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Hyperparameter Optimization of CNN for Coffee Berry Disease Classification Using the Artificial Bee Colony Algorithm

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ABSTRACT

Indonesia is one of the world's largest coffee producers, with a significant contribution to the global market. However, extreme weather challenges, such as the El Nino phenomenon, have led to a decline in coffee production of up to 30%, affecting the quality and quantity of coffee beans. A major challenge in coffee cultivation is coffee berry diseases, such as the coffee berry borer and coffee berry damage, which can cause up to 60% crop loss. Early detection of these diseases is essential to reduce losses and preserve coffee quality. This study seeks to enhance the performance of a Convolutional Neural Network (CNN) model for coffee berry disease classification by optimizing hyperparameters using the Artificial Bee Colony (ABC) algorithm. The research dataset consists of 2100 images with three categories: Healthy Berry, Berry Borer, and Berry Damage. The research stages include data preprocessing, CNN model design, hyperparameter optimization, training, and model evaluation. The results showed that the application of the ABC algorithm succeeded in significantly improving the accuracy of the CNN model compared to the method without optimization. The accuracy result obtained is 97.14% with an architecture consisting of 3 convolutional layers and 3 fully connected layers. This finding makes a real contribution to the development of meta-heuristic-based optimization techniques for coffee fruit disease classification, as well as supporting efforts to improve coffee quality amid the challenges of global climate change.

Keywords: *Coffee Berry Disease, Artificial Bee Colony, Convolutional Neural Network, Optimization*

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INTRODUCTION

Coffee is one of the leading commodities in international trade. Global coffee production in the 2022/2023 period reached 168.2 million bags per 60kg (ICO, 2023). Meanwhile, world coffee consumption in the period 2022/2023 amounted to 173.1 million bags (ICO, 2023). Indonesia is the third largest coffee producer in the world, with a production of 11.85 million bags in 2022/2023 (Muhamad, 2023). However, in 2023, it is estimated that coffee production will decline due to the El Nino phenomenon, especially in Indonesia. It is estimated that coffee production in Indonesia in 2023 will decrease by 30% (ICO, 2023). This decline in production emphasizes the need to improve coffee quality as a strategy to maintain competitiveness in the global market. Coffee quality not only has a significant impact on economic value, but also affects consumer satisfaction and Indonesia's competitiveness as one of the world's largest producers.

The quality of coffee is determined by multiple factors, including harvesting techniques, geographical region, climate, and genetic traits (Freitas et al., 2024). One of the main pre-harvest challenges is extreme weather, such as the El Nino phenomenon, which can cause drought, reduced yields and coffee bean quality. Extreme weather can cause various diseases and pests that impact coffee bean quality. Coffee bean diseases, such as coffee berry borer and coffee berry damage pose a serious threat. These diseases not only damage yields but also affect 30% to 60% of coffee bean quality and quantity (Kurnianto et al., 2024). Early and accurate identification of diseases is necessary to minimize losses and maintain coffee quality.

The application of deep learning, especially the Convolutional Neural Networks (CNN) model, has become a promising solution in the classification of coffee fruit images, including the identification of coffee berry diseases. CNN is one type of neural network algorithm that excels in its ability to achieve high classification accuracy (Anton et al., 2021). With the ability to automatically extract complex features from images, it allows CNNs to recognize patterns such as shape, texture and color related to disease symptoms (Michael & Rusman, 2023). However, there is a challenge of limited datasets in the case of coffee berry disease both in number and variety. In addition, different lighting factors, inconsistent backgrounds and other objects present in the image affect the classification performance. Therefore, CNN architecture optimization remains a significant challenge, especially in hyperparameter optimization.

This study focuses on optimizing the hyperparameters of CNN using the Artificial Bee Colony (ABC) algorithm to enhance the accuracy and performance of the model in classifying coffee berry diseases. The Artificial Bee Colony is a meta-heuristic algorithm modeled after the foraging behavior of bee swarms in nature (Özdemir et al., 2021). ABC algorithm is proven to be more effective with good solution exploration (Alaidi et al., 2021). By integrating the advantages of ABC in solution exploration and exploitation, this study aims to explore the effect of hyperparameter optimization on CNN performance, especially in improving model accuracy and stability in coffee berry disease classification. The results of this research are expected to make a real contribution to the development of meta-heuristic-based optimization, as well as increase understanding of the effect of hyperparameter optimization on CNN performance, especially in the case study of coffee berry disease classification.

METHOD

This research aims to improve the performance of Convolutional Neural Network (CNN) through hyperparameter optimization using Artificial Bee Colony (ABC) algorithm. Some previous studies such as those conducted by (Özdemir et al., 2021) and (Ghosh & Jana, 2022) using the ABC algorithm as CNN optimization showed high success of hyperparameter optimization results and showed that the ABC algorithm has good potential for CNN architecture optimization. Therefore, the method used in this research is the ABC method. The stages of this research use a systematic approach that includes dataset preparation, data preprocessing, CNN model design, hyperparameter optimization, training model and evaluation model. The flow of this research can be seen in the following figure.

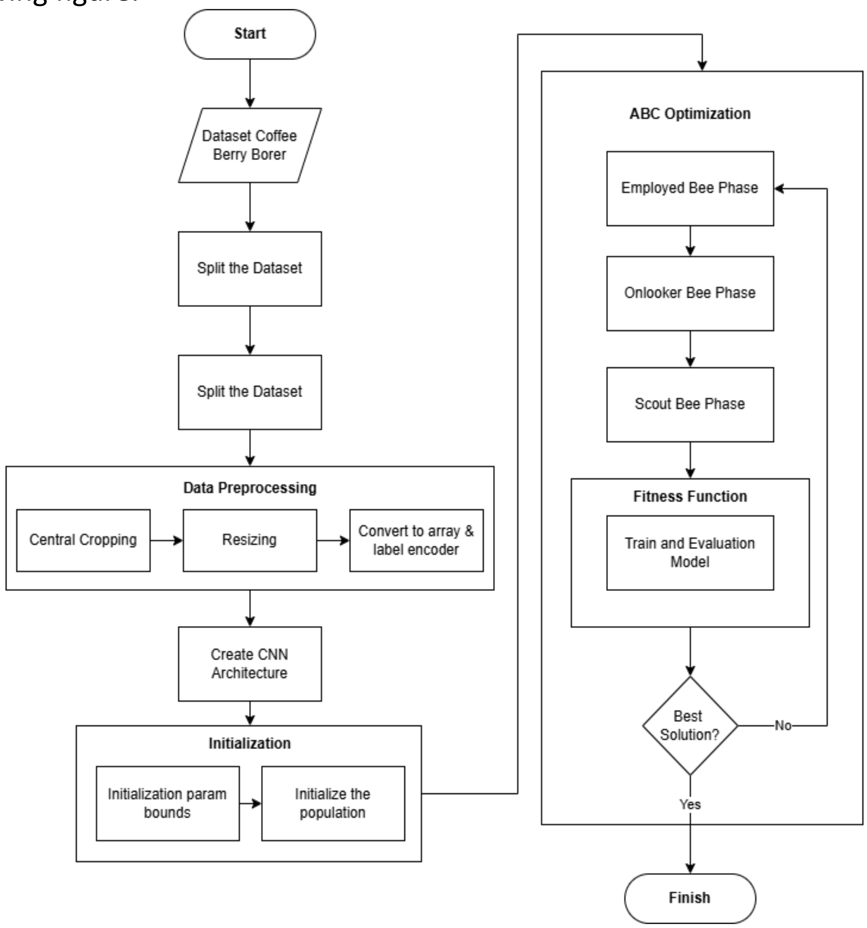

Figure 1 Research Flowchart

Dataset

This research uses a public dataset called berry borer from the Roboflow platform. This data consists of 2100 images which are divided into 3 classes namely Coffee Healthy Berry, Coffee Berry Borer, and Coffee Berry Damage. The following image is an example of each class.

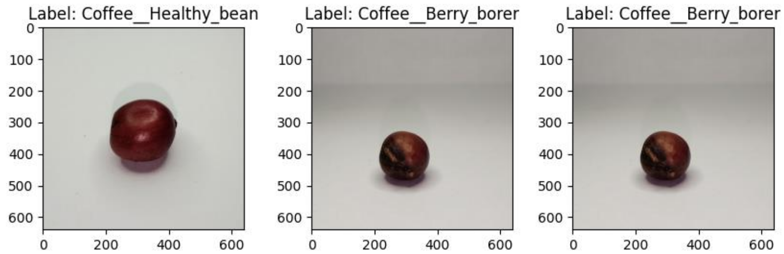

Figure 2 Sample Dataset

The dataset is split into three sections: training data, validation data, and testing data. Training data consists of 70% data containing 1470 images. 20% validation data containing 420 images and 10% testing data containing 210 images.

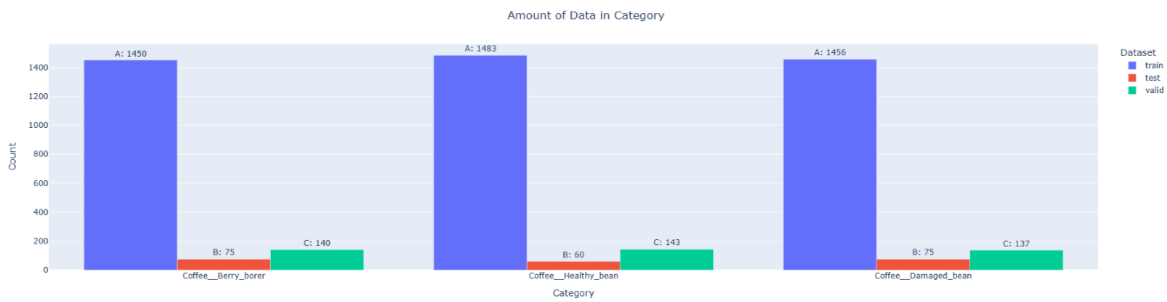

Figure 3 Data Distribution (A) Training data 70% (B) Test data 10% (C) Data validation 20%

Data Preprocessing

In this research, data preprocessing is carried out to improve data quality and reduce computational complexity when the model is run. In this research, 3 preprocessing methods are used, the first is central cropping. Central cropping is used to remove the edges of the image, so that the resulting image will focus on the object in the center. The second is resizing, this method is used to homogenize the image dimensions while reducing the image dimensions to reduce the computational process, so that the training process becomes more efficient. The third is conversion to array and label encoder, this process is used to convert the image into an array and convert the label into a numeric format, then converted into a one-hot vector for use in classification. The following are the settings used for preprocessing.

Table 1 Preprocessing Technique

Preprocessing	Value
Central Cropping	25% - 75%
Resizing	240, 240

Convolution Neural Network

Convolutional Neural Network (CNN) is one of the popular categories of neural network algorithms used for segmentation, image recognition and image classification

(Khan & Al-Habsi, 2020). CNNs are inspired by how human neural networks work. It comprises three primary layers: the convolutional layer, the pooling layer, and the fully connected layer (Asyrofiyyah & Sugiharti, 2024). The convolutional layer is used to extract features from the data that will be used for training. While the pooling layer is used to create a new filter based on the specified rules, and finally the fully connected layer which is a multilayer perceptron consisting of several neurons connected with their respective weights. The following is a picture of the CNN algorithm architecture used in this research.

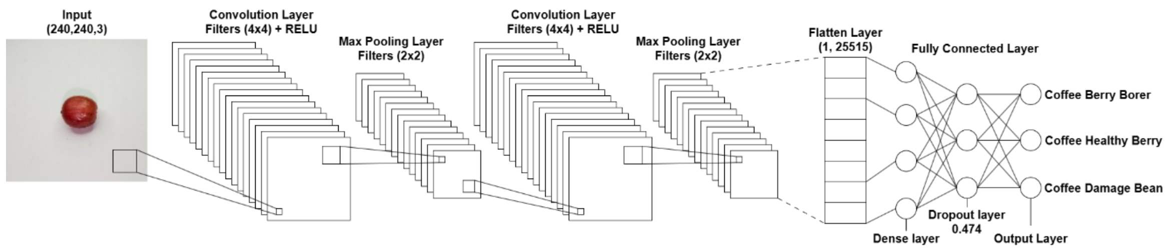

Figure 4 CNN Architecture

Artificial Bee Colony

The Artificial Bee Colony (ABC) algorithm is a metaheuristic algorithm that uses a population-based approach (Karaman et al., 2023). This algorithm was first proposed by (Karaboga & Basturk, 2007) to solve multivariable and multimodal function optimization problems (Su et al., 2022). The optimization process in ABC is divided into two phases: the exploration phase and the exploitation phase. In this algorithm, the bee colony is categorized into three groups: worker bees, observer bees, and scout bees. Worker bees will go looking for food sources and will store information, while observer bees will look for food source areas that have better potential based on information from worker bees. On the other hand, reconnaissance bees will be responsible for conducting global and random searches in new food source areas. The ABC algorithm process is divided into four main phases: initialization phase, worker bee phase, observer bee phase and scout bee phase. In general, the structure of the ABC algorithm is as follows.

Table 2 Architecture of ABC Algorithm

Input: Parameter bounds (param_bounds), colony size (N), maximum iterations (T), fitness function (f)

1. Initialize food_sources randomly within param_bounds
2. Evaluate fitness_values for all food_sources
3. Set best_solution = food_source with max fitness
4. for iteration = 1 to T do:
   # Employed Bee Phase
5. For each food_source: Generate neighbor → Update if fitness improves
   # Onlooker Bee Phase
6. Select food_sources based on fitness probabilities →

Generate neighbor → Update if fitness improves
Scout Bee Phase
7. Replace food_sources exceeding trials limit with random solutions
8. Update best_solution if current best fitness improves
9. end for
10. Return best_solution, best_fitness

In the ABC algorithm, parameter values are set at the beginning, and the positions of food sources or solutions are initialized randomly. The initial population is created randomly within the specified lower and upper bounds. The following formula is used to generate the initial population.

$$X_{ij} = X_j^{min} + rand\ (0,1) \left(X_j^{max} - X_j^{min}\right) \quad (1)$$

Where X_j^{max} is the upper limit and X_j^{min} is the lower limit. So, this formula determines all the initial solution values or X_{ij} to be between the predefined upper and lower ranges with uniform random distribution. This is very important to establish the diversity of initial solutions to be processed by the ABC algorithm, which helps the exploration of solutions more effectively. The worker bee, observer bee, and scout bee phases will be repeated until the stopping criterion is satisfied, while maintaining the current best solution. During the worker bee phase, a new solution is generated by examining the neighborhood of the existing solution using the following formula 2.

$$X'_{ij} = X_{ij} + \phi_{ij} \left(X_{ij} - X_{kj}\right) \quad (2)$$

The formula above shows where X'_{ij} is the new candidate solution vector, while ϕ_{ij} is a random number formed in the range [-1,1]. X_{kj} it is a vector of neighboring solutions chosen randomly. According to the formula, after generating a new solution, the best solution between the new and old solutions is selected using a greedy selection method. In the observer bee phase, the new solution is generated using equation 1, similar to the worker bee phase, but the solution selection follows a probabilistic method. This approach ensures that the best solution, with the highest probability, is chosen and explored locally, reducing the chances of exploring solutions with lower probabilities. Below is the formula for the selection process in the observer bee phase.

$$P_i = \frac{f_i}{\sum_{k=1}^{N} f_k} \quad (3)$$

Where P_i the probability of selecting the i-th solution obtained from the fitness value of the i-th solution divided by the total fitness value of all existing solutions. The result of the observer bees, the longer it will cause the food source (solution) to decrease and eventually run out. In the ABC algorithm, solutions that do not improve within a few iterations will be considered ineffective or exhausted. This determination is based on a control parameter called the “limit”, which specifies the maximum number of attempts that can be made to improve the quality of a solution (X_i) before the solution is abandoned. If the trial count of a solution surpasses the "limit," the associated resource will be deemed irrelevant, and the solution will be discarded. Then, the previously exploratory bees will turn into scout bees. Scout bees will randomly explore for potential new solutions. This process aims to ensure that population diversity is maintained and prevent the algorithm from getting stuck in local solutions, thus improving the efficiency of solution space exploration and enabling better global solution finding.

Hyperparameter Optimization

A good hyperparameter value will greatly affect the performance of the machine learning model (Dogan & Prestwich, 2024). Hyperparameters have a significant impact on the model's quality, as they influence both the architecture and the training process of the machine learning model. (Blume et al., 2021). In this study, hyperparameter optimization is performed using the ABC algorithm. This research limits the search space for hyperparameter value optimization in the CNN algorithm. The value limits used in this study can be seen in table 3 below.

Table 3 Hyperparameter value

Hyperparameter	Nilai
Learning_rate	0.0001 – 0.01
Conv_layer	2 – 5
Filters	32 – 128
Kernel_size	2 – 5
Dense_units	64 – 128
Dropout_rate	0.1 – 0.5

Model Evaluation

Model evaluation aims to assess the performance of CNN models that have been trained with test data (Asyrofiyyah & Sugiharti, 2024). The evaluation metrics employed in this study include accuracy, precision, recall, F1 score, and mAP (mean Average Precision). Accuracy is used to measure how many model predictions are correct overall. Accuracy is the simplest and most direct performance measurement matrix, which consists of the ratio of accurate result expectations and the ratio of observations predicted by the model (Talha et al., 2023). The formula for calculating the model's accuracy is as follows.

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (4)$$

TP (True Positive) = The count of positive data accurately predicted as positive.
TN (True Negative) = The count of negative data correctly identified as negative.

FP (False Positive) = The count of negative data mistakenly predicted as positive.

FN (False Negative) = The count of positive data incorrectly predicted as negative.

Precision is used to calculate model performance by validating accurate positive predictions or true positive results (Talha et al., 2023). To calculate it, the following formula is used.

$$P = \frac{TP}{TP+FP} \tag{5}$$

Recall is used to assess the proportion of positive data that is correctly identified, using the following equation formula (Asyrofiyyah & Sugiharti, 2024).

$$R = \frac{TP}{TP+FN} \tag{6}$$

The F1 score is the mean of the precision and recall values and is computed using the following formula (Asyrofiyyah & Sugiharti, 2024)

$$F1 - Score = 2\frac{P.R}{P+R} \tag{7}$$

mAP is one of the performance evaluation matrices taken from the average of the accuracy values at all ranks or calculations taken from the average of all precision averages (AP)(Talha et al., 2023). The following calculation is used for mAP.

$$MAP = \frac{1}{|U_{all}|}\sum_{u=1}^{|U_{all}|} AP(u) \tag{8}$$

The next step is to analyze the results after performing evaluation calculations and getting the value of the calculation results on each evaluation calculation metrics. In this research, the evaluation model is used to measure the performance of the CNN algorithm that has optimized its hyperparameters on the coffee berry diseases dataset.

FINDING AND DISCUSSION

RESEARCH RESULT

This study aims to achieve the highest accuracy and optimal hyperparameter values for a Convolutional Neural Network (CNN) in coffee fruit classification. The hyperparameters being optimized include the learning rate, the number of convolutional layers (conv_layers), the number of filters (filters), the kernel size (kernel_size), the number of units in the dense layer (dense_units), and the dropout rate (dropout_rate). The optimization results are presented in the table.

Table 4 Hyperparameter optimization results

Iteration	Hyperparameter						
	Learning Rate	Conv Layer	Filters	Kernel Size	Dense Units	Dropout Rate	Accuracy
1	0.0027	3	34	3	72	0.413	94.28%
2	0.0027	3	34	3	72	0.413	94.28%
3	0.0027	3	34	3	72	0.413	94.28%
4	0.0008	3	35	4	128	0.474	97.14%
5	0.0008	3	35	4	128	0.474	97.14%

Based on Table 4, the best hyperparameter combination is obtained with a learning rate of 0.0008, conv_layers of 3, filters of 35, kernel size of 4, dense units of 128, and dropout rate of 0.474. This combination produced the best accuracy of 97.14% on the 5th trial or iteration. In contrast, the lowest hyperparameter combination includes a learning rate of 0.0027, conv_layers of 3, filters of 34, kernel size of 3, dense units of 72, and dropout rate of 0.413, with an accuracy of 94.28% on the first trial. The best results were used to build and train the CNN model. The accuracy and loss graphs during the training period are as follows.

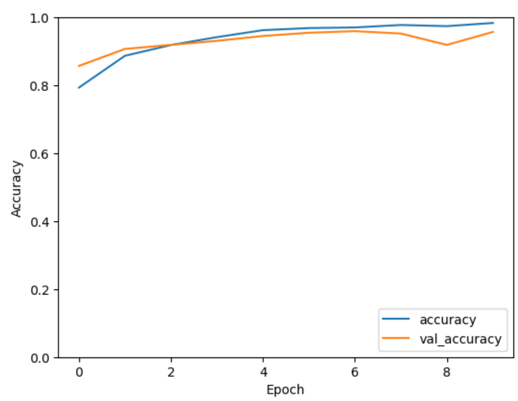

Figure 5 Graph of model training accuracy

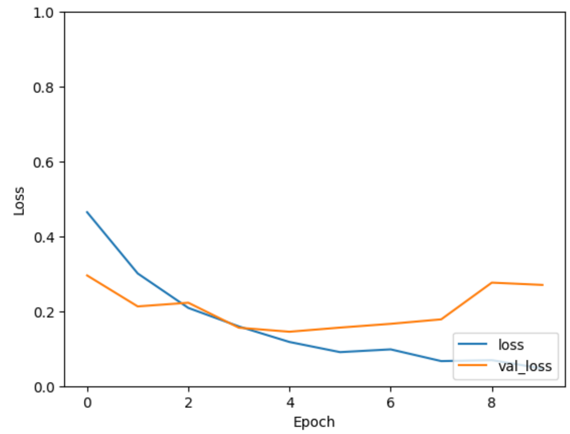

Figure 6 Graph depicting the model's training loss values

The trained model is subsequently tested with test data to assess its performance. This assessment evaluates the effectiveness of the trained model. Table 5 presents the accuracy and loss values obtained from the coffee bean disease classification process.

Table 5 Accuracy and loss from model evaluation

Accuracy	Loss
95.71%	0.2702

In addition, the performance of the model was further tested using the confusion matrix, the results of which are presented in the figure below.

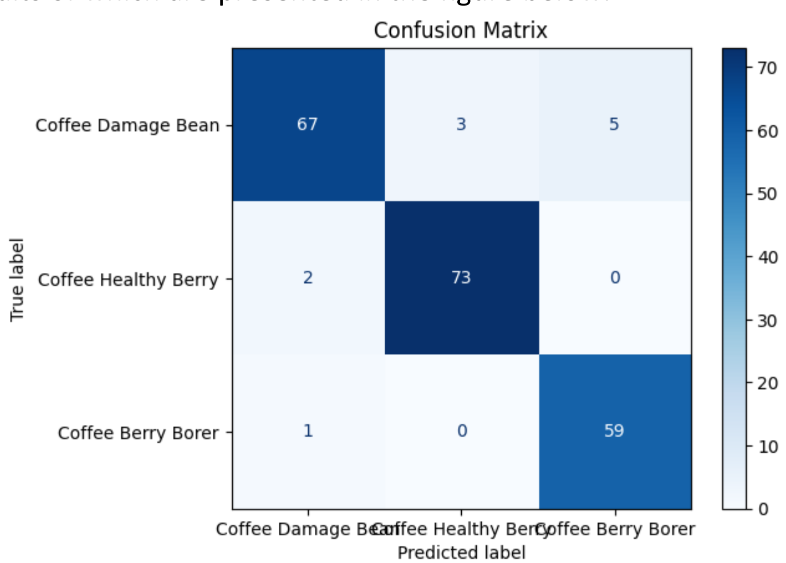

Figure 7 The outcomes of the confusion matrix from the model evaluation

Based on the confusion matrix results, performance metrics including precision, recall, and F1 score are computed for each class. The calculated precision, recall, and F1 score for each class are presented in Table 6.

Table 6 Precision, Recall, and F1 Scores from each class

Class	Precision	Recall	F1 Score
Coffee Damage Bean	0.96	0.89	0.92
Coffee Healthy Bean	0.96	0.97	0.97
Coffee Berry Borrer	0.92	0.98	0.95

Based on the table above, it can be concluded that the confusion matrix results from testing the optimized CNN model show good results. This is evidenced by the average values of precision, recall and f1-score which are not too far different from each other.

DISCUSSION

This research focuses on optimizing the hyperparameters of the CNN algorithm for classifying coffee fruit diseases. The dataset used, named Berry Borer, was obtained from Roboflow. The model's performance is evaluated through its accuracy, with the best accuracy value from the experiments presented in Table 7.

Table 7 The Best Accuracy

Data	Accuracy
Training	97.71%
Validation	95.71%
Testing	94.76%

The experimental results show that the developed model successfully classifies coffee fruit diseases well. This study also compares the accuracy values obtained with previously conducted experiments using similar datasets with the CNN algorithm without optimization. The comparison is presented in Table 8.

Table 8 Comparison of Testing Accuracy Values with Previous Experiments

Method	Accuracy
CNN 24 Layer	18%
CNN 3 Layer + Hyperparameter Optimization	94.76%

The use of hyperparameter optimization for the CNN with the ABC algorithm has demonstrated its ability to achieve impressive accuracy in coffee fruit disease classification. The classification task is particularly challenging due to the small size of the disease-affected area and the similarity in characteristics of coffee fruits. This approach can be further enhanced by incorporating additional hyperparameter variations during the optimization process.

CONCLUSION

This research successfully classifies 3 types of diseases in coffee fruit using Convolutional Neural Network (CNN) which is optimized using Artificial Bee Colony (ABC) algorithm on its Hyperparameter value. This model achieved an accuracy of 97.14% with optimal parameters generated in the form of, learning rate of 0.0008, number of convolutional layers of 3, filters of 35, kernel size of 4, dense units of 128, and dropout rate of 0.474. In the future, this research can be further developed with various approaches such as increasing the number of dataset variations, such as in terms of lighting, shooting angles and variations in the surrounding environment. The use of hybrid models so that the model can capture more complex temporal patterns in order to improve model performance and be more sensitive to pattern differences.

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