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Coral Reef Image Classification Using Multilayer Perceptron

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Abstract—**Coral reefs are one of the marine organisms that play many important roles for other organisms within them. Coral reefs are often referred to as the tropical rainforests of the sea because they protect small fish and provide food for other marine organisms. Over time, threats have emerged that disrupt the stability of marine ecosystems, one of which is coral reef damage, such as bleaching or destruction caused by various factors. Damaged coral reefs are caused by several factors, including climate, chemicals from blast fishing, and pollution. As a result, coral reefs become damaged and can no longer serve as a refuge for small species. Therefore, this research aims to reduce the impact of coral reef damage by building a coral reef classification model using one of the deep learning algorithms, namely Multilayer Perceptron (MLP), which involves the use of multiple hidden layers in the modeling process. The result of the classification using this algorithm is an accuracy of 76%, indicating that the model can also be used in the process of classifying coral reefs in image form. Thus, it is hoped that innovations in deep learning for coral reef classification can make a significant contribution to coral reef conservation and marine resource management.**

Index Terms— **Multilayer Perceptron, Classification, Deep Learning, Coral Reef.**

I. INTRODUCTION

CORAL reefs are one of the marine ecosystems often referred to as the tropical rainforests of the sea, playing a crucial role in marine life [1]. Coral reefs contain germplasm, which is a collection of genetic resources encompassing various types of genes, species, and ecosystems within the coral reefs. These resources are essential to help coral reefs adapt, evolve, and remain stable over time. Coral reefs [2] are marine organisms classified as part of the benthic group. Coral reefs are coastal ecosystems that support the life of various marine biota, making their existence highly significant, both environmentally and economically [3]. Coral reefs offer a variety of benefits, such as being used as raw materials for medicines, supporting marine tourism activities, serving as aquarium decorations, construction materials, and acting as natural coastal protection against waves and abrasion [4]. Coral reefs also function as carbon dioxide absorbers and provide a food source for approximately 25% of fish species and other marine animals [5]. The presence of healthy coral reefs supports the fishing industry and provides a source of protein for humans.

The preservation of coral reefs is crucial for maintaining the balance of marine ecosystems. However, it cannot be denied that threats to coral reef damage continue to arise. These threats are caused by several factors, including [6] climate change, pollution, and overfishing. According to [7], research from the Oceanography Research Center indicates that the health of the oceans is declining due to global climate change. Rising global temperatures increase the acidity of seawater, which threatens the existence of coral reefs. Coral reefs play a vital role as a source of food, provide employment opportunities, and protect hundreds of millions of people from storms. It is estimated that coral reefs could become extinct by 2050.

Threats to coral reefs also arise from natural factors such as earthquakes and tsunamis, as well as human activities (anthropogenic), including the use of explosives and potassium cyanide in fishing, land reclamation for hotel development, and dredging for port basins [8]. The consequences of such damage include severe and prolonged coral bleaching, which can lead to mass coral mortality. This, in turn, threatens marine biodiversity and reduces the functionality of ecosystems that depend on coral reefs.

Monitoring and classification of coral reefs are important conservation efforts, as they help identify which coral reefs are damaged and which are still healthy. Classification is [9] the process of finding a model for data to assign it into specific categories from existing classes. One method that can be used for classification is the Multilayer Perceptron (MLP) algorithm. Previous research [10] has demonstrated the successful application of the Multilayer Perceptron (MLP) in various fields, including its use for predicting the spread of tuberculosis cases, achieving an accuracy of 77.62%. Another study [11] also showed that the

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Multilayer Perceptron (MLP) can be used for heart disease risk classification using an image dataset and the Multilayer Perceptron (MLP) algorithm, achieving a good accuracy of 80.25%. Further research on classifying sugarcane leaf diseases [12] using the Multilayer Perceptron algorithm resulted in an accuracy of 97.4%. This indicates that the Multilayer Perceptron (MLP) algorithm is capable of addressing classification problems across various fields.

The Multilayer Perceptron (MLP) algorithm [13] is a type of artificial neural network that has demonstrated significant potential across various fields. A perceptron [14] is the basic processing element, where the value of each perceptron is a local function of its input and connection weights within the network. The ability of the Multilayer Perceptron (MLP) algorithm to learn from data and generalize patterns makes it a compelling tool for application in marine ecology, particularly in the classification of coral reef types and conditions.

This research takes a different approach by developing an architecture for the Multilayer Perceptron (MLP) algorithm specifically designed to handle more complex environmental data. Additionally, this study employs regularization techniques and hyperparameter optimization to enhance prediction accuracy and the model's ability to recognize new patterns. Not only does this research focus on classifying coral reef types, but it also assesses their ecological conditions, thereby providing more meaningful information to support conservation efforts and sustainable coral reef management. It is hoped that this research will make a significant contribution to coral reef conservation and marine resource management.

II. RESEARCH METHOD

This section provides a detailed explanation of the techniques and methods used to collect and analyze data in order to achieve results that align with the research objectives.

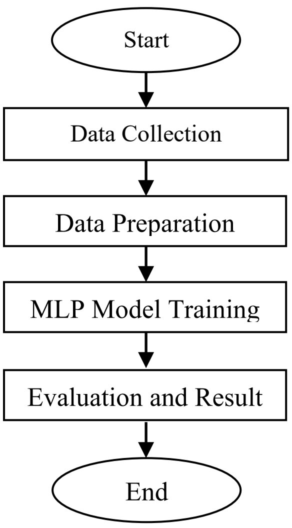

Fig. 1. Research Stages

A. Data Collection

The first step in this research is data preparation or data collection. The dataset used was obtained from the Kaggle website at the address (https://www.kaggle.com/datasets/sonainjamil/bhd-corals) and downloaded in zip format.

B. Data Preparation

The data obtained from the data collection process is still in a zip format. Therefore, the data will first be extracted into a new file in Google Colaboratory using Python. After the extraction process is completed, it is found that the dataset consists of 923 images divided into two classes, the healthy corals class with 438 images and the bleached corals class with 485 images, as shown in Figure 2. To balance the dataset between the two classes, an additional 15 images are added to the healthy corals class. As a result, the total dataset now consists of 938 images.

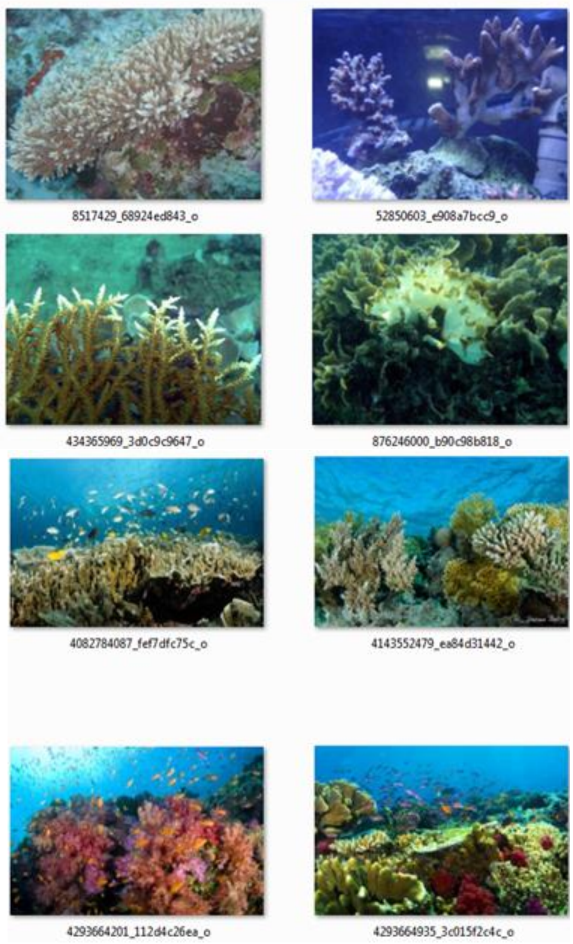

Fig. 2. Bleached dan Healthy Coral Images

C. Multilayer Perceptron Model Training

The next step is model training for the Multilayer Perceptron (MLP) algorithm. The Multilayer Perceptron (MLP) algorithm is a type of deep learning that can be used for classification [15] and is one of the algorithms within Artificial Neural Networks (ANN). Artificial Neural Networks (ANN) mimic the functioning of neural networks in the human brain. They consist of a number of neurons that act as simple processors, analogous to neurons in the brain. These neurons are connected by weighted links that transmit signals from one neuron to another. Additionally, they consist of an input layer, one or more hidden layers, and an output layer [16]. The architecture of this model is illustrated in Figure 3.

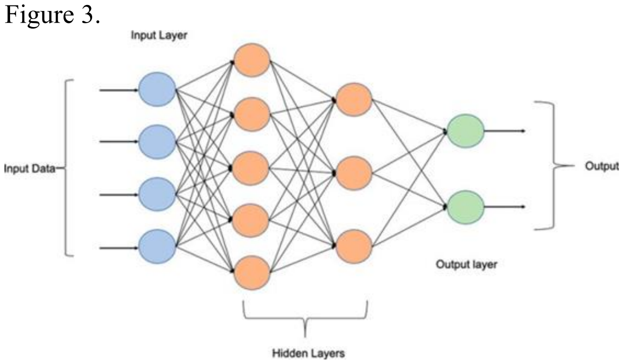

Fig. 3. Multilayer Perceptron (MLP)

There are three main stages in Multilayer Perceptron (MLP) training. The first stage is feedforward, which calculates the output of each neuron, as shown in Equation (1). In this process, the input neurons are forwarded by multiplying them with their respective weights and adding a bias, resulting in an output that serves as the input for the next layer [10].

$$z_j^{(l)} = \sum w_{ij}^{(l)} a_i^{(l-1)} + b_j^{(l)} \quad (1)$$
$$a_j^{(l)} = f(z_j^{(l)})$$

Next is loss calculation, which is used to measure the prediction error by comparing the predicted values with the target values.

$$L = \frac{1}{N}\sum_{i=1}^{N} L(\hat{y}_i, y_i \quad (2)$$

Next is backpropagation, which utilizes the error from the loss calculation stage to adjust and correct the weights.

$$\delta_j^{(l)} = \begin{cases} a_j^{(l)} - y_j, \\ f'(z_j^{(l)})\sum_k \delta_k^{(l+1)} w_{jk}^{(l+1)} \end{cases} \quad (3)$$

D. Evaluation and Result

Next, the model evaluation stage is conducted to determine the effectiveness of using the Multilayer Perceptron (MLP) algorithm for classifying two classes of coral reef images. After the training process, the model generates new weights, which can be evaluated using a confusion matrix to determine metrics such as accuracy, recall, precision, and F1-score. The model evaluation in this research utilizes a confusion matrix [17]. Additionally, learning curve analysis is performed to assess the consistency of the model during the training and testing processes. This evaluation not only measures the success of model optimization but also provides a deeper understanding of data patterns and features that have the most significant influence on the coral reef classification process [18]. The test results indicate that the optimized model is expected to significantly improve performance, both in terms of classification accuracy and the ability to generalize complex environmental data. The findings from this evaluation serve as an essential foundation for recommending the application of the model in more effective coral reef conservation and management efforts.

Tabel. 1. Confusion Matrix

Actual \ Predicted	Positive (1)	Negative (0)
Positive (1)	TP (True Positive)	FN (False Negatif)
Negative (0)	FP (False Positive)	TN (True Negatif)

The formulas for each component of the confusion matrix are shown below :

- True Positive (TP) : The prediction is positive, and it is actually positive.

$$TP = \sum(y_{true} = 1 \land y_{pred} = 1) \quad (4)$$

- False Negative (FN) : The prediction is negative, but it is actually positive.

$$FN = \sum(y_{true} = 1 \land y_{pred} = 0) \quad (5)$$

- False Positive (FP) : The prediction is positive, but it is actually negative.

$$FP = \sum(y_{true} = 0 \land y_{pred} = 1) \quad (6)$$

- True Negative (TN) : The prediction is negative, and it is actually negative.

$$TN = \sum(y_{true} = 0 \land y_{pred} = 0) \quad (7)$$

In the confusion matrix, several evaluation metrics can be calculated, including:

- Accuracy $= \frac{TP+TN}{TP+TN+FP+FN}$ (8)
- Precision $= \frac{TP}{TP+FN}$ (9)
- Recall $= \frac{TP}{TP+FN}$ (10)
- Specificity $= \frac{TN}{TN+FP}$ (11)
- F-1 Score $= 2 \times \frac{Precision \times Recall}{Precision + Recall}$ (12)

III. RESULT AND DISCUSSION

After the coral reef data extraction is completed, the next step is to normalize the dataset by scaling the pixel values to 255.0 and resizing the image parameters to a width of 64 pixels and a height of 64 pixels, as shown in Figure 4.

Fig. 4. Image Data Size 64 x 64 Pixels

The next step involves using TensorFlow Keras to define the input shape. Additionally, the flatten function is used to convert the coral reef images into a uniform 1D vector format, as the Multilayer Perceptron (MLP) model can only process datasets that have been transformed into 1D vectors. The dataset is resized uniformly to facilitate model training using the Multilayer Perceptron (MLP) algorithm. Following this, during the splitting stage, the dataset is divided into training and testing data with a ratio of 20% and 80%, respectively, using a random state of 75. After splitting the data for model training, the next step involves adding a dense layer to process the hidden layer. Here, a dense layer with 128 neurons and ReLU activation is used, along with dropout to reduce overfitting during dataset processing. For model optimization [19], this research employs the Adam Optimizer, which helps accelerate training and learn errors during training by updating the network weights.

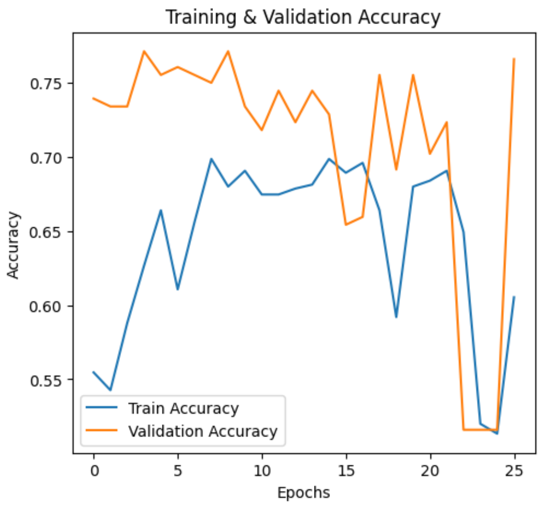

Fig. 5. Model Accuracy

The graph in Figure 5 illustrates the accuracy during the training and validation processes. Accuracy refers to how well the model makes correct predictions. The blue line, represents the model's accuracy on the training data, while the orange line, represents the accuracy on the validation data. It can be observed that both lines increase as the number of epochs (training iterations) increases, indicating that the model is improving in its ability to predict the data.

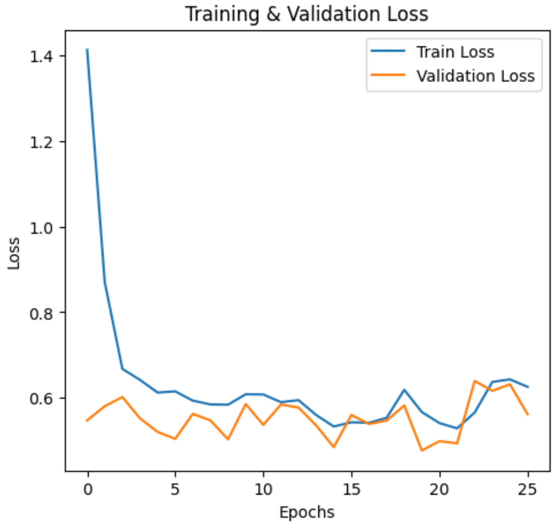

Fig. 6. Loss Model

The graph in Figure 6 shows the loss during training and validation. Loss measures how far the model's predictions are from the actual values. The training loss, and validation loss decrease as the number of epochs increases, indicating that the model is improving in reducing prediction errors.

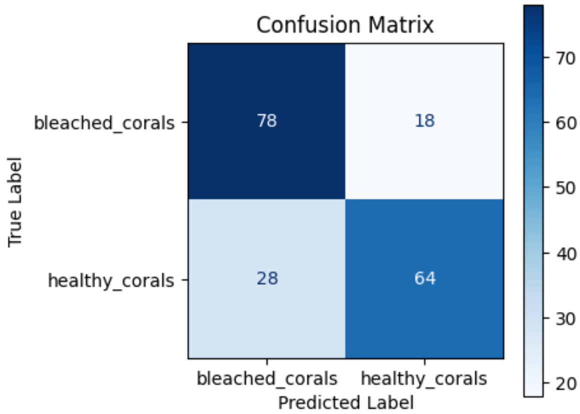

Fig. 7. Confusion Matrix

The confusion matrix provides a clear overview of how the classification model performs, showing where the model is correct and incorrect in its predictions [20]. In this coral case, the model performs reasonably well in predicting bleached corals (78 correct, 18 incorrect) and also performs fairly well in predicting healthy corals (64 correct, 28 incorrect). However, there is still room for improvement, particularly in reducing the misclassification of healthy corals as bleached corals.

Table. 2. Classification Report

Classification Repport :

	precisio	recal	f1-	suppo

	n	l	scor e	rt
bleached_corals	0.74	0.81	0.77	96
healthy_corals	0.77	0.65	0.71	92
Accuarcy			0.76	188
macro avg	0.76	0.75	0.75	188
weighted avg	0.76	0.76	0.75	188

Table 2 presents the classification report, which includes precision, recall, and F1-score. Precision measures how accurate the model is in predicting the positive class. For bleached corals, the precision is 0.74, meaning that out of all the corals predicted as bleached by the model, 74% are indeed bleached. For healthy corals, the precision is 0.77, meaning that out of all the corals predicted as healthy by the model, 77% are indeed healthy. Recall measures how well the model identifies all actual positive instances. For bleached corals, the recall is 0.81, indicating that the model successfully detects 81% of all truly bleached corals. For healthy corals, the recall is 0.65, indicating that the model only detects 65% of all truly healthy corals. The F1-score is the harmonic mean of precision and recall, used to balance precision and recall, especially when there is an imbalance in the number of data points between classes. For bleached corals, the F1-score is 0.77, and for healthy corals, it is 0.71.

The F1-score is used to balance precision and recall, particularly when there is an imbalance in the number of data points between classes. For bleached corals, the F1-score is 0.77, and for healthy corals, it is 0.71. Support refers to the actual number of data points for each class. For bleached corals, there are 96 samples, and for healthy corals, there are 92 samples. The model performs reasonably well, with an accuracy of 76%. The model is better at identifying bleached corals compared to healthy corals, as evidenced by the higher recall for bleached corals. However, there is still room for improvement, particularly in increasing the recall for healthy corals.

IV. CONCLUSION

Coral reef classification using images with the Multilayer Perceptron (MLP) algorithm, a type of deep learning, achieved an accuracy of 76%, which can be considered reasonably good. However, further improvements are needed, particularly in enhancing the model's ability to detect healthy corals more precisely. The results demonstrate that the MLP algorithm holds potential for classifying coral reefs from images, making it a viable tool for such tasks. It is hoped that ongoing innovations in deep learning for coral reef classification will contribute significantly to coral reef conservation efforts and sustainable marine resource management.

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