing accuracy and decreasing losses looks smoother and more stable between epochs. This makes it easier to analyze model convergence and detect potential overfitting.

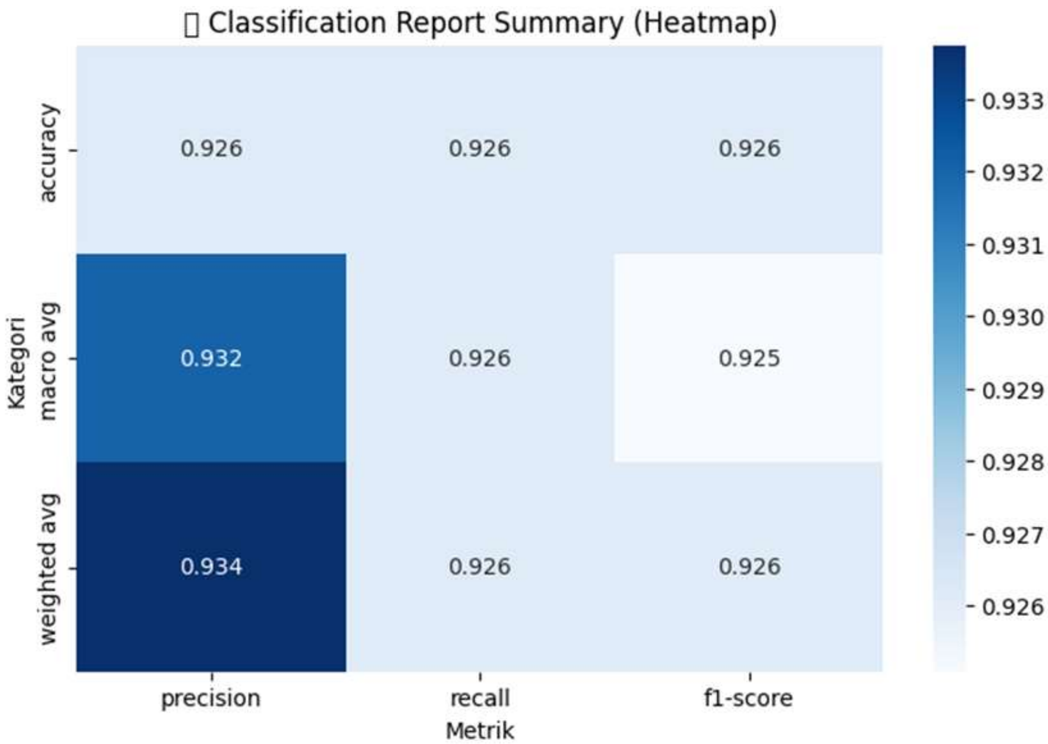

Figure 3. Classification Report Summary (Heatmap) – EfficientNet-B2 (Adam lr = 5e-4)

The heatmap in Figure 4.2 shows a summary of evaluation metrics (Precision, Recall, F1-Score) for the EfficientNet-B2 + Adam model (5e-4). The dark blue color on the weighted avg line indicates the highest metric values that are consistent across all aspects (average ≈ 0.926). This visualization helps to see the balance of performance between classes and reinforces the numerical results that the B2 + Adam (5e-4) combination works very stably.

Discussion:
Based on the experimental results, EfficientNet-B2 optimized with the Adam optimizer (learning rate $= 5 \times 10^{-4}$) demonstrated the best performance and was used as the primary reference model. In comparison, EfficientNet-B3 optimized with the AdamW optimizer (learning rate $= 6 \times 10^{-4}$) produced slightly lower performance, indicating that both model architecture and optimization strategy significantly influence classification results.

EfficientNet-B2 achieved a validation accuracy of 0.9262 and an F1-score of 0.9261, while EfficientNet-B3 reached an accuracy of 0.9000. These findings highlight the importance of selecting appropriate learning rates and optimizers to achieve optimal performance.

Additional analysis using visualization techniques further supports these findings. The Smoothed Trend Chart provides insights into training stability by illustrating smoother learning curves, while the Confusion Matrix heatmap offers a clearer interpretation of classification performance across different classes. Furthermore, the use of Batch Normalization and Dropout contributes to improved training stability and helps prevent overfitting. Reducing the number of training epochs from 50 to 15 also improves computational efficiency without significantly affecting performance.

The results of this study demonstrate that EfficientNet-based models are highly effective for butterfly species classification, particularly when combined with appropriate optimization strategies. Among the evaluated models, EfficientNet-B2 optimized using the Adam optimizer achieved the best performance, indicating its strong capability in extracting discriminative features from butterfly images.

The superior performance of EfficientNet-B2 can be attributed to its balanced architecture, which provides an optimal trade-off between model complexity and computational efficiency. Compared to EfficientNet-B3, which has a deeper and more complex structure, EfficientNet-B2 appears to generalize better on the given dataset. This suggests that increasing model complexity does not always lead to improved performance, especially when the dataset size and variability are limited.

In addition, the choice of optimizer plays a crucial role in determining model performance. The Adam optimizer demonstrated better convergence behavior compared to AdamW in this study. This may be due to its adaptive learning rate mechanism, which allows more stable updates during training. Meanwhile, the slightly lower performance of AdamW indicates that its regularization effect may not be fully optimal under the given experimental conditions, particularly with the selected learning rate.

The findings also highlight the importance of learning rate selection. A properly tuned learning rate significantly affects the model's ability to reach optimal convergence and avoid overfitting. The results suggest that even small differences in learning rate configuration can lead to noticeable changes in performance outcomes.

From an application perspective, the high classification accuracy achieved in this study demonstrates the potential of deep learning models for supporting automated biodiversity monitoring systems. Accurate butterfly classification can assist researchers and conservationists in tracking species distribution and environmental changes more efficiently.

However, this study has several limitations. The dataset used may not fully represent the diversity of butterfly species in real-world environments, which could affect model generalization. Additionally, external validation using independent datasets was not conducted. Future research should consider incorporating larger and more diverse datasets, as well as exploring other advanced architectures and optimization techniques to further improve classification performance.

Implications:
The findings of this study have important implications for the development of automated biodiversity monitoring systems. The high classification performance achieved by EfficientNet-B2 demonstrates that deep learning models can effectively support species identification tasks with high accuracy and stability. This can assist researchers, conservationists, and environmental agencies in monitoring butterfly populations more efficiently and consistently. Furthermore, the results emphasize the importance of selecting appropriate optimization strategies, as the choice of optimizer and learning rate significantly affects model performance in real-world applications.

Research Contribution:
This study contributes to the field of image-based classification by providing a comparative analysis of EfficientNet architectures combined with different optimization strategies. It highlights that a less complex model (EfficientNet-B2) can outperform a more complex variant (EfficientNet-B3) when paired with suitable hyperparameter configurations. Additionally, this study demonstrates the practical impact of optimizer selection and training strategies, such as learning rate tuning, batch normalization, and dropout, in improving classification performance and training efficiency.

Limitations:
Despite its promising results, this study has several limitations. The dataset used may not fully represent the diversity of butterfly species in real-world environments, which may affect the generalizability of the model. In addition, the study only evaluates two EfficientNet variants and limited optimizer configurations, which may not capture the full potential of other architectures or optimization methods. Furthermore, external validation using independent datasets was not conducted, limiting the robustness of the findings.

Suggestions**:**
Future research should consider using larger and more diverse datasets to improve model generalization. Exploring additional deep learning architectures and advanced optimization techniques, such as adaptive learning rate schedulers or hybrid optimizers, may further enhance performance. Moreover, incorporating real-world deployment scenarios and testing models on external datasets would provide stronger validation. The integration of explainable AI (XAI) techniques is also recommended to improve model interpretability and support decision-making in biodiversity conservation.

CONCLUSION

Based on the results of the experiments and analyses that have been carried out, it can be concluded that the change of the model from EfficientNet-B2 (baseline) to EfficientNet-B3 is able to increase the efficiency of training and enrich the analysis of model results. The baseline model with the Adam optimizer (learning rate = 5e-4) provides the best performance with a Validation Accuracy value of 0.9262 and an F1-Score of 0.9261. Meanwhile, the use of the AdamW optimizer (learning rate = 6e-4) on EfficientNet-B3 resulted in a slightly lower performance, an Accuracy of 0.9000, which was likely due to setting the learning rate too high. Improvements were also made in the aspect of visualizing results, namely through the use of the Smoothed Trend Chart and Heatmap Confusion Matrix which facilitate the interpretation of the training process and clarify the performance of the model in each class. In addition, additional experiments using EfficientNet-B0 (lr = 1e-4) showed lower results, but still strengthened the consistency of the parameter tuning direction between model variants. Overall, the modifications made succeeded in improving training efficiency, enriching evaluation methods, and producing more informative visualizations of results without requiring a long training time.

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