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Classification of coastal shrimp species using deep learning InceptionResNetV2 with data augmentation

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Abstract. Coastal areas that are rich in shrimp natural resources usually have a strong fishing industry. Shrimp consumption can contribute to the local economy. Several types of shrimp have higher utilization potential in the fishing industry and human consumption. Classification helps sort out shrimp species in coastal waters. Deep learning technology helps identify and separate shrimp species through deep learning with the Convolutional neural network. The seven classes observed were Vaname Shrimp, Tiger Shrimp, Jerbung Shrimp, Giant Prawns, Red Shrimp, Ronggeng Shrimp, and Prawns. The data used is 50 per class, so 350 images are used. Due to dataset limitations, the proposed contribution is an initial Resnet architecture with augmentation. Resnet helps perform in-depth training to save training computation time, and improvements add variety to limited amounts of data. The result is that the average accuracy of the model is 99.4%, with an average training computation time of 7 and a half minutes. The MSE misclassification value was 0.0143, RMSE was 0.1195, and MAE was 0.0086. Testing tests and testing data on the model only takes 1-2 seconds. Prediction accuracy ranges from 90.01%-99.8%.

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1 Introduction

Shrimp cultivation is carried out to obtain a better level of feed conversion efficiency when compared to the production of land livestock. In shrimp farming, the feed given will be converted into animal protein with a higher efficiency level to contribute more to food fulfillment. Food Needs among Others The demand for shrimp products as a source of animal protein continues to increase worldwide in line with the growth of the human population. Shrimp cultivation helps meet high food needs and contributes as a high protein food source. The shrimp farming industry is a source of income and employment for local communities in coastal and rural areas. Shrimp farming creates job opportunities for shrimp farmers, workers in the processing, logistics, and trade sectors. Economic Diversification in Shrimp Aquaculture can be an alternative to reduce dependency on specific economic sectors and assist in diversifying livelihoods for coastal and agricultural communities. In selling shrimp in the retail market, consumers usually look for specific species based on taste and taste preferences. Classification of the types of shrimp will help maintain the integrity and authenticity of the product so that consumers can buy and enjoy shrimp according to what they want [1].

A lot of commodities are exchanged in the global food system, according to the literature on aquaculture goods. A substantial source of aquatic animal food for human consumption, aquaculture is one of the animal food industries with the quickest growth rates worldwide. The rapid growth of aquaculture over the past few decades has been driven by factors including the depletion of coastal fisheries populations, rising global population, ongoing need for food fish, and international trade. To the circumstances of today, aquaculture is relevant. Furthermore, it influences how local, regional, and environmental repercussions are distributed. Assessment is carried out with a quantitative value of the expansion, distribution, and dynamics related to the volume and weight of fishery production. Because aquaculture is usually established in valuable fertile coastal areas, this can result in widespread changes in land use, the destruction and loss of coastal wetlands, and water and soil pollution. In light of our planet's soil and water resources, this article outlines the necessity for sustainable aquaculture management. A complimentary review of satellite remote sensing studies addressing aquaculture observations, including site selection, site detection, and environmental impact monitoring, is necessary [2].

As illustrated in Fig. 1, shrimp types are crucial aquaculture animals. Prawn production still faces several severe problems and challenges, including disease, production costs, poor seed quality, and feed quality and availability issues. Global prawn output has steadily increased during the previous fifty years. Shrimp production will reach 5.5 tonnes in the coming years, with many countries increasing production and output. There are various diseases, including black gill illness and white spot. Delayed disease discovery can result in prawn death and infection. In this study, the scientists utilized a transfer learning model to detect two forms of prawn disease: white spot disease and black gill disease. They were catching sick prawns. The author aims to find the best learning transfer model with the highest accuracy in prawn illness detection

. The architecture employed employs five methods of learning transfer. With 95% in the first trial and 92.5% in the second, the model test results with MobileNetV1 obtained the best validation accuracy. [3] [4].

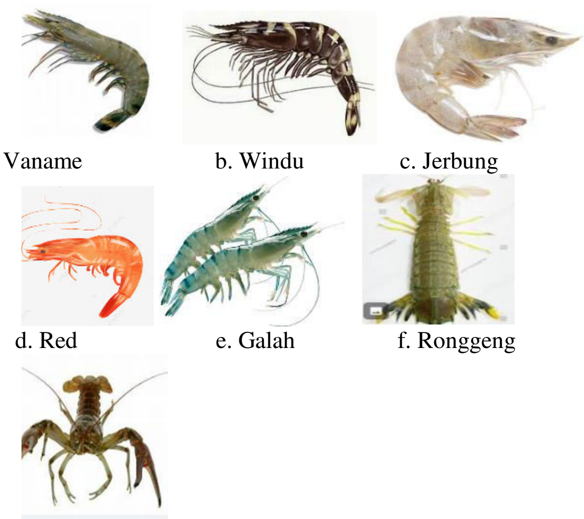
Vaname b. Windu c. Jerbung
d. Red e. Galah f. Ronggeng
g. Karang

Fig. 1. Types of Consumption of Shrimp in Coastal Waters

The following literature review addresses deep learning to discuss the classification of vannamei shrimp that can be approved by the shrimp trade, which is classified into two classes based on pigmentation level. This study aims to identify prawns in terms of price parity and processing. It can help the prawn business. The shrimp distribution supply chain is heterogeneous, with varying requirements. Knowing the price level and the manufacturing process will boost output. A program configured on a mobile device can do image recognition with deep learning architecture for this image classification. It is required for continuous support in the prawn supply chain. The suggested method employs a light model based on HSV color space prawn pictures. A short channel demonstrating the most important techniques for discovering patterns and classifying them based on pigmentation. The photographs of the prawns for the research and databases obtained using various brands and models of mobile devices were used. The findings in the RGB and HSV color spaces enable assessing the suggested model's effectiveness [5].

Computer vision is used in the method for identifying conventional shrimp. We performed shrimp picture segmentation, normalization, and preliminary data augmentation. The fully connected layer is supplemented by a combination classification technique to improve the feature expression in the associated class. Human-designed characteristics are

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employed in image processing research. The LeNet-5 structure was converted into a triple-layered parallel

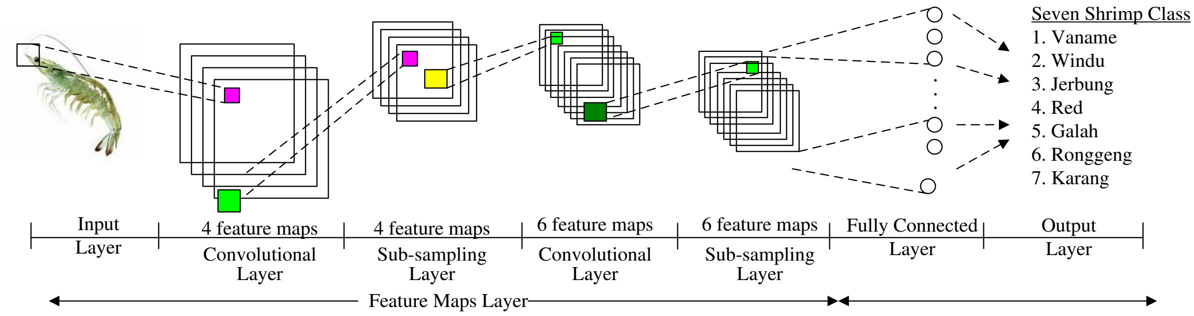

Fig. 2. Convolutional neural network

system to account for the morphological variations in the shrimp's exterior characteristics for effective matching and identification. Specialists must first evaluate and verify the features used to detect shrimp in traditional machine learning. The LeNet-5 architecture, later improved to the ShrimpNet architecture, is anticipated to solve this issue by utilizing an intelligent convolutional neural network. ShrimpNet is used to investigate various designs by reducing the depth and width to create a helpful network structure that can replace real-world applications. According to the experimental findings, the ShrimpNet-3 model, which is smaller, can validate datasets with an accuracy of 96.84% and in 0.47 hours on average. The suggested CNN, therefore, shows promise for shrimp classification and production line quality measurement [6].

Evaluation of shrimp quality is crucial for creating high-grade shrimp products. Shrimp goods that contain soft-shell shrimp are of lower quality. Preventing this is the most challenging imaging task due to the similarity in appearance between spoken shrimp (o-shrimp) and soft-shelled shrimp (s-shrimp). Its inability to be distinguished from conventional machine vision techniques is further hampered by this resemblance. This issue offers a novel method using the Deep-ShrimpNet deep convolutional neural network. The shrimp image was initially normalized using several image processing processes. The batch size, dropout ratio, learning rate, and number (size) of local receptive fields are four hyper-critical parameters enhanced via comparison analysis. To further examine Deep-ShrimpNet's underlying workings, self-learning merge features in each convolution layer are shown. By deleting the CNN layer, an effective method, ablation research was also applied. Finally, by comparing the proposed algorithm to other cutting-edge CNNs, the superiority of the algorithm is demonstrated. Deep-ShrimpNet achieved a mean accuracy precision (mAP) of 0.972 in the test data set and a modeling time of 0.54 hours. Deep-ShrimpNet's successful implementation is supported by the suggested method's good performance across the shrimp data set [7].

From the literature above, the author feels the need to take the theme of shrimp classification for coastal farmers because it can help farmers sort out the types of shrimp caught. For new farmers, it can be used to identify the kinds of consumption shrimp caught on the coast. The gap with previous research is that shrimp research is still a little discussed, and the proposals used use existing architectures. The strengths of prior research have been using convolutional neural networks. Still, the drawbacks of this research are the computation time, the amount of data, and the accuracy of the model used is still around 95%. The contribution offered in this research is using the resnet inception architecture, which is expected to reduce computation time and increase the number of data variations through augmentation of scale, rotation, shears, and reflection to improve the amount of data, computation time, and accuracy.

2 Background

2.1 Shrimp farming in coastal waters

The shrimp farming industry strongly impacts the economic position of coastal towns—the direct effects of shrimp farming on their socio-economic-related condition. There are sustainability, resilience, and cultural environment. This study looks into the financial responses and perspectives of shrimp producers. Compared to their socio-economic situation before learning about the shrimp pond, the local shrimp farming community reported pleasure with their current income. The farming community's financial gains have increased due to shrimp farming. For the income range group of USD 101-150, shrimp farming increases people's income levels from 26% to 36% and is better than USD 150. Participants were divided on whether shrimp farming or rice farming was more profitable, with 60% favoring shrimp farming. Fish from freshwater. After the introduction of shrimp aquaculture, household construction methods, and materials grew, and salinity and the short rice growing season were the main factors stated by shrimp producers (56%) for converting to shrimp farming. Shrimp farmers exhibit a degree of satisfaction of 72% as measured by their income level. Profits and daily fish requirements are the beneficial effects of shrimp aquaculture. However, animal feed shortages and plant destruction are terrible effects. Due to growing shrimp farming activities, fewer farms and trees are dedicated to raising cattle and poultry. In conclusion, the socio-economic conditions of the community of shrimp

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farmers have improved due to shrimp farming. This example is an excellent lesson for economically vulnerable and marginalized coastal populations in developing and impoverished nations [8].

2.2 Convolutional neural network

Neural networks include convolutions or CNN. Machine learning and deep learning are contained there. The necessary static environment factors for shrimp pond growth can be analyzed using either method. Image recognition and sensor data collection technologies can regulate various dynamic aspects, such as feeding, growth, mobility, and accident warning. With these parameters, an intelligent monitoring system can be used to analyze the requirements of shrimp larvae to grow in different environments. Computing is expected to help farmers deal with land, seeds, types of shrimp, and diseases through embedded systems, both in text and video. [9]. A Deep Learning architecture called a convolutional neural network (CNN) is made for processing structured data, including pictures and movies. CNNs are very effective in pattern recognition and visual representation tasks, making them the preferred choice for many applications in computer vision [9]—The Block diagram of CNN shows in Fig. 2.

Convolutional neural networks are divided into two parts, namely feature maps and convolutional neural networks. There are four dominant layers for feature maps to get features and classification to get output classes. Convolutional Neural Network (CNN) is a type of neural network architecture specialized for processing structured data, primarily visual data such as images and videos. In various computer vision applications, including object recognition, picture classification, face detection, and image segmentation, CNN is gaining popularity and is quite effective. [11].

- Convolutional layer
  This layer performs convolution operations on input images or other high-dimensional data. The goal is to extract the essential features from the data by shifting the filter (also known as the kernel) over the entire input data area. The convolution process involves a filter, a small matrix smaller than the input data, and affects the results of the desired feature [12].

  $$(f * g)(x, y) = \sum_a \sum_b f(a, b) g(x - a, y - b) \quad (1)$$

  With:
  h= height, f(x,y) = input function, g(x,y) = kernel function,
  a = $2h$ + 1 kernel height and b = $2w$ + 1 kernel width

  This filter plays a role in extracting special features from the input data. For example, in image processing, a filter could be a 3x3 matrix that detects the edges of the image. Shift (Sliding): The filter is shifted throughout the input data area with a particular step (stride). Each shift generates convolution values that indicate how the filter fits into a portion of the input data. The filter elements and the input data area elements that coincide at each dress are calculated by multiplication and addition to produce a single value at a given location in the convolution output [13].

- Batch Normalization
  Batch normalization helps accelerate convergence and allows for more excellent learning rates to be used in network training. In addition, this technique also has a slight regularization effect, which can help reduce the overfitting of the model.

  $$y_{tijk} = \frac{x_{tijk} - \mu_i}{\sqrt{\sigma_i^2 + \epsilon}},\ \mu_i = \frac{1}{HWT} \sum_{t=1}^{T} \sum_{l=1}^{W} \sum_{m}^{H} x_{tilm},\ \sigma_i^2 = \frac{1}{HWT} \sum_{t=1}^{T} \sum_{l=1}^{W} \sum_{m}^{H} (x_{tilm} - mu_i)^2 \quad (2)$$

  with
  y_{tijk} = output batch norm, μ_i=variance, H=Height, W= Width, ϵ=Epsilon, T=time [14].

  In many cases, batch normalization occurs after convolution operations or fully connected layers but before the activation function. It makes the training process more stable and helps the neural network to learn more quickly and accurately [15].

- ReLu layer
  The main reason behind ReLU's popularity is its ability to overcome the vanish gradient problem, which often occurs when using sigmoid or tanh activation functions on intense neural networks.

  $$ReLU\ (x) = f(x) = \begin{cases} x, & jika\ x \geq 0 \\ 0, & lainnya \end{cases} \quad (3)$$

  with x = input value, and $f(x)$ = ReLU. Output With ReLU, the gradient value for positive values is 1 (the gradient will not dissipate), enabling faster and more efficient learning in deep networks [16].

- Pooling layer
  The pooling process is carried out by dividing the input image or data into regions (for example, a 2x2 set of subregions) and aggregating (aggregating) the values from these regions into one representative value. The commonly used aggregation methods are max pooling and average pooling [17].

2.3 Error Accuration RMSE, MAE

- Root Mean Square Error (RMSE) is the root of the squared average value of a function.

  $$RMSE = \sqrt{\frac{1}{N_d} \sum_{k=1}^{N_d} (y_k - \hat{y}_k)^2} \quad (4)$$

  with N_d= number of sample data, i=indexing, y_k=actual label, and $\hat{y}_k$ = prediction label [18].

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- The absolute average of prediction mistakes is positive or negative. It is known as a mean fundamental error (MAE).

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right| \tag{5}$$

with N= Number of sample data, j=indexing, y_j=actual label, and $\hat{y}_j$ = prediction label [19].

3. Methods

3.1. Architecture of CNN

"Depthwise separable convolution" separates spatial and depthwise convolution (convolutions on each channel or channel separately). This approach significantly reduces the number of parameters and computational complexity without sacrificing network performance. Convolution works independently on each input channel. It means the information between the tracks is not mixed during the convolution process, allowing the model to capture each channel's specific features better. It can improve the quality of feature representation in the model. The architecture used shows in Fig. 3, Fig. 4, Fig. 5.

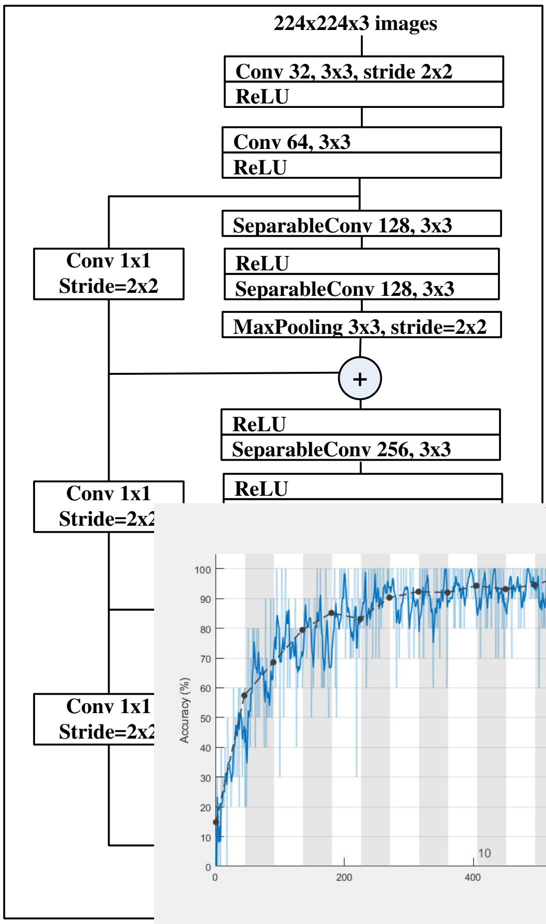

Fig. 3. Inception Entry Flow

The Inception architecture, which is a complex CNN architecture that has many variations (InceptionV3), was initially referred to as "stem" or "entry flow." This subset generally consists of the initial convolution, normalization, and activation layers that form the basis of feature extraction in the Inception architecture. So, "entry flow" in the context of various CNN architectures, including the Inception architecture, refers to the initial part responsible for extracting the essential features from the input image.

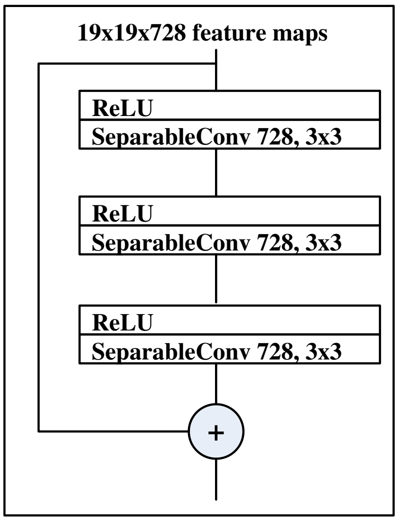

Fig 4. Middle Flow

After each convolution operation in the Inception Module, it is generally followed by a Batch Normalization layer and ReLU activation. Hierarchical Feature Extraction Capability: Middle Flow extracts increasingly complex and hierarchical features from the image. By combining information of various scales and levels of complexity, Middle Flow helps in understanding the deeper structure and content of the picture.

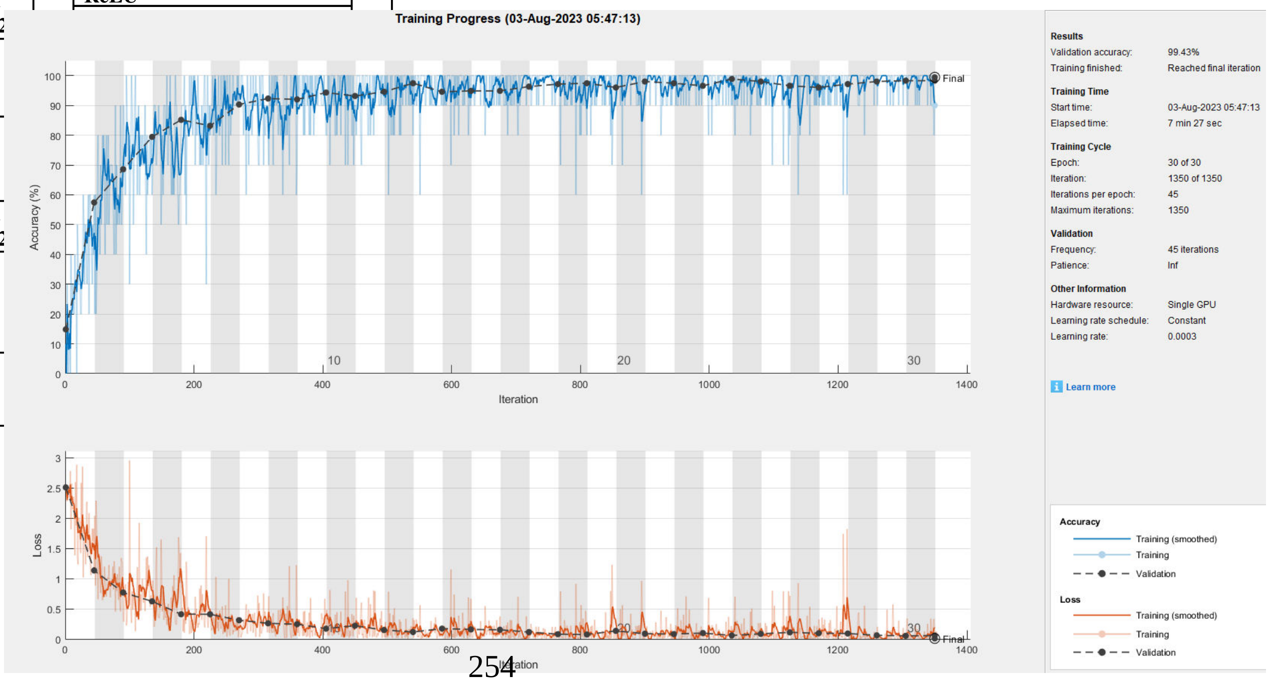

Fig. 6. The Training Process uses the Resnet inception architecture

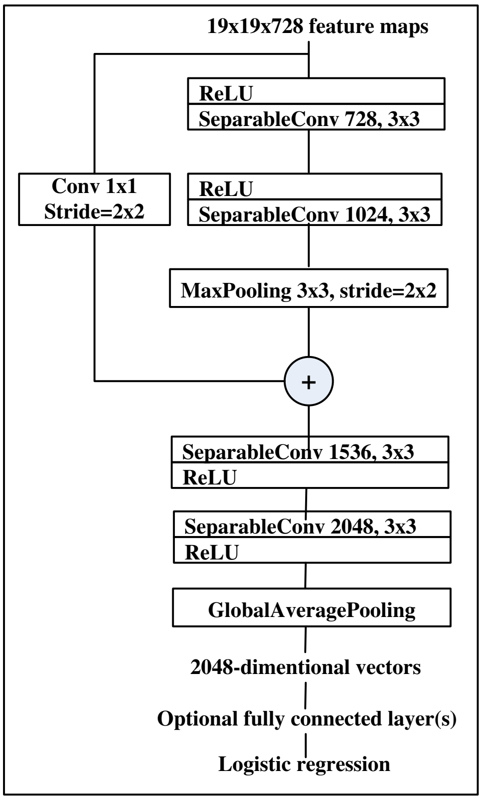

Fig 5. Exit Flow

In the final stage of Exit Flow, the image will usually be assigned to the Global Average Pooling layer. It replaces the traditional fully connected layer and averages pooling across images, resulting in a vector representation that includes information from all appearances.

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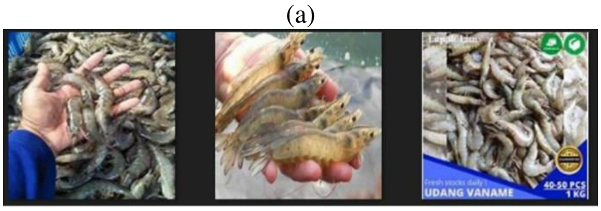
4. Result and Discussion

4.1. Pre-processing

The transformations are applied to data before entering into a Deep Learning model. Pre-processing aims to change, clean, or change the data representation to match the format desired by the Deep Learning model and improve data quality to assist the training process and improve model performance. The steps are resizing the image into size [224 224 3]. It shows in Fig.7.

(a)



(b)

Fig. 7. Pre-processing (a) Original Image, (b) Image after pre-processing

2.4 Training Process

In the training process stage, the optimization parameters are set using training optimizers including adam, sgdm, and rmsprop, Initialize Learning Rate = 3e-4, Maximum Epochs = 30, Shuffle = every-epoch, validation data = imds Validation, Validation Frequency = 30, and Verbose = accurate. It is used to train the data and get the model's accuracy. The training process's stability is a concern because the system can experience a diminishing gradient or overfitting. The training process in Fig. 6. shows that the model has a curation of 99.4% with a training time of about seven minutes and a half.

4. Result and Discussion

2.5 Data Augmentation

At this stage, scale, rotation, shears, and reflection techniques are used to get new data points of view. This technique is used to overcome data limitations and an unbalanced number of classes.

(a)

(b)

Fig. 8. Data Augmentation (a) Scale Rotation, (b) Shears and reflection

Results Fig. 8 shows the results of the transformation from the original image to a new reference dataset. It around 50 validation data were used. At this stage of the training process, if there is a lack of data in the class, the augmentation will cover the lack of data per class so that the training process can still run well.

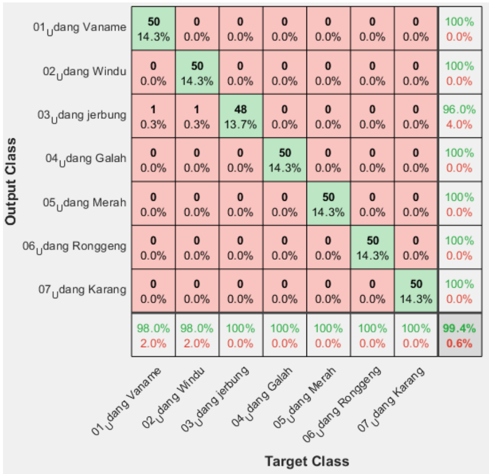


Fig. 9. Confusion Matrix Output vs. target

The CNN training stage process will produce a model, which is then used as a reference in the prediction process. The confusion matrix results in Fig. 9 show that several images are classified incorrectly in the output class vs. the target class. Namely, the jerbung shrimp are classified into the Vaname and Windu classes. It can also be seen where the correct category is classified as wrong. From the confusion matrix process, the model accuracy is 99.4%.

2.6 Prediction

At the prediction stage of the process carried out is a comparison to the model obtained from the training process results. The data used can be test or experimental data outside the training data. The concept of prediction is to compare the input vector matrix derived from experimental data with the model matrix obtained from the training process. The model used is the result of training with the best accuracy from several training scenarios that have been carried out.

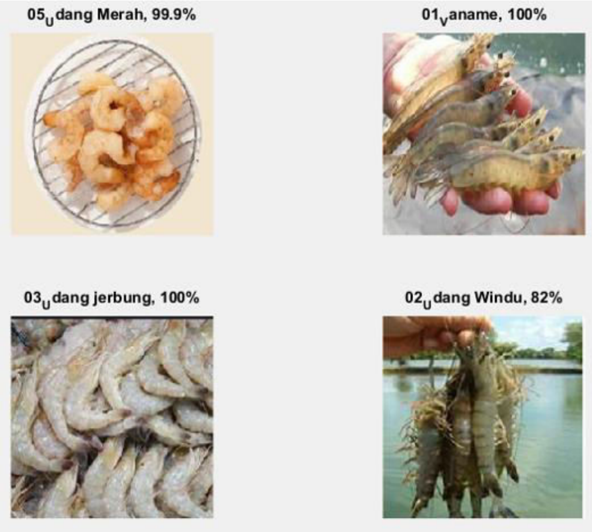


Fig. 10. Prediction 01

This trial stage in Fig. 10 was carried out by directly comparing several images to the model and obtaining several different accuracy results. In the first image, the system recognizes red shrimp well, with a confidence level of 99.9%; in the last photo, tiger prawns are identified with an accuracy rate of 82%. For other shrimp, images can be recognized well.

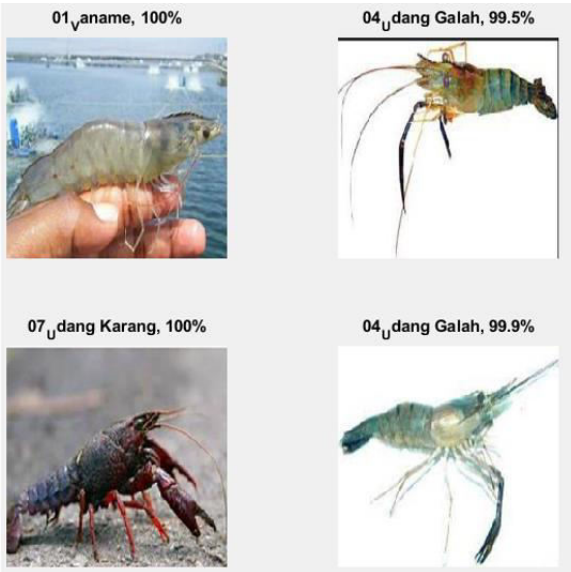


Fig. 11. Prediction 02

In the second trial, Fig.11, using experimental data, the system recognized the Galah Prawns well, with a confidence level of the prediction process of 99.5% and 99.9%. Other types of shrimp can be recognized well by the system. It shows that the higher the accuracy of the model, the better the prediction process results. Repeated trials are carried out in the model development process to get the best scenario, including changing the architecture or the parameter settings used. The plan shown above shows that the system has been successfully built with reasonable accuracy.

2.7 Research Comparison

There are two tables to compare system results, including comparing systems using other architectures from CNN, including Alexnet, Googlenet, VGG19, densenet 201, Resnet50, mobilev2net, and Squeezenet.

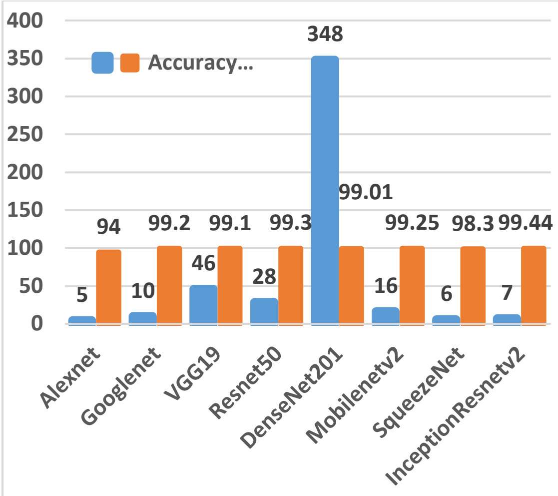


Fig. 12. Comparison between CNN Architectures

In comparison between CNN architectures, the results show that the accuracy obtained is better. ResNet is known for overcoming vanishing gradient problems in intense networks, while Inception has good parameter efficiency and feature recognition through different convolution operations. As shown in Fig.12, in terms of training time, Inception Resnetv2 takes an average of seven and a half minutes to build a model. It's less compared with alexnet and Squezenet, which require an average of 4.5-5.8 minutes, but the resulting accuracy results are better than both, namely 99.4%.

5. Conclusion

The results of the trial scenario show that a classification system has been successfully built and implemented to recognize shrimp species properly. Research contributions were made on selecting a combined resnet and inception architecture to obtain accuracy and optimal computation time and augmentation for the problem of limited data. Seven classes were observed: Vaname Shrimp, Windur Shrimp, Jerbung Shrimp, Galah Shrimp, Red Shrimp, Ronggeng Shrimp, and Coral Shrimp. The dataset was 50 images per class, so 350 images were used. Due to these limitations, scale, rotation, shears, and reflection augmentation techniques are used to add temporary data variations to save training computation time using a combination of resnet and Inception. The result is that the average accuracy of the model is 99.4%, with an average training computation time of 7 and a half minutes. MSE misclassification value 0.0143, RMSE

0.1195, and MAE 0.0086. Testing tests and experimental data on models only takes 1-2 seconds. Prediction confidence accuracy ranges from 90.01%-99.8%.

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