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Enhanced RegNetY-400MF for Fruit Fly Species Classification: Fine-Tuning Strategies and Data Balancing for Improved Accuracy

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Abstract

Fruit fly infestations are a severe threat to agricultural output, particularly in chili plantations, and can result in large yield losses. Accurate and speedy species classification is critical for carrying out tailored pest control tactics. This study develops a computationally efficient fruit fly species classification model that focuses on improving accuracy with refinement and class balancing strategies. The dataset consists of 1049 images across 4 fruit fly species, captured in a natural plantation environment and available at www.inaturalist.org. This model evaluates several lightweight Convolutional Neural Network (CNN) architectures, including MobileNetV3-Small, RegNetY-400MF, and SqueezeNet, among others, with RegNetY-400MF being the best performing model, achieving a validation accuracy of 96.10% and a macro F1 score of 95.70%. The models tested in this study included several lightweight CNN architectures, including MobileNetV3-Small, RegNetY-400MF, and SqueezeNet, among others. RegNetY-400MF proved to be the best performing model, achieving a validation accuracy of 96.10% and a macro F1 score of 95.70%. Compared to other state-of-the-art models, RegNetY-400MF demonstrated higher accuracy while maintaining a lower number of parameters (8.3 million) and reduced computational complexity (0.41 GFLOPs). This makes the model highly suitable for real-time applications in resource-constrained agricultural environments. The model offers a practical solution for fruit fly species detection, enabling early and accurate identification of pest infestations in chili plantations, thereby reducing the risk of crop failure. By providing an efficient and scalable pest control tool, the model supports precision pest management, improves yield stability, and contributes to sustainable agriculture.

Keywords: balancing; CNN; fruit fly classification; precision agriculture; Regnety-400MF

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1. Introduction

Fruit flies are a highly detrimental pest to various agricultural commodities, such as fruits, vegetables, and other crops [1]. Fruit fly infestations can cause significant damage to crops, reducing the quality and quantity of agricultural products, and even leading to crop failure. In chili farming, fruit fly infestations can significantly reduce yields, especially given that chili is a highly sensitive crop to pest attacks [2]. Yield losses due to these infestations can have a significant impact on farmers and markets.

Fruit fly classification is a crucial step in managing this pest. By identifying the invading fly species, we can design more precise and effective control strategies [3], [4]. A better understanding of the types of fruit flies present in an area allows for the implementation of more targeted control methods, such as the use of specific traps [5], [6], the selection of more efficient pesticides [7], [8], or better cropping patterns.

Deep learning algorithms, notably Convolutional Neural Networks (CNNs), play an important role in fruit fly classification due to their capacity to automatically extract and learn discriminative features

from picture data with great accuracy. CNNs can automatically and profoundly process images [9], [10], allowing for the rapid and efficient identification and classification of fruit fly species [11].

Despite advances in fruit fly control strategies, many existing models focus on high computational power or fail to balance accuracy with efficiency, making them unsuitable for resource-constrained agricultural settings. For example, Parallel-CNN achieved 94.87% accuracy [11], Alexnet-DNA Sequence 94.00% [12], and Yolo V5 94.30% [13], with Yolo V8 reaching 95.00% [14]. However, these models remain computationally expensive.

To overcome these challenges, this research emphasizes the optimization of a compact CNN framework that achieves a balance between classification performance and computational cost, making it suitable for real-time fruit fly identification in agricultural settings with constrained resources. Specifically, lightweight CNNs like MobileNet V2 [15], MobileNet V3 [16], RegNet [17], SqueezeNet [18], ShuffleNet [19], and EfficientNet [20] are designed to have a lower parameter count and FLOPs without sacrificing accuracy, making them ideal for use in portable devices or IoT-based agricultural systems. These models enable high-efficiency real-time classification, providing practical, on-the-ground solutions for farmers.

A comprehensive optimization framework is proposed to improve CNN performance for fruit fly recognition tasks. The workflow integrates data preprocessing and augmentation techniques [21], lightweight model selection, and fine-tuning strategies using Early Stopping [22] and learning rate schedulers to enhance training stability. To handle data imbalance, a balancing mechanism [23] is applied prior to optimization [24]. The resulting models demonstrate efficient computation and competitive accuracy, which are benchmarked against existing state-of-the-art methods.

This study is unique in that it combines class-balancing approaches, optimizer tweaking, and the use of the lightweight CNN model RegNetY-400MF in the context of chili farming under computing restrictions. Unlike previous works that mainly focus on heavy detection frameworks or single-aspect tuning, this study introduces a practical and efficient pipeline by combining (i) class-balancing and augmentation strategies to handle species imbalance, (ii) fine-tuning of Enhanced RegNetY-400MF for state-of-the-art accuracy with minimal computation, (iii) joint hyperparameter and optimizer optimization for efficiency on limited hardware, and (iv) sensitivity analysis of computation cost to accuracy for practical IoT deployment. To the highest level of our comprehension, this is the first work to integrate these strategies for fruit fly classification in chili plantations, bridging the gap between lab-based CNN research and real-world smart agriculture applications.

2. Methods

This research follows a structured approach to optimize the performance of CNN models in classification tasks. The first step is Data Preparation and Augmentation, which ensures the data is properly processed and augmented to improve model performance. The first phase involves Classification with Existing CNN Models, where various CNN architectures are explored to determine which provides the best baseline performance.

After classifying with existing models, the next step is to Obtain the Best Three Lightweight Models. This helps identify the most efficient and accurate models in terms of computational cost and accuracy. Fine-tuning is then performed using Early Stopping and a Scheduler to improve model performance by preventing overfitting and dynamically adjusting the learning rate for better optimization.

After selecting the most suitable model, additional improvements are carried out through the application of data balancing mechanisms to handle class imbalance and the adjustment of optimization algorithms to refine training performance. The resulting accuracy is then compared to proven state-of-the-art methodologies to emphasize the study's significance and innovation. Figure 1 summarizes the research procedure.

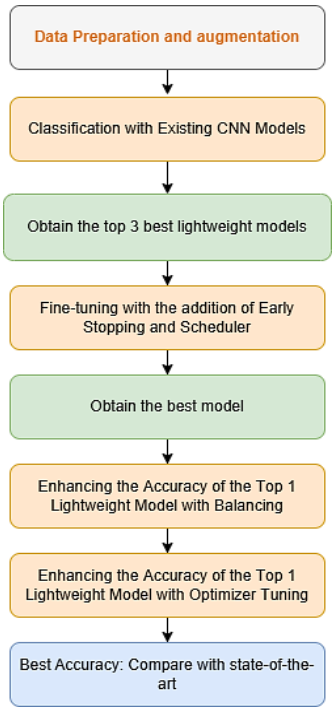


Figure 1. Research Methodology

2.1. Existing CNN

CNNs have been indispensable in the field of computer vision in recent years, owing to their capacity to extract characteristics from images rapidly. Several CNN designs have been designed to establish a balance between performance and computational efficiency, particularly for usage in mobile and embedded systems. In agricultural settings, lightweight CNN models are

particularly valuable for quickly classifying plant diseases and pests, while keeping computational costs low. Below are some of the leading lightweight CNN models currently in use:

RegNetY-400MF [25], a member of the RegNet family, was created with an emphasis on computational economy and performance optimization, which makes it ideal for real-time applications on devices with limited resources. For jobs requiring quick inference and low power consumption, like smart agricultural applications, its architecture provides a great balance between accuracy and computational cost [26], [27]. Compared to larger variations such as the RegNetY-800MF or 1.6GF, as well as the RegNetX [28] series, which lacks the Squeeze-and-Excitation (SE) module, the RegNetY-400MF was chosen for its best balance of accuracy and computing efficiency. The addition of the SE module improves the model's capacity to adjust channel-wise feature responses without incurring considerable computational complexity, giving RegNetY-400MF an edge over RegNetX in feature representation. This makes it ideal for agricultural image analysis on devices with minimal computing capacity. The architecture of the RegNetY-400MF is shown in Table 1.

Table 1. RegNetY-400MF Architecture

Layer	Output Size	Channels	Blocks	Stride	Description
Stem	56 × 56	32	1	2	3×3 Conv, BN, ReLU
Stage 1	28 × 28	32	1	2	Bottleneck + SE
Stage 2	14 × 14	56	1	2	Bottleneck + SE
Stage 3	7 × 7	152	4	2	Bottleneck + SE
Stage 4	7 × 7	368	7	1	Bottleneck + SE
Global Pooling	1 × 1	368	-	-	Adaptive Average Pooling
FC Layer	1 × 1	1000	-	-	Fully Connected Layer (Classifier)

MobileNet is a suite of lightweight CNNs designed for efficient mobile and embedded applications, balancing accuracy with computational efficiency. MobileNetV2 utilizes depthwise separable convolutions and linear constraints to minimize computational costs, making it ideal for mobile devices in agricultural applications such as automated pest detection [29], [30]. MobileNetV3-Large builds on V2 by incorporating Neural Architecture Search (NAS) and Squeeze-and-Excitation (SE) modules [31], [32], improving performance and accuracy, making it suitable for more challenging tasks such as agricultural applications [33]. MobileNetV3-Small, a more compact variant optimized for severely resource-constrained environments, sacrifices some accuracy for smaller size and lower computational overhead, making it well-suited for portable pest detection systems in precision agriculture [34]. The following are the differences between the different types of MobileNets, as shown in Table 2.

Table 2. Different Types of MobileNets

Variant	Depthwise	Bottleneck	SE	NAS	Model Size
MobileNetV2	Y	Y	N	N	Moderate
MobileNetV3-Large	Y	Y	Y	Y	Larger
MobileNetV3-Small	Yes	Y	Y	Y	Small

ShuffleNetV2 introduces an efficient channel shuffle operation that enhances the mixing of feature maps, significantly reducing the computational complexity of large models. By utilizing depthwise convolutions and group convolutions, it minimizes the number of parameters while maintaining high accuracy. Unlike its predecessor, ShuffleNetV1, which used a simpler channel shuffle operation, ShuffleNetV2 optimizes this approach, improving both accuracy and speed [35], [36]. This makes it particularly well-suited for real-time image processing on mobile devices, such as handheld pest detection systems in agricultural applications, where efficiency and low computational cost are critical.

SqueezeNet is an extremely lightweight CNN known for its fire modules, which drastically reduce the number of parameters by squeezing input features into a lower-dimensional space before expanding them. Despite its small size, it delivers competitive performance for image classification tasks. This makes SqueezeNet a strong candidate for edge devices used in agriculture, particularly for real-time pest detection and monitoring on low-power systems [37] - [39].

EfficientNet-B0 serves as the reference architecture within the EfficientNet family and is recognized for its compound scaling strategy, which jointly optimizes network depth, width, and input resolution. By applying this balanced scaling approach, EfficientNet-B0 delivers strong performance while maintaining a relatively low number of parameters. Owing to its computational efficiency, the model is particularly suitable for agricultural applications that demand both accuracy and resource efficiency, including automated pest detection in chili cultivation systems [40].

Each of these models was created with a focus on lightweight architecture while maintaining a high level of accuracy, making them ideal for use in mobile and

embedded environments with limited computational resources, particularly in precision agriculture applications like fruit fly classification in chili farms.

2.2. Datasets

This study used a dataset collected directly from a chili plantation in Medan, North Sumatra, Indonesia. Special traps were designed and placed in the field to capture fruit flies. Trapped fruit flies were photographed, and the images were cropped to generate training and validation datasets. However, in the chili plantation in Medan, the only fruit fly species captured was Bactrocera cucurbitae. Therefore, additional datasets for Ceratitis capitata, Bactrocera latifrons, and Bactrocera dorsalis were obtained from public databases, including www.inaturalist.org. The following is the process of capturing fruit flies in agricultural fields, as shown in Figure 2.



Figure 2. Data Collection Process in Chili Farming

This study focuses on four species of fruit flies, namely Ceratitis capitata, Bactrocera latifrons, Bactrocera dorsalis, and Bactrocera cucurbitae. These species were selected for analysis based on their prevalence in agricultural environments, particularly in chili farming areas. Figure 3 illustrates the different fruit fly species captured and used in the dataset for this research.

Table 3 summarizes the dataset utilized in this study and describes the distribution of photos across fruit fly species. Table 3 shows the distribution of images for training and validation, as well as the overall sample size for each class. Such a summary contributes to the evaluation and implementation of the proposed classification model.

Table 3. Fruit Fly Datasets

Fly Species	Training Data	Validation Data	Total Data
Bactrocera Cucurbitae	204	50	254
Bactrocera Dorsalis	181	45	226
Bactrocera Latifrons	224	55	279
Ceratitis Capitata	232	58	290

Each dataset underwent augmentation, which increased the data by four times using techniques like flipping, rotation, and color alterations. These augmentations were used to increase the diversity and robustness of the training data. Figure 4 shows the results of the data augmentation process.



Figure 3. Fruit Fly Species



Figure 4. Image Augmentation

Table 4 highlights the datasets obtained using data augmentation strategies. It shows the number of photos in the training and validation sets after using augmentation techniques including flipping, rotation, and color modifications. These modifications increased the dataset size for each fruit fly species, boosting the model's generalization ability and performance during training and validation.

Table 4. Augmented Datasets

Fly Species	Training Data Augmentation	Validation Data Augmentation	Total Data
Bactrocera Cucurbitae	821	196	1017
Bactrocera Dorsalis	764	140	904
Bactrocera Latifrons	916	202	1118
Ceratitis Capitata	928	232	1160

3. Results and Discussions

This research adopts a structured approach to optimize CNN performance in classifying fruit fly species. It begins with data preparation and augmentation to enhance the dataset, followed by exploring existing CNN models to establish a baseline for classification performance. The best three lightweight models are identified based on accuracy and computational efficiency, after which fine-tuning is done using early

stopping and a scheduler to prevent overfitting and optimize the learning rate.

The next step is to improve the accuracy of the highest-performing model using class balance approaches and advanced tuning procedures. Finally, the model's performance is tested and compared to cutting-edge methodologies to demonstrate the effectiveness and creativity of the suggested strategy.

3.1 Hyperparameter

The hyperparameters and settings used to train the CNN models are crucial in ensuring optimal model performance. These parameters define the structure and training process of the models, influencing factors such as image size, learning rate, and the split of the dataset. Table 5 outlines the key hyperparameters applied during the training phase, which guided the model's ability to effectively learn and classify fruit fly species.

Table 5. Hyperparameter

No.	Component	Hyperparameter / Setting
1	Image Size	224 × 224
2	Batch Size	32
3	Epochs	10
5	Normalization	mean = [0.485, 0.456, 0.406] std = [0.229, 0.224, 0.225]
7	Fine-Tuning	Only the classifier layer (model.fc) is trained
9	Loss Function	Cross Entropy Loss
10	Optimizer	Adam
11	Learning Rate	0.001
13	Dataset Split	80% Training, 20% Testing
15	Evaluation Metrics	Accuracy, Confusion Matrix, Classification Report

Table 5 presents the hyperparameters and their corresponding values used in the CNN model training process. These settings were carefully chosen to balance model accuracy, training efficiency, and computational cost. Each component, such as the batch size, learning rate, and loss function, plays an integral role in shaping the final model's performance and ensuring reliable classification results.

3.2 Comparative Analysis of Lightweight CNNs

In this study, we compared multiple lightweight CNN models to find the best economical and accurate architecture for precision smart farming, namely fruit fly species classification. These models were chosen for their ability to function effectively on resource-constrained devices while yet providing adequate accuracy for pest detection tasks. Table 6 summarizes the comparison of the models, including validation correctness, parameter count, and computational efficiency (measured in FLOPs). Table 6 presents a clear overview of the models' performance, emphasizing the trade-offs between accuracy and computational cost.

The results presented in Table 6 highlight the validation accuracy of several lightweight CNN models. Among the tested models, MobileNetV3-Small, representing the MobileNet family, achieved the highest accuracy of 89.91%, followed by RegNetY-400MF with 87.29% accuracy, and SqueezeNet with 86.70%. These models not only demonstrated competitive accuracy but also varied significantly in computational efficiency.

Table 6. Comparative Analysis of Lightweight CNN

No.	Model	Val Accuracy (%)	Parameters (M)	FLOPs (G)
1	RegNetY-400MF	87.29	8.3	0.41
2	MobileNetV2	84.40	3.5	0.30
3	MobileNetV3-Large	88.53	5.4	0.22
4	MobileNetV3-Small	89.91	2.9	0.06
5	ShuffleNetV2	75.23	2.3	0.15
6	SqueezeNet	86.70	1.2	0.83
7	EfficientNet-B0	76.00	5.3	0.39

Based on these results, we conclude that MobileNetV3-Small, RegNetY-400MF, and SqueezeNet are the top three models in terms of accuracy and efficiency. To further optimize their performance, these models will be tested with augmented data in subsequent phases of the study. Additional data will help assess the models' robustness and generalizability across a wide range of conditions in fruit fly classification.

3.3 Comparison of Top Three Lightweight CNN

We compared the performance of three top lightweight CNN models MobileNetV3-Small, RegNetY-400MF, and SqueezeNet before and after applying data augmentation. The purpose of this comparison was to evaluate how dataset augmentation affects model accuracy and to assess the effectiveness of augmentation in improving the generalization ability of these models. By increasing the diversity of the training data, we aimed to see whether the models became more robust and achieved higher accuracy in classifying fruit fly species. Table 7 illustrates the model accuracy before and after augmentation. As shown, MobileNetV3-Small saw the largest improvement, with its accuracy increasing from 89.91% to 91.40%. RegNetY-400MF also showed a significant improvement, from 87.29% to 91.17%. Although SqueezeNet saw a smaller improvement, its accuracy increased from 86.70% to 88.05%. This demonstrates the positive effect of data augmentation on model performance, improving their ability to classify fruit flies more accurately.

Table 7. Comparison Before and After Augmentation

Model	Accuracy Before Augmentation (%)	Accuracy After Augmentation (%)
MobileNetV3-Small	89.91	91.40
RegNetY-400MF	87.29	91.17
SqueezeNet	86.70	88.05

3.4 Accuracy Improvement of Lightweight CNN with EarlyStopping and Scheduler

Incorporating Early Stopping and a learning rate scheduler (ReduceLROnPlateau) into the training

process of MobileNetV3-Small, RegNetY-400MF, and SqueezeNet is intended to enhance model performance by mitigating overfitting and improving training efficiency. Early Stopping terminates the training process once validation performance no longer improves, thereby reducing redundant computations and limiting overfitting. In parallel, the learning rate scheduler adaptively lowers the learning rate as training advances, facilitating smoother convergence and more stable optimization. Together, these strategies promote efficient training while improving the models' generalization capability and overall classification accuracy.

As summarized in Table 8, the MobileNetV3-Small model trained with Early Stopping and learning rate scheduling demonstrates stable classification results across the evaluated fruit fly species. High precision, recall, and F1-score values are consistently observed, particularly for Bactrocera latifrons and Ceratitis capitata, which achieve F1-scores of 0.95 and 0.96, respectively. The overall accuracy of 93% indicates reliable discriminative capability, supported by the applied training strategies that enhance convergence and robustness. Further evidence of the classification performance is provided through the confusion matrix presented in Figure 5.

Table 8. Classification Report MobileNetV3-Small with EarlyStopping and Scheduler

Class	Precision	Recall	F1-Score	Support
Bactrocera cucurbitae	0.92	0.93	0.92	196
Bactrocera dorsalis	0.86	0.88	0.87	140
Bactrocera latifrons	0.94	0.96	0.95	202
Ceratitis capitata	0.98	0.94	0.96	232
Accuracy			0.93	770
Macro Avg	0.93	0.93	0.93	770
Weighted Avg	0.93	0.93	0.93	770

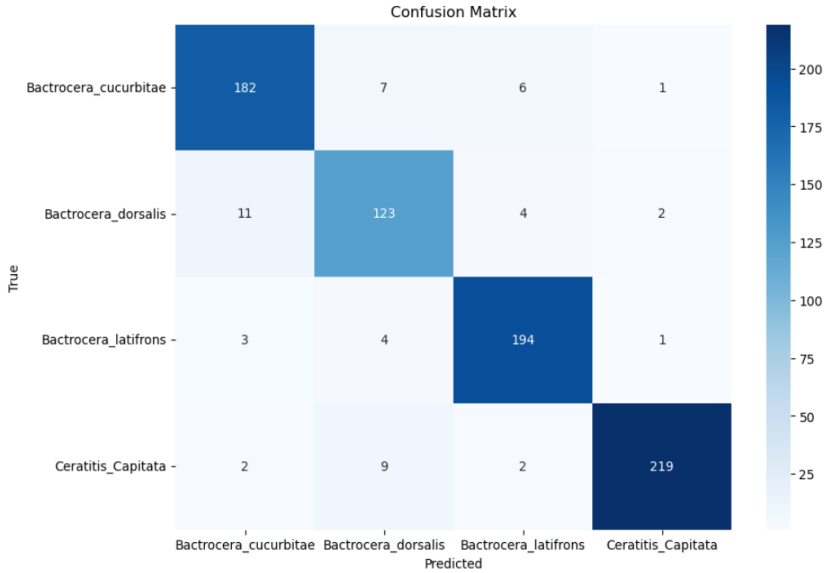


Figure 5. Confusion Matrix MobileNetV3-Small with EarlyStopping and Scheduler

Table 9 shows the classification report for RegNetY-400MF with EarlyStopping and Scheduler, which demonstrates the model's effectiveness across a variety of fruit fly species.

Table 9. Classification Report RegNetY-400MF with EarlyStopping and Scheduler

Class	Precision	Recall	F1-Score	Support
Bactrocera cucurbitae	0.92	0.92	0.92	196
Bactrocera dorsalis	0.86	0.89	0.87	140
Bactrocera latifrons	0.95	0.98	0.97	202
Ceratitis capitata	1	0.95	0.97	232
Accuracy			0.94	770
Macro Avg	0.93	0.94	0.93	770
Weighted Avg	0.94	0.94	0.94	770

The model attained an overall accuracy of 94%, indicating excellent competence in properly recognizing species. Ceratitis capitata had the maximum precision of 1.00 in each class, as well as an F1 score of 0.97, indicating exceptional detection performance. Bactrocera latifrons likewise performed well, with a precision of 0.95 and recall of 0.98, yielding an F1 score of 0.97.

The macro-average and weighted-average values of 0.93 and 0.94, respectively, reflect stable classification behavior across fruit fly categories, indicating the absence of strong class dominance. The integration of Early Stopping and learning rate scheduling contributes to balanced learning dynamics by reducing overfitting and supporting robust generalization. Consistently high accuracy and F1-score values across species suggest that RegNetY-400MF is well suited for fruit fly identification tasks in precision agriculture. A visual summary of the classification outcomes is provided in Figure 6.

Table 10 shows the classification performance of SqueezeNet trained with Early Stopping and the addition of a learning rate scheduler, which achieved an

overall accuracy of 88%. This model performed better at recognizing Ceratitis capitata, with a precision of 0.95, a recall of 0.96, and an F1 score of 0.96. Although its performance decreased significantly for Bactrocera cucurbitae, Bactrocera dorsalis, and Bactrocera latifrons, the model maintained high precision and recall across all classes. The macro-average and weighted average scores of 0.87 and 0.88 indicate balanced classification performance, suggesting SqueezeNet is a viable option when processing efficiency is important, although its accuracy is somewhat lower compared to other models. Figure 7 displays the corresponding classification results.

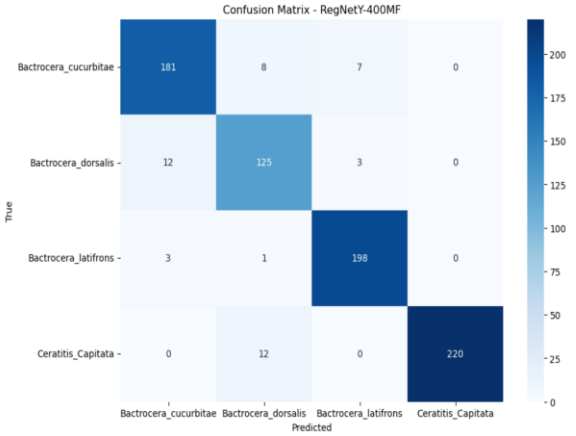


Figure 6. Confusion Matrix RegNetY-400MF with EarlyStopping and Scheduler

Table 10. Classification Report SqueezeNet with EarlyStopping and Scheduler

Class	Precision	Recall	F1-Score	Support
Bactrocera cucurbitae	0.88	0.82	0.85	196
Bactrocera dorsalis	0.76	0.84	0.80	140
Bactrocera latifrons	0.90	0.89	0.89	202
Ceratitis lapitata	0.95	0.96	0.96	232
Accuracy	0.88			770
Macro Avg	0.87	0.88	0.87	770
Weighted Avg	0.88	0.88	0.88	770

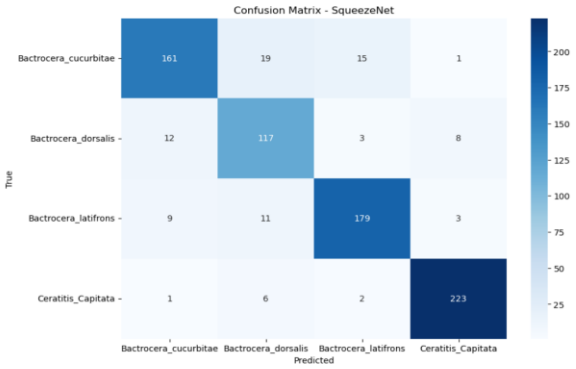


Figure 7. Confusion Matrix SqueezeNet with EarlyStopping and Scheduler

To evaluate the performance of the three models trained using Early Stopping and learning rate scheduling on augmented data, validation accuracy and F1-score measures were used. RegNetY-400MF had the best performance, with an accuracy rate for validation of 94.03% and an F1-score of 0.94, indicating its robust ability to differentiate fruit fly species. MobileNetV3-Small achieves nearly identical results, with a validation accuracy of 93.25% and an F1-score of 0.93, demonstrating its competitive effectiveness despite its tiny architecture. In contrast, SqueezeNet has a lower validation accuracy (91.56%) and F1-score (0.91). however, its performance remains satisfactory, particularly when computational efficiency is prioritized. A detailed comparison of validation accuracy and F1-score values for each model after applying data augmentation, Early Stopping, and learning rate scheduling is provided in Table 11.

Table 11. Comparison of Accuracy Models with Earlystopping and Scheduler on Augmented Data

Model	Validation Accuracy (%)	F1-Score
MobileNetV3-Small	93.25	0.93
RegNetY-400MF	94.03	0.94
SqueezeNet	91.56	0.91

After analyzing the findings, RegNetY-400MF emerges as the top-performing model, with the highest accuracy and F1-score. Therefore, it is selected for further improvement in the next stage of the research. By applying balancing techniques and optimizer tuning, we aim to improve its classification performance, particularly for underrepresented classes, and improve the model's robustness. This step is expected to increase the overall accuracy and make the model even more reliable for real-world applications in precision farming.

3.5 Enhancing the Accuracy of RegNetY-400MF

Incorporating balancing techniques into the training data is crucial for addressing class imbalance, which can hinder a model's ability to accurately classify less represented classes. By balancing the dataset, we ensure that the model encounters a more even distribution of each class, preventing it from favoring the more prevalent ones. This ultimately enhances the model's ability to generalize, improving its performance across all classes, particularly those with fewer samples. As a result, the classifier becomes more reliable and precise. In this case, the data balancing technique applied is Weighted Sampling, which ensures that each class is given appropriate representation during training.

Table 12 shows the RegNetY-400MF classification report after using the balancing procedure. The model scored an outstanding 95% overall accuracy, with Ceratitis capitata having the greatest precision of 1.00 and F1 score of 0.98. Bactrocera latifrons likewise did remarkably well, with an F1 score of 0.98. The Macro-Mean and Weighted Mean scores of 0.94 and 0.95, respectively, demonstrated that the model performed well in all classes. This shows that the balancing strategy considerably enhanced the model's performance, resulting in fair and accurate classification of all fruit fly species. Figure 8 depicts the

confusion matrix of the RegNetY-400MF with balancing.

Table 12. Classification Report RegNetY-400MF with Balancing

Class	Precision	Recall	F1-Score	Support
Bactrocera cucurbitae	0.92	0.94	0.93	196
Bactrocera dorsalis	0.87	0.88	0.87	140
Bactrocera latifrons	0.98	0.99	0.98	202
Ceratitis capitata	1	0.96	0.98	232
Accuracy			0.95	770
Macro Average	0.94	0.94	0.94	770
Weighted Average	0.95	0.95	0.95	770

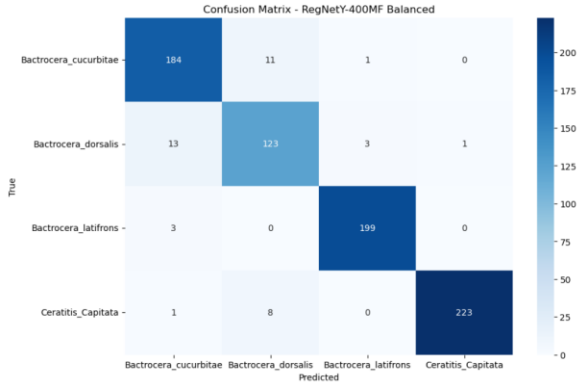


Figure 8. Confusion Matrix RegNetY-400MF with Balancing

After applying data balancing techniques, the next step is to focus on optimizing model performance by tuning the optimizer. Optimizer selection is crucial because it impacts the model's learning effectiveness during training. Each optimizer adjusts the learning rate and weights differently, which can significantly impact model accuracy and efficiency. By fine-tuning the optimizer, we aim to find the ideal balance between learning rate and weight decay, allowing the model to learn more efficiently and avoid issues such as slow convergence or overfitting, ultimately resulting in better performance.

Table 13. Comparison of Accuracy of RegNetY-400MF with Optimizer Tuning

Optimizer	Learning Rate	Weight Decay	Accuracy	F1 Macro
	0.001	0	88.83%	88.03%
	0.001	0.0001	88.57%	87.83%
	0.0001	0	67.66%	65.83%
SGD	0.0001	0.0001	66.75%	65.35%
	0.001	0	92.99%	92.11%
	0.001	0.0001	93.38%	92.68%
	0.0001	0	94.81%	94.44%
RMSprop	0.0001	0.0001	94.81%	94.29%
	0.001	0	93.38%	92.92%
	0.001	0.0001	94.81%	94.35%
	0.0001	0	93.77%	93.14%
AdamW	0.0001	0.0001	95.19%	94.70%
	0.001	0	91.95%	91.21%
	0.001	0.0001	94.16%	93.68%
	0.0001	0	96.10%	95.70%
Adam	0.0001	0.0001	94.16%	93.52%

Table 13 compares RegNetY-400MF accuracy with different optimizer tuning setups. The Adam optimizer, with a rate of learning of 0.0001 and no weight decay, earned the greatest accuracy of 96.10% and a macro F1 score of 95.70%. This illustrates that the Adam optimizer, especially at lower learning rates, is extremely effective at fine-tuning the model and producing the best outcomes. Optimizer tweaking was critical in considerably enhancing the model's capacity to classify fruit fly species, resulting in increased accuracy and robustness.

3.6 Comparison with State of The Art

To evaluate the improvements achieved by our research, we compared our model with previous studies in smart agriculture, particularly in fruit fly classification. The comparison focused on accuracy, number of parameters, and FLOPs. The accuracy comparison with state-of-the-art models is presented in Table 14.

Table 14. Accuracy Comparison

Model	Validation Accuracy (%)
Parallel-CNN [11]	94.87
Alexnet-DNA Sequence[12]	94.00
Yolo V5 [13]	94.30
Yolo V3 + CD3 Network [41]	93.46
Yolo V8 [14]	95.00
Enhanced RegNetY-400MF (Our)	96.10

Table 14 compares our model with leading techniques based on validation accuracy. The results show that, after tuning with the Adam optimizer, our model achieved an impressive 96.10% accuracy, surpassing models such as Yolo V8 (95.00%) and Yolo V5 (94.30%). This significant improvement highlights the effectiveness of our model and its innovative approach to fruit fly classification. The combination of high accuracy and efficient use of computing resources positions our model as a strong contender in the field, with great potential for practical applications in precision agriculture, where accuracy and efficiency are crucial. The comparison of the number of parameters is shown in Table 15.

Table 15. Comparison of Number of Parameters

Model	Number of Parameters (M)
Parallel- CNN [11]	469.00
Alexnet-DNA Sequence [12]	60.00
Yolo V5 [13]	21.50
Yolo V3 + CD3 Network [41]	63.00
Yolo V8 [14]	25.90
Enhanced RegNetY-400MF (Our)	8.30

Table 15 compares the number of parameters across the various models, highlighting their complexity and computational requirements. The Parallel-CNN has the largest size with 469 million parameters, followed by YOLOv3+CD3 (63M) and AlexNet-DNA Sequence (60M). Meanwhile, YOLOv5 and YOLOv8 are lighter, containing 21.5M and 25.9M parameters, respectively. In contrast, the Enhanced RegNetY-400MF model used in this study has only 8.3M parameters, making it the most lightweight option among the compared models. This smaller parameter count enables more efficient computation, which is crucial for real-time applications

such as precision agriculture, without sacrificing model performance. To further understand the computational overhead, FLOPs are compared in Table 16.

Table 16. Comparison of Number of Flops

Model	Number of FLOPs (G)
Parallel-CNN [11]	140
Alexnet-DNA Sequence[12]	1.30
Yolo V5 [13]	19.00
Yolo V3 + CD3 Network [41]	63.00
Yolo V8 [14]	155.00
Enhanced RegNetY-400MF (Our)	0.41

Table 16 compares the number of FLOPs (floating-point operations) across various models, which reflects their computational complexity. The Parallel-CNN is the most computationally demanding with 140 GFLOPs, followed by YOLOv3+CD3 at 63 GFLOPs. YOLOv8 is also highly complex at 155 GFLOPs, while YOLOv5 requires 19 GFLOPs. In contrast, AlexNet-DNA Sequence is relatively moderate with 1.30 GFLOPs. Among all models, the Enhanced RegNetY-400MF stands out with only 0.41 GFLOPs while still achieving the highest accuracy. This indicates its effectiveness and adaptability for real-time deployment in resource-constrained settings. The comparison emphasizes the trade-off between model complexity and computational efficiency, with RegNetY-400MF providing a lightweight but high-performing solution. It is important to note that while YOLO-based detectors are optimized for real-time localization and bounding-box detection, our study addresses a different task-species classification within trap images. In this context, computational efficiency and accuracy are more critical than detection speed, as the insects are already captured. Thus, the proposed Enhanced RegNetY-400MF offers a more practical solution for IoT-based field traps than heavier detection models like YOLO. The comparison of computation cost to accuracy is further visualized in Figure 9.

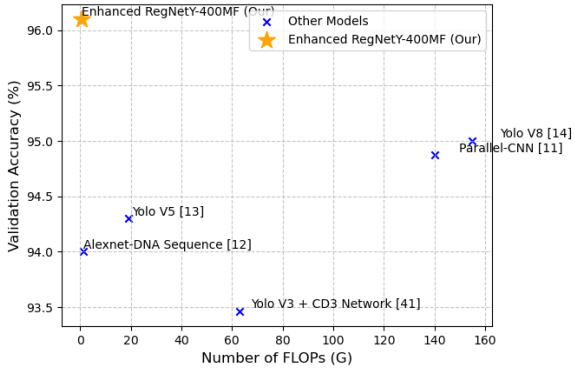


Figure 9. Sensitivity of Computation Cost to Accuracy across Different Models

Figure 9 shows the trade-off between the cost of computing, as measured in GFLOPs, and validation accuracy for several models. While Parallel-CNN, YOLOv3+CD3, and YOLOv8 achieve relatively good accuracy, they have extremely large computational needs, making them unsuitable for deployment in resource-constrained situations. In comparison, the suggested Enhanced RegNetY-400MF obtains highest accuracy (96.10%) while using the fewest computation resources (0.41 GFLOPs), clearly surpassing previous models in terms of efficiency. This finding demonstrates RegNetY-400MF's exceptional sensitivity, as improvements in accuracy do not come at the expense of disproportionate increases in processing complexity, making it very feasible for real-time smart agriculture applications.

In this study, we structured the comparisons into two categories. First, we directly compared the proposed Enhanced RegNetY-400MF with other lightweight CNN architectures such as MobileNetV3-Small, SqueezeNet, ShuffleNetV2, and EfficientNet-B0, which belong to the same family of classification models. These results (Tables 6–13) confirm that our model consistently achieves higher accuracy while maintaining low parameter counts and FLOPs. Second, we also presented comparisons with more computationally expensive models (YOLOv5, YOLOv8, Parallel-CNN, AlexNet-DNA) to highlight the trade-off between accuracy and computation cost. While these heavy detection models achieve competitive accuracy, their complexity makes them impractical for deployment in resource-limited agricultural environments. By combining both perspectives, we demonstrate that the novelty of our approach lies in achieving state-of-the-art accuracy within the lightweight CNN category, while also emphasizing its better efficiency compared to heavier detection models.

4. Conclusions

This study successfully developed a lightweight yet highly accurate deep learning model for fruit fly species classification, focusing on four primary species commonly found in chili plantations. Using a structured data-centric approach, the research optimized Convolutional Neural Networks (CNN) through data augmentation, class balancing, and optimizer tuning. Comparative analysis showed that MobileNetV3-Small, RegNetY-400MF, and SqueezeNet achieved the best balance between accuracy and computational efficiency.

Further refinement using EarlyStopping, learning rate schedulers, and weighted sampling techniques led to significant performance improvements. RegNetY-400MF, enhanced with data balancing and the Adam optimizer, achieved the highest classification accuracy of 96.10%, outperforming several state-of-the-art models such as Yolo V5 and Yolo V8, while maintaining far lower computational complexity (only 8.3M parameters and 0.41 GFLOPs). This makes the enhanced RegNetY-400MF model ideal for real-time deployment on resource-limited devices, such as mobile or IoT systems used in agricultural environments.

The findings demonstrate that lightweight CNN architectures, when combined with data-centric

strategies, can provide practical and scalable solutions for precision agriculture, particularly in fruit fly monitoring and management. The proposed model offers a significant contribution towards reducing crop losses through early and accurate pest detection, supporting sustainable agricultural practices.

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