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Image Data Acquisition and Classification of Vannamei Shrimp Cultivation Results Based on Deep Learning

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ABSTRACT

This research aimed to employ deep learning techniques to address the classification of Litopenaeus vannamei cultivation results in land ponds and tarpaulin ponds. Despite their similar appearance, distinguishable differences exist in various aspects such as color, shape, size, and market price between the two cultivation methods, often leading to consumer confusion and potential exploitation by irresponsible sellers. To mitigate this challenge, **the research proposed a** classification method utilizing two Convolutional Neural Network (CNN) architectures: Visual Geometry Group-16 (VGG-16) and Residual Network-50 (ResNet-50), renowned for their success in various image recognition applications. The dataset comprised 2,080 images per class of vannamei shrimp from both types of ponds. Augmentation techniques enhanced the dataset's diversity and sample size, reinforcing the model's ability to discern shrimp morphology variations. **The research results** are learning rates of 0.001 and 0.0001 on the Stochastic Gradient Descent (SGD) and Adaptive Moment Estimation (ADAM) optimizers to evaluate their effectiveness in model training. The VGG-16 and ResNet-50 models were trained with a learning rate parameter of 0.0001, taking advantage of the flexibility and reasonable control provided by the SGD optimizer. Lower learning rate values were chosen to prevent overfitting and increase training stability. Model evaluation showed promising results, with both architectures achieving 100 % accuracy in classifying vannamei shrimp from earthen ponds and tarpaulin ponds. Additionally, **the conclusion** of this study is to highlight the superiority of using SGD with a learning rate of 0.0001 versus 0.001 on both architectures, underscoring the significant impact of optimizer selection and learning rate on the effectiveness of model training in image classification tasks.

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1. INTRODUCTION

The development of vannamei shrimp in the agricultural sector is considered to have far more advantages than other types of shrimp [1]. There are differences between water quality treatment in earthen and tarpaulin ponds. Water quality treatment in earthen ponds is usually limited to water treatment at the initial stage, namely when the color of the water starts to change to dark greenish while checking water quality such as dissolved oxygen, temperature, pH, alkalinity, and salinity are not carried out, the water quality treatment of plastic ponds or tarpaulin ponds is generally carried out with strict control, measurement parameters include dissolved oxygen levels, ammonia levels, alkalinity, water pH, and so on [2]. There has yet to be a published dataset to differentiate vannamei shrimp from ground ponds and tarpaulin ponds. Previous research has classified peeled shrimp data and stated that CNN is the right choice to handle this problem because of its superiority in extracting features from image data [3].

The following are several studies that have been carried out to produce shrimp quality evaluations with good results using the CNN method, namely in [3–6]. The advantage of CNN in this research lies not only in its ability to extract essential features from images but also in the use of a combined classification strategy that makes it possible to exploit the advantages of several individual classifiers to improve the overall performance in the vannamei shrimp image classification task [3]. Convolutional Neural Networks (CNN) is a compelling image analysis and pattern recognition method. One of the main advantages of CNN is its ability to extract essential features from images automatically without manual feature extraction [7]. How a CNN works starts with a convolution layer, where convolution filters move across the input image to produce a feature map that highlights essential patterns. This convolution layer is followed by a pooling layer, which serves to reduce the spatial dimensions of the resulting feature map, retaining relevant information. Next, the feature maps converted into vectors are used as input for fully connected layers, where the model performs classification or other tasks. The importance of activation functions in each layer, such as ReLU, is to introduce non-linearity into the model, allowing CNNs to learn complex patterns from image data [5]. By leveraging these features, CNNs can recognize objects in images with high accuracy and even handle more complex tasks such as object detection and image segmentation [8].

The results of shrimp cultivation have a similar appearance. Still, differences between the two cultivation methods can be recognized in various aspects, such as color, shape, size, and market price. CNN is the right choice to handle this problem because of its superiority in extracting features from image data. Using CNNs, the model can learn complex and abstract patterns from shrimp images, including subtle differences that may be difficult to identify manually. These features can then be used to differentiate between shrimp farming in soil ponds and tarpaulin ponds with high accuracy. In addition, using CNN also makes it possible to improve model performance by using architectures that have been proven effective in image recognition, such as VGG-16 and ResNet-50 [3]. VGG-16 is a sixteen-layer model based on the convolutional neural network architecture used by the Visual Geometry Group of the University of Oxford. This model provided extraordinary results in the ILSVRC 2014 (Large Scale Visual Recognition Challenge 2014) competition [3]. ResNet-50 is the main foundation for developing a system of multiscale attention mechanisms and feature pyramid networks to improve small animal species' detection significantly. ResNet-50 is relatively easy to train, even with large and complex datasets, because it has a stable and good convergent architecture [9].

The VGG-16 and ResNet-50 architectures have succeeded in various image recognition applications, providing confidence that they can address the complex classification problems in this study. VGG-16 is built with a depth of 16 layers, which is faster than ResNet-50, which is built with a depth of 50 layers, which means training time will be affected by this difference [3]. Thus, using CNN in this study not only provides an effective solution in overcoming image classification problems but also provides strong confidence in the accuracy and reliability of research results [9]. In the CNN training process, the selection of hyperparameters is very influential. The optimizer and learning rate are two vital elements in the model training process in deep learning [10]. The optimizer is responsible for optimizing or reducing the loss function by updating the model parameters during training. One commonly used optimizer is Stochastic Gradient Descent (SGD), which updates model parameters based on the gradient of the loss function for each training data example [11]. ADAM (Adaptive Moment Estimation) is an optimization algorithm used in artificial neural network training, especially in deep learning; ADAM can handle the problem of different learning rates for each parameter and usually produces faster convergence [12]. Learning rate is a parameter that determines how much the parameter changes during the training process. Appropriate learning rate values are essential to prevent slow or divergent training [13]. Optimizer selection and learning rate tuning are critical aspects in ensuring efficient and effective model training in the context of deep learning [14, 13].

Water quality affects the cultivation of shrimp or fish produced. One important aspect is water, so it can be said that shrimp yields will differ depending on the type of water used [15]. Research [16] focuses on Pacific white shrimp, also known as Vannamei shrimp with the Latin name Litopenaeus Vannamei, but research [16] **there are gaps** or discrepancies that have not been resolved by previous research, namely does not explain the shrimp dataset used, whether from earthen ponds or tarpaulin ponds. Hence, this research aims to build primary data (data obtained directly by researchers), especially on objects resulting from Vannamei shrimp cultivation from earthen ponds and tarpaulin ponds. **The difference between this research and previous research** is that it provides dataset information from earthen ponds or tarpaulin ponds, builds models using deep learning methods with VGG-16 and ResNet-50 architectures, and compares training time values and evaluation metrics. The VGG-16 and ResNet-50 architectures are widely used to identify fish and other aquatic animals [17, 18, 8, 19, 20].

From the exposition of **the objectives of this quantitative research**, the researcher utilized images as the primary source of information. The data collection process involved capturing relevant images of vannamei shrimp objects related to the study. Subsequently, the researcher employed image processing software. The processing method involved the VGG-16 and ResNet-50 architectures. After the image data was processed and successfully classified, the researcher calculated the accuracy values by comparing the analysis results with the predetermined classifications. Thus, this study yielded accuracy values that reflect the precision level in recognizing or analyzing the collected image data. **The contribution of this research** It is hoped that the model developed can provide vannamei shrimp classification results with high accuracy. This will help distinguish shrimp cultivation in land ponds and tarpaulin ponds and offer benefits to efficient management of shrimp cultivation.

2. RESEARCH METHOD

In this section, Figure 1 shows the methodology to be used, including the Convolutional Neural Network (CNN) technique, the approach to obtain the shrimp image dataset, and the data augmentation process for shrimp. The methodology presented has been designed to ensure the accuracy and reliability of the analysis performed on the shrimp image dataset. In addition, integrating the CNN technique is expected to improve the performance and accuracy of shrimp image identification in this study.

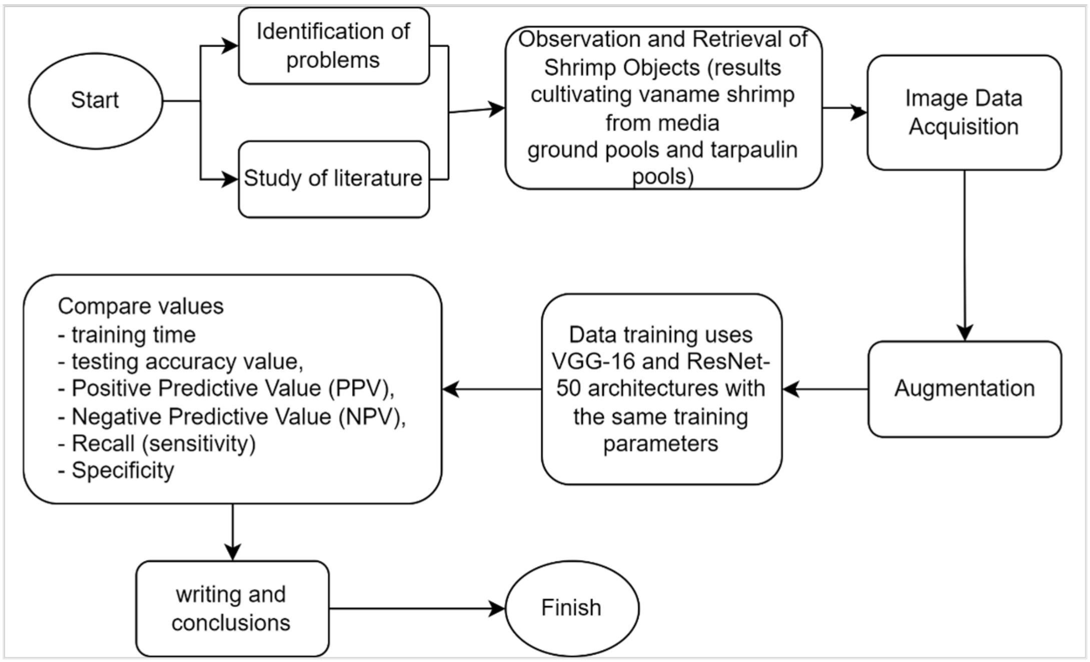

Figure 1. Research Flow

2.1. Material

This study uses primary data images of tarpaulin pools. This research used the results of cultivating vannamei shrimp with a cultivation time of 3 months and shrimp size. The total shrimp purchased for research was 230 from cultivating vannamei shrimp in earthen ponds and 230 from cultivating vannamei shrimp in tarpaulin ponds.

2.2. Image Data Acquisition

Shrimp were taken directly from the pond at 08:00 WIB and image data collection was taken at 10:30 WIB. The image data acquisition process was taken in a room measuring 3 x 3 m, with an area where the equipment was placed as in Figure 2 and Figure 3. The dataset samples taken are shown in Figure 4.

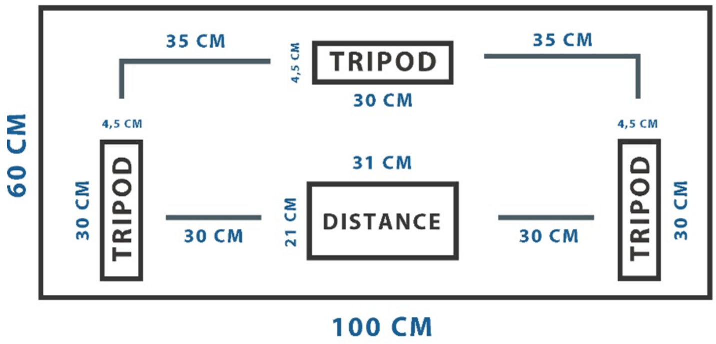

Figure 2. Area of Placement of Image Data Acquisition Process Tool

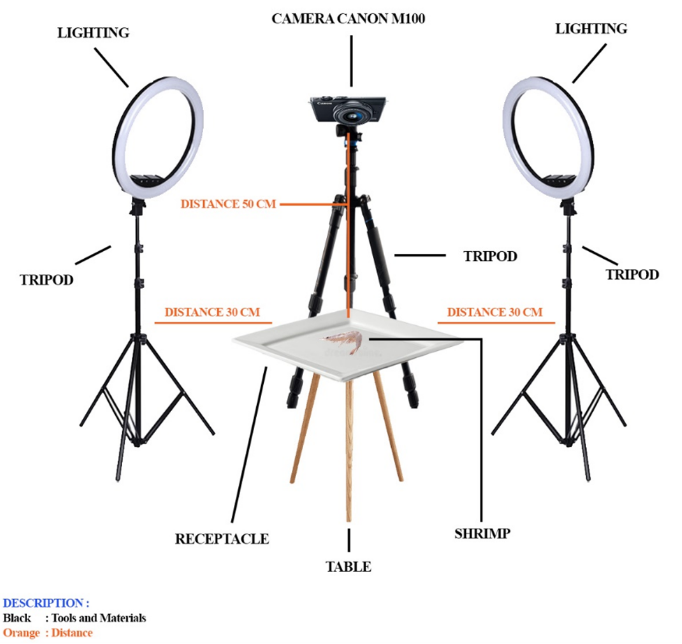

Figure 3. Distance to Laying Image Data Acquisition Process Tool

Vannamei Shrimp from pond media soil

Vannamei Shrimp from pond media tarpaulin

Figure 4. Image of Vannamei Shrimp

Based on Figure 2 and 3, image data acquisition processes were taken using a Canon Eos M-100 digital camera containing 32 GB storage memory with additional equipment, namely a tripod, a white container for placing shrimp objects, and 22-watt lighting. The technique for taking shrimp objects is the same as reference [21], using ISO 800, aperture (amount of incoming light) set to f/5.6, and exposure time, namely 1/25s. The exposure time value differs from [21] because The lighting used in this study was brighter, using an autofocus in automatic mode. The camera is placed above at a distance of 50 cm from the white container, and the lighting is on the right and left of the shrimp object so that the color of the shrimp becomes clearer and sharper without reducing the original color of the shrimp taken using the camera.

2.3. Augmentation of Image Data

Augmentation is carried out to increase the number of datasets without taking additional objects and can reduce the risk of overfitting [22]. The images taken were 130 with shrimp heads facing right and 130 shrimp heads facing left in each class, resulting in 260 images of vannamei shrimp from earthen pond media and 260 images of vannamei shrimp from pond media. Table 1 presents the results of the image augmentation with horizontal flip and rotation at 5, 10 and 15 degrees. In the column "original and flip" is the sum of the original image plus the flip process, namely 260 original plus 260 flip, then the total of the original and flip image is augmented rotation at 5, 10 and 15 degrees, resulting in 2,080 images in each class, namely the results of cultivating Vannamei shrimp in earthen ponds and tarpaulin ponds.

Table 1. Number of datasets horizontal flip and degrees augmentation

Image	Soil Pond	Tarpaulin Pond
Original and Flip	520	520
5 Degrees	520	520
10 Degrees	520	520
15 Degrees	520	520
Amount	2.080 Image	2.080 Image

2.4. Convolutional Neural Network (CNN)

CNN is one of the most well-known deep learning algorithms and is widely used to process data [20]. The basic structure of CNN is as shown in Figure 5. Based on Figure 5, the input image classification process will go through several stages, namely the convolution layer, pooling layer, and fully connected layer [23]. Each stage has a different process; convolution is the first layer that takes the input image, pooling to reduce the dimensions of the input image, and a fully connected layer that will perform classification [24–26]. CNNs are very important in image-related applications, such as image classification, object recognition in images, and many others [27, 28]. CNNs can process information incrementally from simple visual representations to higher levels of abstraction, enable effective learning on image data, extract important features from images, and produce accurate predictions efficiently [28].

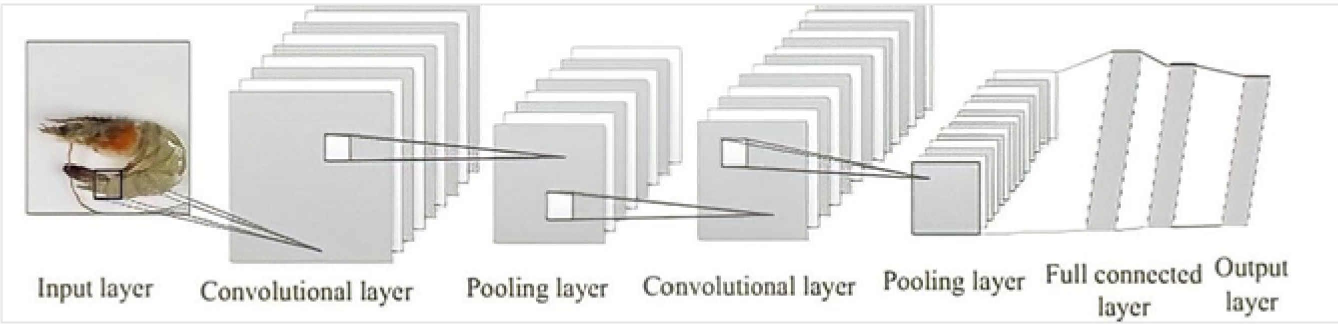

Figure 5. CNN Algorithm Structure

2.5. Visual Geometry Group (VGG)-16 and Residual Network (ResNet)-50

This study uses VGG-16 and ResNet-50 (See Figure 6). Model training steps include image processing, transfer learning techniques by utilizing pre-trained weights, and tuning model parameters such as optimizer and learning rate; this will be discussed more fully in the Results section.VGG-16 is a Convolutional Neural Network pre-trained model. VGG-16 has 138 million parameters [29], so VGG-16 has better generalization ability and can adapt to various datasets [30]. Residual Network architecture, abbreviated as ResNet, is a type of pre-trained neural network learning that is efficient and accurate [22]. The ResNet-50 structure speeds up neural network training because it has a total of 25 million parameters with 50 hidden layers [31]. The training process can use transfer learning, with the main advantage being time efficiency [12, 32].

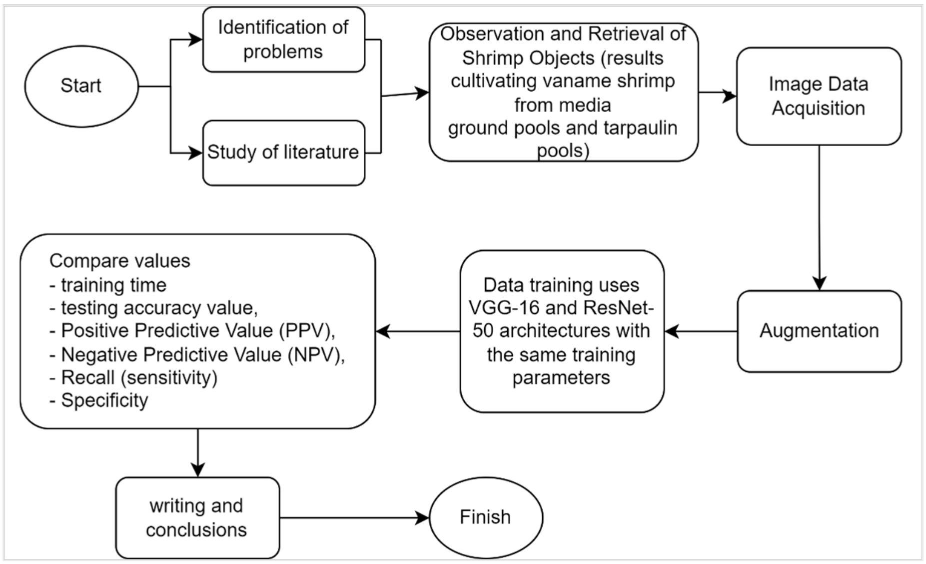

Figure 6. Algorithm Structure

2.6. Matrix Evaluation

Evaluation metrics refer to the model's ability to run a system well [33]. Evaluation matrices are fundamental in CNN classification systems because they provide objective metrics to measure model performance. This is especially important in vannamei shrimp classification, where the differences between earthen and tarpaulin ponds must be precisely identified. Therefore, these formulas enable a systematic evaluation of the model's ability to differentiate between these two types of shrimp farming, which in turn can provide valuable insights for effective shrimp farming management [33, 34]. This research will use several performances that are evaluated using Equations 1, 2, 3, 4 and 5. TP (True Positive) represents the cases correctly identified as positive, FP (False Positive) refers to cases incorrectly classified as positive, TN (True Negative) indicates the cases correctly identified as negative, and FN (False Negative) stands for cases that were mistakenly classified as negative.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$PositivePredictValue/Precision = \frac{TP}{TP + FP} \tag{2}$$

$$NegativePredictValue = \frac{TN}{TN + FN} \tag{3}$$

$$Recall(sensitivity) = \frac{TP}{TP + FN} \tag{4}$$

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

3. RESULT AND ANALYSIS

This research's findings are collecting the dataset vannamei shrimp, alongside the classification of the dataset using the VGG-16 and ResNet-50 with a combination of hyperparameter optimizers and learning rates. The dataset was collected using a digital camera without taking it from other sources. The number of images from the dataset from cultivating vannamei shrimp from earthen ponds and tarpaulin ponds in each class is 2,080. The condition dataset has dimensions of 224 x 224 pixels with a white background and has a balanced number of weights in each class. The total images that have been augmented will be divided into three folders with a composition of 60:20:20 [35].

3.1. Training VGG-16 and ResNet-50 Classification Models

The classification model was trained using Pytorch transfer learning on Google Colab Pro. The parameters in the training process used were Epoch 100, Batch Size 2, Loss Function Cross-Entropy, Momentum 0.9, Optimizer Adam, and SGD combined with a learning rate of 0.001 and 0.0001. At the training stage, the model uses transfer learning. Training times for the VGG-16 and ResNet-50 models with the Adam and SGD optimizers can be seen in Table 2.

Table 2. Comparison of VGG-16 training time using different learning rate values from the Adam and SGD optimizers

Optimizer	Learning Rate (lr)	VGG-16	ResNet-50
Adam	0.001	256 m 47 s	202 m 13 s
	0.0001	248 m 39 s	209 m 35 s
SGD	0.001	165 m 58 s	177 m 16 s
	0.0001	186 m 27 s	169 m 44 s

In the VGG-16 model training experiments, it is observed that using ADAM with a learning rate of 0.001 requires a training time of 256 minutes and 47 seconds. When the learning rate in ADAM is reduced to 0.0001, the training time slightly decreases to 248 minutes and 39 seconds. Employing SGD with a learning rate (lr) of 0.001 results in more efficient training, taking only 165 minutes and 58 seconds. However, when the learning rate (lr) for SGD is reduced to 0.0001, the training time increases to 186 minutes and 27 seconds. Meanwhile, in the ResNet-50 model, using ADAM with a learning rate of 0.001 requires approximately 202 minutes and 13 seconds for training. Using ADAM with a learning rate of 0.0001 yields a similar training time of 209 minutes and 35 seconds. For SGD, a learning rate of 0.001 results in a training time of 177 minutes and 16 seconds, while a learning rate (lr) of 0.0001 requires 169 minutes and 44 seconds. In conclusion, for VGG-16, reducing the learning rate in ADAM does not significantly improve training time, whereas in SGD, it increases training time. For ResNet-50, adjusting the learning rate does not substantially impact training time. Therefore, careful consideration is necessary when selecting the learning rate, and the outcomes may vary depending on the model architecture. Training graphs for the VGG-16 and ResNet-50 models with Adam and SGD optimizers can be seen in Figures 7, 8, 9, 10, 11, 12, 13 and 14.

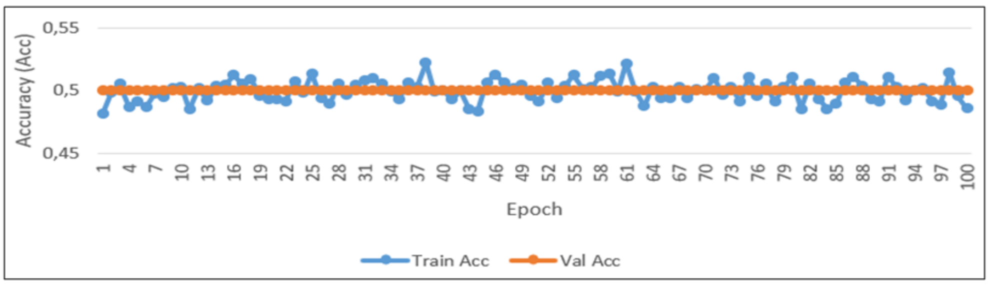

Figure 7. Curves Train Accuracy and Validation Accuracy VGG-16 Architecture with Optimizer Adam and Learning Rate 0.001

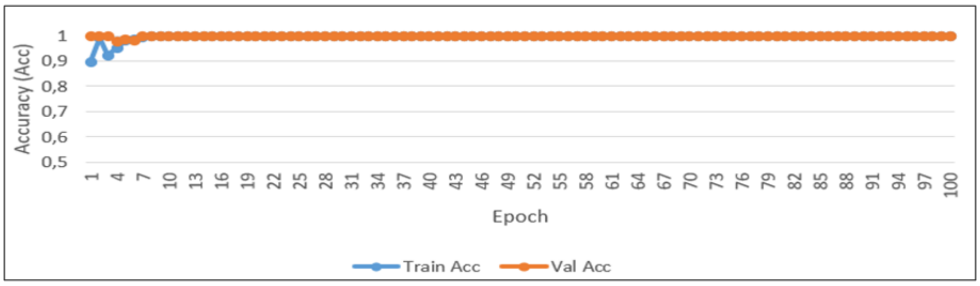

Figure 8. Curves Train Accuracy and Validation Accuracy VGG-16 Architecture with Optimizer Adam and Learning Rate 0.0001

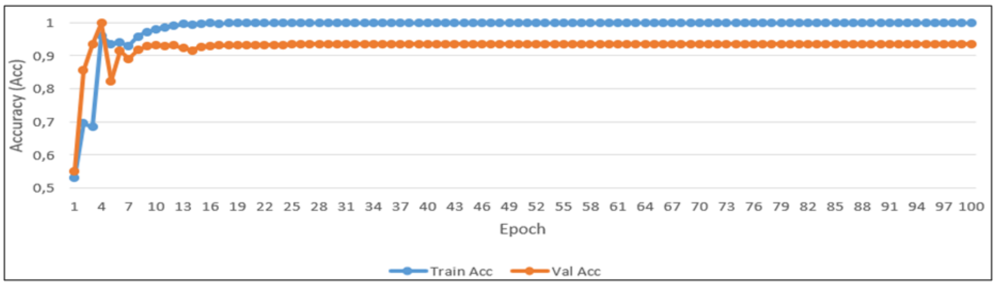

Figure 9. Curves Train Accuracy and Validation Accuracy VGG-16 Architecture with Optimizer SGD and Learning Rate 0.001

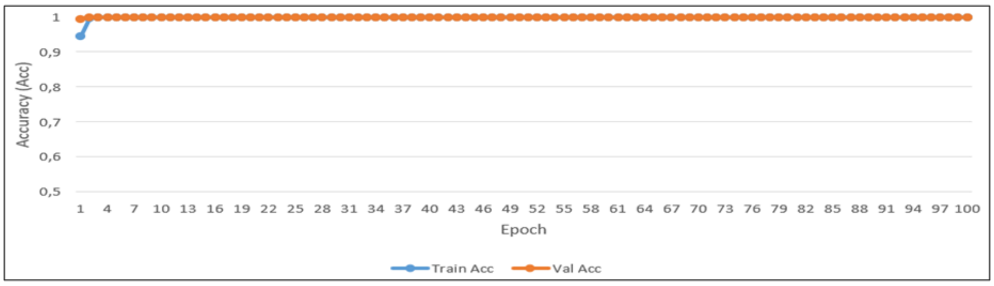

Figure 10. Curves Train Accuracy and Validation Accuracy VGG-16 Architecture with Optimizer SGD and Learning Rate 0.0001

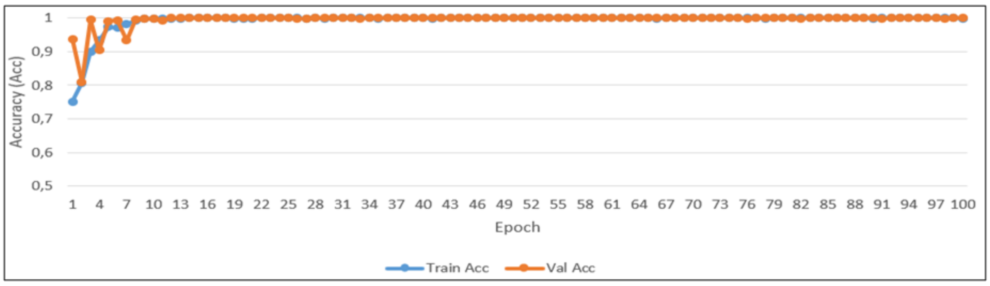

Figure 11. Curves Train Accuracy and Validation Accuracy ResNet-50 Architecture with Optimizer Adam and Learning Rate 0.001

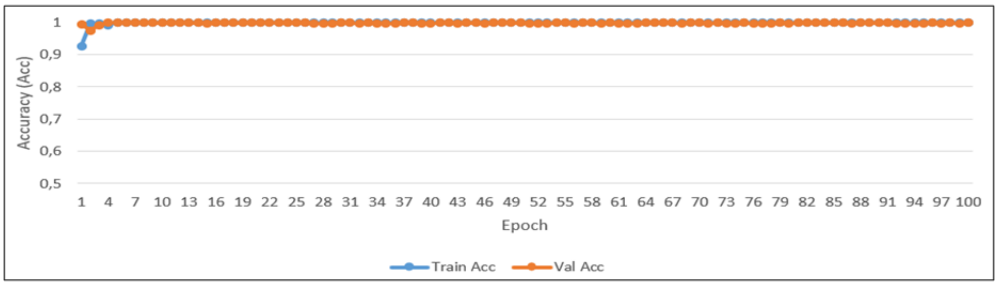

Figure 12. Curves Train Accuracy and Validation Accuracy ResNet-50 Architecture with Optimizer Adam and Learning Rate 0.0001

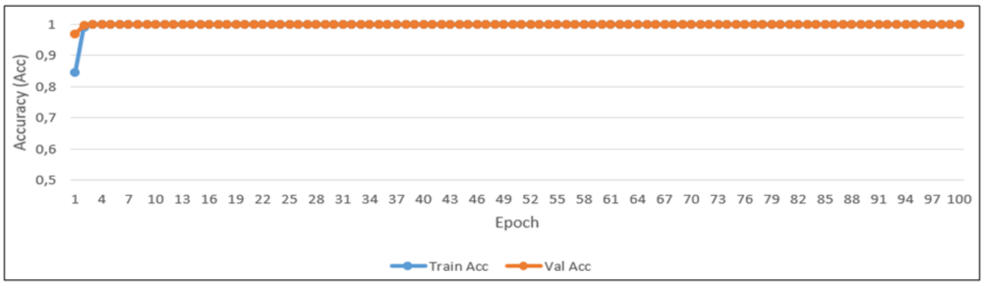

Figure 13. Curves Train Accuracy and Validation Accuracy ResNet-50 Architecture with Optimizer Adam and Learning Rate 0.0001

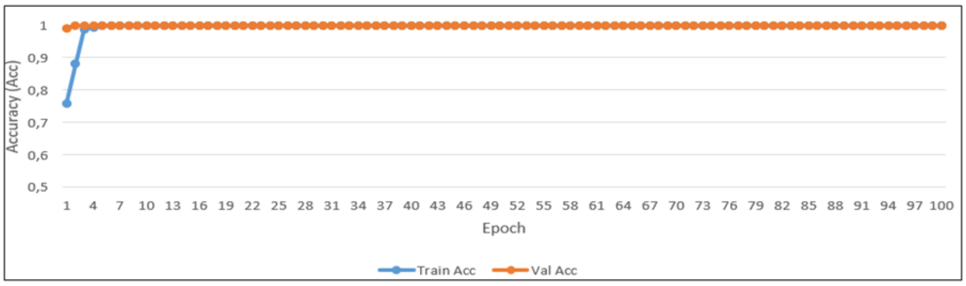

Figure 14. Curves Train Accuracy and Validation Accuracy ResNet-50 Architecture with Optimizer SGD and Learning Rate 0.0001

Figures 7, 8, 9, 10, 11, 12, 13 and 14 shows the value of train accuracy with a blue line and validation accuracy with an orange line, Figs. 7 and 8 are the results of VGG-16 training using the Adam optimizer and learning rate (lr) 0.001 and 0.0001, Figure 7 can be seen from the very bad graph shape with the line at 0.5, whereas in Figure 8 it can be seen using a learning rate of 0.0001, that the graph is getting better. In Figure 9, when using VGG-16 with SGD optimizer and lr 0.001, the values of train acc and val acc are closely aligned, but in comparison to Figure 10, the lines of train acc and val acc are juxtaposed at the early stages of training. In Figure 11, 12, 13 and 14, employing the ResNet-50 architecture with various combinations of optimizer and learning rate, the train acc and val acc graphs tend to converge closely. Consequently, it can be concluded that the validation accuracy closely mirrors the train accuracy data, suggesting that the model generalizes well during validation, indicating a highly successful training process. Figure 7 and 8 shows that using SGD optimizer with a learning rate of 0.0001 produces a more rapidly stabilizing graph compared to the Adam optimizer. This aligns with the theory that ”SGD with a small learning rate tends to stabilize the training process, helping prevent overshooting and ensuring that the model progresses in the right direction” [31]. To confirm the training results, the researcher will employ testing data using the confusion matrix evaluation method.

3.2. Testing and Evaluation Matrix

After obtaining the accuracy and loss values during model training, the model is tested using test data that has never been used before to ensure that the model is good enough to test new data. Figures 14, 15, 16 and 17 shows the confusion matrix on the VGG-16 and ResNet-50 architecture. Figures 15, 16, 17 and 18 show the confusion matrix values of the VGG-16 and ResNet-50 architectures using different learning and optimizer values. True Positive (TP), namely the class image of the results of vannamei shrimp cultivation in soil pond media, is predicted as earth pond media, and vice versa with True Negative (TN), namely the class image of the results of vannamei shrimp cultivation in tarpaulin pond media is predicted as tarpaulin pond media. False Positive (FP), namely the data image that has the value of a tarp, is predicted as the earth pond media class, and vice versa with False Negative (FN), namely the image of the class of vannamei shrimp cultivation produced by tarpaulin pond media, which is predicted as the earth pond media. From these values, the evaluation metrics in Table 3 can be calculated.

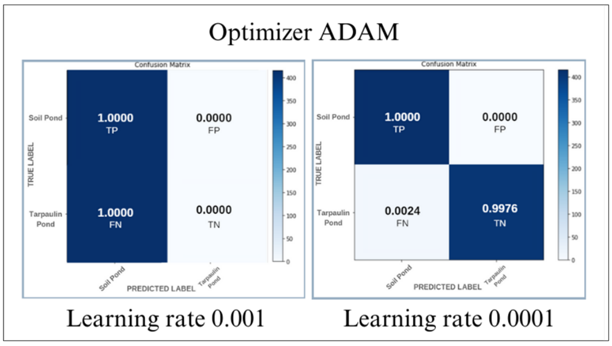

Figure 15. Confusion Matrix Test Results VGG-16 with Optimizer Adam

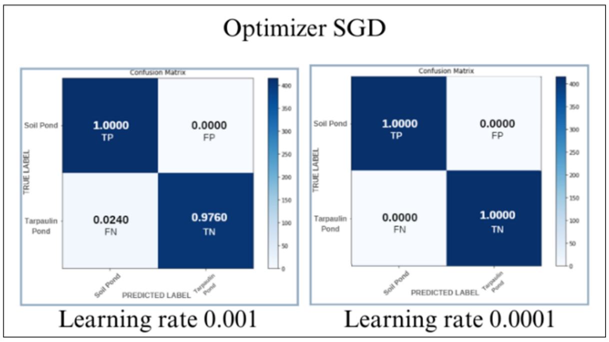

Figure 16. Confusion Matrix Test Results VGG-16 with Optimizer SGD

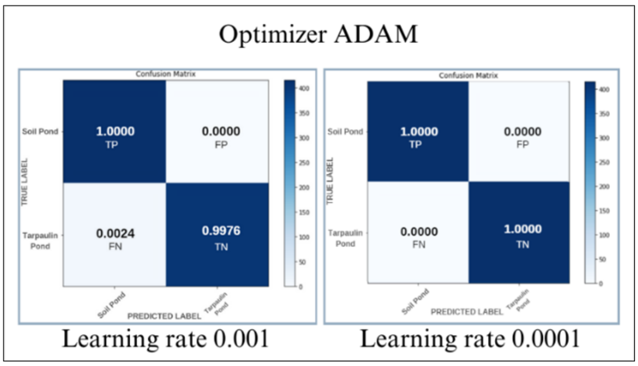

Figure 17. Confusion Matrix Test Results ResNet-50 with Optimizer Adam (a) lr 0.001; (b) lr 0.0001.

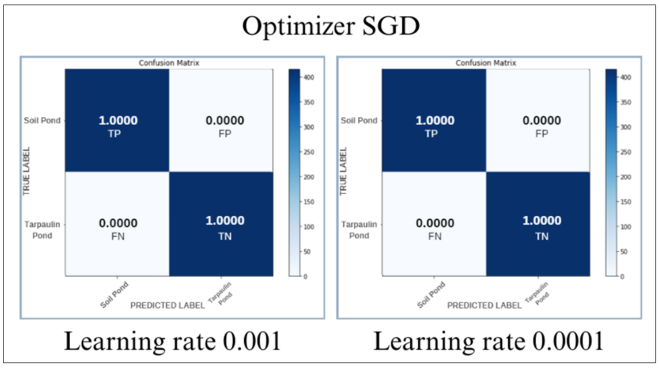

Figure 18. Confusion Matrix Test Results in ResNet-50 with Optimizer SGD (a) lr 0.001; (b) lr 0.0001.

Table 3. Evaluation matrix

Measures	**Adam**				**SGD**			
	VGG-16	**ResNet-50**	**VGG-16**	**ResNet-50**	**VGG-16**	**ResNet-50**	**VGG-16**	**ResNet-50**
	lr = 0.001		**lr = 0.0001**		**lr = 0.001**		**lr = 0.0001**	
Accuracy	0.5	0,9988	0,9980	1	0,9880	1	1	1
PPV	1	1	1	1	1	1	1	1
NPV	0	0,9976	0,9970	1	0,9760	1	1	1
Sensitivity	1	0,9976	0,9970	1	0,9760	1	1	1
Specificity	-	1	1	1	1	1	1	1

Based on the results of the metric evaluation, this research obtained the highest score when using the SGD optimizer and a learning rate of 0.0001. In Figure 19 and Figure 20, there is actual information, namely the actual data; predictions 1 and 2 provide information on the data's name while displaying the probability value.The metric evaluation conducted proves that the use of SGD optimization and the right learning rate value can improve the accuracy and performance of the model trained in this study.

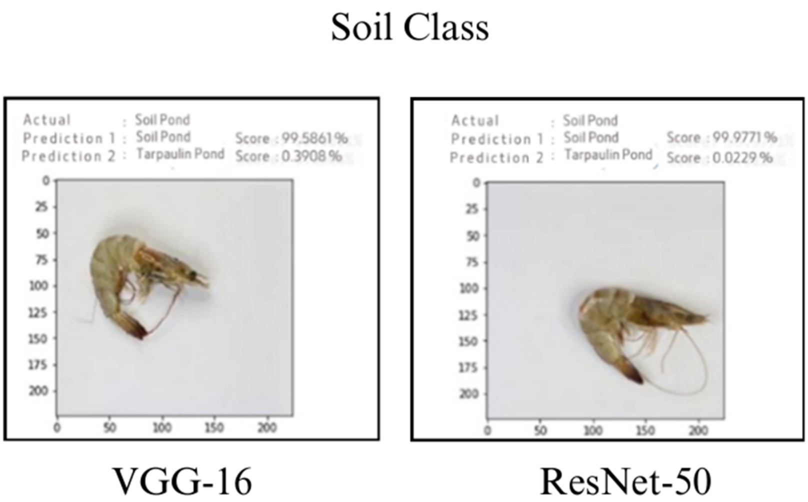

Figure 19. Comparison of Test Results using Soil Class Test Data

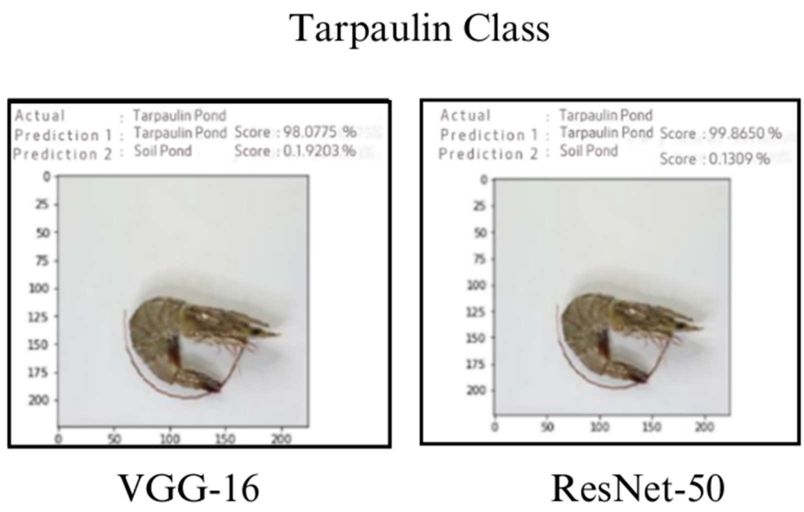

Figure 20. Comparison of Test Results using Tarpaulin Class Test Data

Figure 19 presents representative test data using a primary dataset. Each image displayed will show the predicted value of Vannamei shrimp from cultivation in earthen ponds and tarpaulin ponds. The highest value will be in prediction 1 and the lowest in prediction 2. This is a probability value because the SoftMax activation function is used during training. This process marks one as the target class for probability. **This study's results align** with the findings reported by reference [16], which revealed that water quality influences the results of shrimp cultivation. Therefore, it can be concluded that shrimp production results will vary depending on the type of water used. Although the study did not specifically discuss the shrimp dataset used, it focused on Vannamei shrimp, which is in line with the focus of this study. Other studies, as mentioned in references [17, 18, 21, 19, 20], supporting this study's approach, have used the VGG-16 and ResNet-50 architectures to identify fish and other aquatic animals.Using the proposed method, the VGG-16 and ResNet-50 models achieved 100% accuracy, which shows that the approach has successfully overcome challenges in shrimp classification. This underlines the significant improvement in model accuracy achieved by the proposed method compared to the referenced approach, providing a valuable contribution to developing a primary dataset for Vannamei shrimp cultivation. Previous research [36] and [37], proposed the VGG-16 and ResNet-50 methods with good accuracy values shown in Table 4, so it can be said that this research is in line with previous research.

Table 4. Performance Comparison Several Methods

References	Accuracy VGG-16	Accuracy ResNet-50
[36]	80.47%	97.44%
[37]	68.65%	80.47%
Proposed method	100%	100%

In the reported research findings, references [36] and [37] present VGG-16 model accuracies of 80.47% and 68.65%, respectively. Additionally, a ResNet-50 model achieves 97.44% and 80.47% accuracy based on other references. In the proposed method, VGG-16 attains a remarkable accuracy of 100% when utilizing the Adam and SGD optimizers with a learning rate of 0.0001. Conversely, the ResNet-50 model also achieves 100% accuracy, achieved through the use of the Adam optimizer with a learning rate of 0.0001 and the SGD optimizer with learning rates of 0.001 and 0.0001. These results underscore the significant enhancement in model accuracy achieved by the proposed method compared to the referenced approaches

These findings provide significant contributions in two main aspects. First, this research overcame the gap in the availability of datasets to differentiate shrimp cultivation from land ponds and tarpaulin ponds. Second, this research shows that transfer learning with CNN architectures such as VGG-16 and ResNet-50 can provide reasonably good results in classifying shrimp farming objects. This is important because it can help manage shrimp cultivation more efficiently and sustainably. Even though the dataset has been well developed, this research still has limitations in representing case variations in farmed shrimp because this research only used two types of ponds. Another limitation is that the test value is 100% because the testing dataset is very similar to the training dataset, even though the images are different. This is because the shrimp are taken from the same pond. The researchers suggest that future research could add new datasets with the aim of testing and confirming new hypotheses for this classification system. The use of more complex CNN architectures or more sophisticated data augmentation techniques might improve the model's ability to handle more complicated cases.

3.3. DISCUSSION

This study highlights the importance of applying deep learning methods, especially CNN architectures such as VGG-16 and ResNet-50, in solving classification problems on aquaculture objects, which is in line with the literature that has demonstrated the effectiveness of these architectures in image recognition of aquatic objects. In this section, we will discuss the process we carried out in our research, from data acquisition to evaluation of results. This process includes the steps we took to ensure the validity and accuracy of the methods used in developing the VGG-16 and ResNet-50 classification models for shrimp image analysis.vbm.

Data Acquisition: A large and balanced primary dataset was obtained from the data collection results, consisting of 2,080 images of vannamei shrimp originating from land and tarpaulin pond cultivation. The data collection process carried out directly by researchers using digital cameras provides the advantage of consistent control and quality, ensuring the availability of high-quality data for further analysis processes. The data that has been successfully collected and processed provides a strong basis for evaluating and comparing the performance of classification models using the VGG-16 and ResNet-50 architecture in identifying vannamei shrimp cultivation objects from various cultivation sources. Figure 21 shows the acquisition stages of the vannamei shrimp dataset.

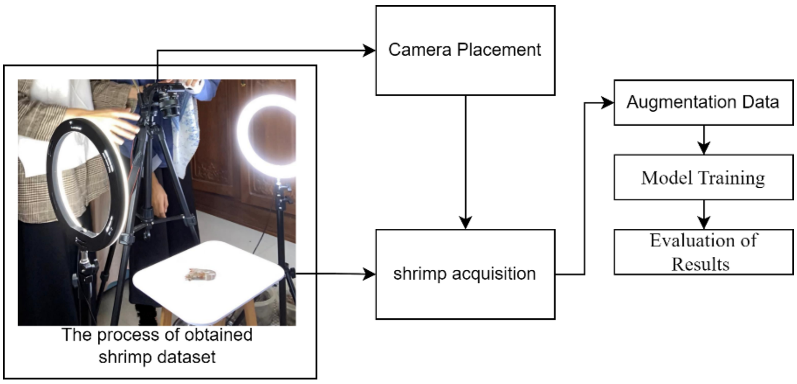

Figure 21. Data Acquisition Process

Data Augmentation: The data augmentation process successfully increases the number of datasets without retrieving additional objects, reducing the risk of overfitting. With a balanced augmentation composition, the resulting dataset is of sufficient quality to train a classification model. These augmentation results provide additional confidence in evaluating the performance of models using the VGG-16 and ResNet-50 architecture in distinguishing Vannamei shrimp cultivation objects from soil and tarpaulin ponds.

Model Training: At the model training stage, transfer learning techniques with optimization using Pytorch in Google Colab Pro allow optimal parameter settings. This research provides insight into the factors influencing training time and model performance by comparing configurations such as Adam and SGD optimization with varying learning rates. The final evaluation shows that using the SGD optimizer with a learning rate of 0.0001 provides the most optimal results in classifying Vannamei shrimp farming objects from both types of ponds, underlining the importance of choosing the correct parameters in model training. The VGG-16 and ResNet-50 classification models were trained with variations in optimization (ADAM and SGD) and learning rate, and the training time required for each variation was observed. The training results can be seen in Figures 7, 8, 9, 10, 11, 12, 13 and 14. The training graphs depict the progression of the model's performance over epochs, with the blue line representing the training accuracy and the orange line representing the validation accuracy. As epochs increase, converging between the two lines indicates improved model generalization. A narrower gap between the two lines suggests better generalization, signifying that the model effectively learns patterns from the training data and can accurately classify unseen data. Conversely, a widening gap may indicate overfitting, where the model performs well on the training set but fails to generalize to new data. Therefore, monitoring the trend of these lines throughout training is crucial for assessing the model's performance and making necessary adjustments to optimize its accuracy and generalization capability.

Evaluation of Results: The confusion matrix method is used to evaluate the performance of the classification model on test data. Figures 15, 16, 17 and 18 show the confusion matrix values of the VGG-16 and ResNet-50 architectures using different learning and optimizer values. These findings also illustrate the importance of optimizer selection and model-parameter tuning to maximize model performance, which agrees with previous research that has identified the importance of these factors in the context of deep learning. Evaluation results show that SGD optimization with a learning rate of 0.0001 produces the highest performance. A small learning rate is generally preferred because it helps prevent overshooting and ensures the model's learning runs stably in the right direction. In addition, the SGD optimization method is often considered better than ADAM with a small learning rate because it tends to produce stable training graphs and can avoid unwanted scatter in the model training process.

4. CONCLUSION

This research succeeded in developing a dataset of images of Vannamei shrimp cultivation results from both types of ponds, namely earth ponds and tarpaulin ponds, without peeling. The use of two Convolutional Neural Network (CNN) architectures, namely VGG-16 and ResNet-50, in combination with the Adam and SGD optimizers and two variations of learning rate (0.001 and 0.0001), has shown a significant influence on the effectiveness of the training system for image classification. The training results show that using the SGD optimizer with a learning rate of 0.0001 produces a perfect level of accuracy, namely 100%, on both architectures, VGG-16 and ResNet-50. This research contributes to developing a more representative dataset for introducing Vannamei shrimp in the context of cultivation in soil and tarpaulin ponds. The findings from this research can provide a foundation for developing better image recognition technology to increase productivity and sustainability in the shrimp farming industry. Even though the dataset has been well developed, this research still has limitations in representing case variations in farmed shrimp because this research only used two types of ponds. Using more complex CNN architectures or more sophisticated data augmentation techniques may improve the model's ability to handle more complicated cases. Future research can expand the use of this dataset in practical applications, such as developing an automation system for the recognition and monitoring of shrimp in pond cultivation or creating new datasets from different cultivation ponds, such as fiber ponds. The main contribution of this research to the general public is the potential to increase efficiency and productivity in the shrimp farming industry and contribute to the development of information technology and artificial intelligence that can be applied in various other fields. The conclusion of this research is the success of developing a representative dataset for introducing Vannamei shrimp from land ponds and tarpaulin ponds. Model evaluation using CNN architecture and variations of optimizer and learning rate shows promising results with high accuracy. Recommendations for the development of practical applications such as websites or mobile applications will facilitate the application of the findings of this research in the general public, increasing the accessibility and usability of the research results broadly.

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6. DECLARATIONS

AUTHOR CONTIBUTION

Melinda; Conceptualization, Methodology, Writing - Preparation of Original Draft. Zharifah Muthiah; Data acquisition, deep learning model training. Fitri Arnia, Elizar, Muhammad Irhamsyah; Writing - Review and Editing.

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The authors declare there is no conflict of interest.

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