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Temporal Forecasting System of Potential Catching Areas of Skipjack Tuna in Bone Sea Using Artificial Neural Network

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Abstract - Indonesia's potential in the field of capture fisheries is very supportive of the economy, one of which is large pelagic fish such as skipjack tuna. The distribution of skipjack tuna in the waters of Bone Regency, South Sulawesi, which tends to be dynamic, is very important to determine its distribution. Therefore, the purpose of this study is to forecast the potential point of distribution of skipjack tuna temporally by utilizing data mining and Artificial Neural Network algorithms. Feature extraction was used in the form of oceanographic data that affects the habitat of skipjack tuna in waters such as Sea Surface Temperature (SST) and chlorophyll-a for the last five years (2017-2021) with a total of 34,800 training data and 8,700 test data. The performance of the system was evaluated using the confusion matrix. The results showed an accuracy value of 94.89% and an F1 score of 92.09%. The application of this forecasting system is very useful for determining the skipjack fishing calendar temporally to increase the effectiveness and efficiency of costs, time, and effort.

Keywords — Forecasting, Potential Catching Areas, Skipjack Tuna, Classification, Artificial Neural Network

I. INTRODUCTION

Fish is a good source of protein for humans. There are many types of fish having high nutritional and economic value. One of them is skipjack tuna (Katsuwonus pelamis) [1]. Skipjack tuna, whose annual production exceeds 3 million tonnes, has become a priority catch in recent decades to support the global economy [2]. Skipjack tuna production in 2010 was 58.1% of the total tuna catch, which is the highest share among other species [3]. Bone Bay is a biologically productive skipjack fishing area [4].

Fishing areas are waters where fish as catch targets are expected to be caught maximally but are still within the limits of resource sustainability. Good fishing areas are waters that have a good physiological and nutritional environment for fish. On a spatial and temporal scale, oceanography is a very complex field of study. Habitat characteristics of aquatic organisms appear to be influenced by various physical, chemical, and biological events [5].

Oceanographic factors greatly affect the life and habitat of skipjack tuna, especially on the content of sea surface temperature (SST) and chlorophyll-a, skipjack tuna can gather in areas that can meet their physiological and nutritional conditions, namely with SST values of 29 - 31°C and concentrations chlorophyll-a value 0.15-0.35 mg/m^{-3}. For this reason, so that fishing is carried out optimally, knowledge of oceanographic conditions and changes is needed to find out the right fishing area [6].

A common problem faced by fishermen is the existence of dynamic fishing areas. Naturally, the fish will choose the appropriate habitat, it is strongly influenced by the oceanographic conditions of the waters. In addition, another problem is how to determine fishing areas that are still based on experience, watercolor, and other traditional methods. Thiscauses the effectiveness and efficiency of fishing operations to decrease with a disproportionate amount of time, cost, and effort [7].

The emergence of problems like this requires a solution, both short-term and long-term. One way to overcome this problem is to create a computerized forecasting system so that skipjack fishing can be carried out optimally.

II. RELATED WORKS

There are several studies that discuss the spatial and temporal forecasting of skipjack habitat, such as R. Hidayat et al [8] Analyzing skipjack fishing areas with physiological and nutritional conditions suitable for skipjack habitat using the Generalized Additive Model and Empirical Cumulative Distribution Function method shows that there is a very important relationship between SST and Chlorophyll-a with a value range of 28.78°C and 31, 25°C for SST, and 0.18 and 0.28 mg/m^{-3}.

According to Mukti Zainuddin et al [9], Seasonal variations have a significant impact on the distribution of skipjack tuna in Bone Bay. According to the findings of this study, the transition season (primarily in May) and the western season (primarily in November) have a positive relationship with SST 30 °C and chlorophyll-a 0.2 mg/m^{-3}, indicating a favorable environment for skipjack fishing grounds.

A. R Rahmadani et al [10] examined the comparison of Single Image Edge Detection and Temperature Gradient Analysis. which was carried out in determining PPI in the southern waters of Java Island and known potential fishing areas in southern Java waters using oceanographic parameters with an accuracy rate of 64%.

In recent years, many studies have discussed forecasting using time series data, for example Ulviyana Cahyati [11] researched and predicted rainfall using the backpropagation method to support a good planting calendar time using time series data with a good Mean Square Error with a value of 0,07. Kala, A and Ganesh Vaidyanathan [12] on prediction of rainfall based on 4 parameters, namely temperature, cloud cover, vapor pressure, and precipitation using the Artificial

Neural Network method, with results showing that the Backpropagation method has an accuracy rate of 93.55%.

According to previous research, oceanographic factors such as SST and chlorophyll-a have a strong influence on the characteristics of potential fishing areas, and the backpropagation forecasting method is a good forecasting method used to predict natural activities using time series data because it produces sufficient good accuracy values.

III. Proposed Methods

A. System Workflow

In this study, the authors forecast the fishing area of the computed skipjack tuna using the Artificial Neural Network (Backpropagation) method. The steps in this workflow system shown in Fig. 1

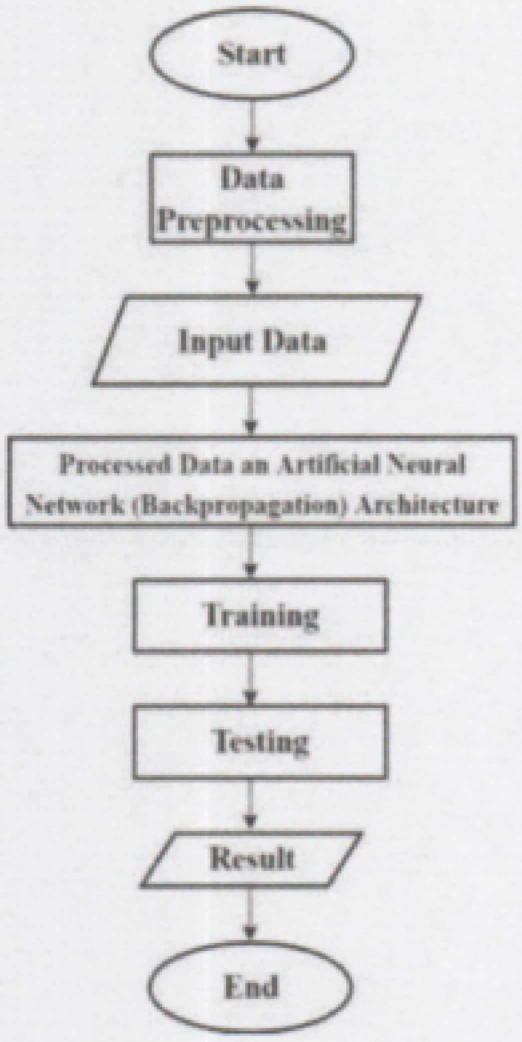


Fig. 1. System workflow diagram

1) Data Preprocessing

This study analyzed chlorophyll-a and sea surface temperature (SST) data from the last five years (2017-2021). The dataset was obtained from satellite imagery, with the MODIS Terra (Moderate Resolution Imaging Spectroradiometer) sensor qualified at level 3 data, SMI (Standard Mapped Image) with file format (NC). This data satellite image with a spatial resolution of 9 km or 4 km was obtained from https://oceancolor.gsfc.nasa.gov/.

This study's site was located in Bone waters, with coordinates of 4.0075 N, 120.348 W, -5.058 S, 121.575 E

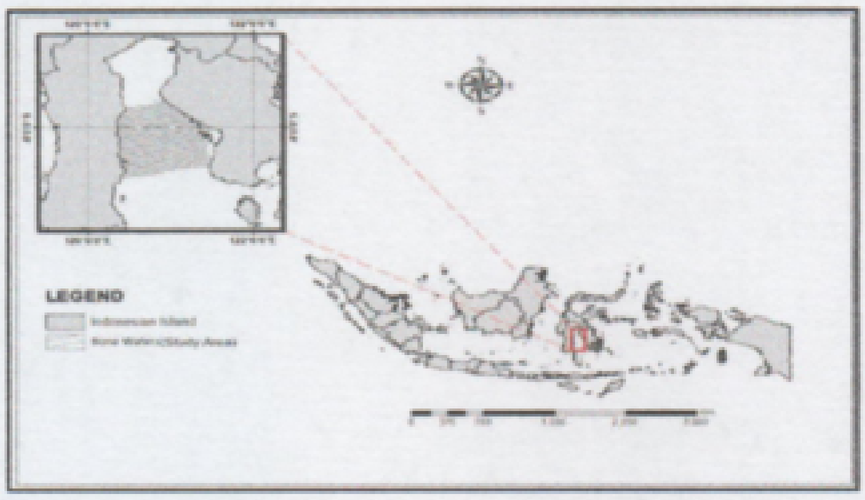


Fig. 2. Study Area

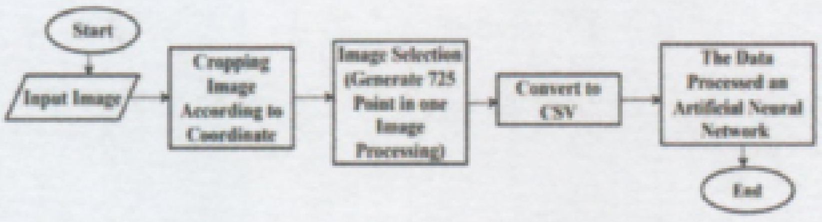


Fig. 3. Flowchart of data processing

The data processing process was carried out as shown in Fig. 3, the stages of data processing were carried out before the data were processed on the system, aiming to convert the data (satellite image) into a more accessible and more effective format to obtain more accurate results. Data were extracted utilizing SeaDas v 7.5.3 software.

Satellite image data was cropped according to the area to be studied. Next, the data were pulled into a file with the extension .txt containing 725 coordinate points with various SST and Chlorophyll-a values at each coordinate point. Furthermore, the data extension was converted to Comma Separated Value (CSV) for easy processing on the system, as shown in Table. I.

2) Data Input

As shown in Table I, the input data for this study are Sea Surface Temperature (SST) and chlorophyll-a data from satellite images that have been processed into numerical data. Sample dataset 10 of 725 after processing satellite image data.

TABLE I. Sample Dataset After Processing From Satellite Image

Coordinate Point	Sea Surface Temperature (SST) (°C)	Chlorophyll-a (mg/m^{-3})
-4.0208335, 120.354164	29,30	0,31
-4.0208335, 120.39583	29,20	0,93
-4.0208335, 120.43749	29,00	0,11
-4.0208335, 121.02083	29,80	0,24
-4.0208335, 120.56249	29,50	0,24
-4.0208335, 120.604164	29,60	0,11
-4.0208335, 120.64583	29,30	0,05
-4.0208335, 120.68749	29,40	0,17
-4.0208335, 120.729164	29,00	0,19

3) Artificial Neural Network (Backpropagation)

A computational method that has the concept of imitating human biological neural networks, namely artificial neural networks. This artificial neural network was designed to solve pattern recognition and classification problems. Artificial Neural Network, one of the training methods in ANN is supervised learning. In guided training, several many inputs and targets are needed which function to train the network until the desired weight is obtained.

Backpropagation is one of the ANN algorithms used in this research. Backpropagation is an algorithm that uses a multi-layer ANN network and the learning process used is supervised learning which is used by perceptrons to change the weights connected to neurons. Using the error output, the Backpropagation algorithm changes the weight value in the opposite direction.

The network architecture used in this study is a multi-layer network with an input layer, a hidden layer, and an output layer. To recognize more data input patterns, this multi-layer network has several hidden layers.

ANN parameters in network formation use 725 input variables for each month of chlorophyll-a and SST data, 20 hidden layers, and one output layer, namely potential or not potential with a target value of chlorophyll-a 0.25 - 0.35 mg/m^{-3} and sea surface temperature 29°C - 31°C, learning rate 0.1, maximum epoch 10000 and activation function using sigmoid activation.

4) Training

In this research, the network architecture used is a multi-layer At this stage, an analysis of the dataset consisting of 34,800 training data will be carried out, the training data flowchart is shown in Fig. 4.

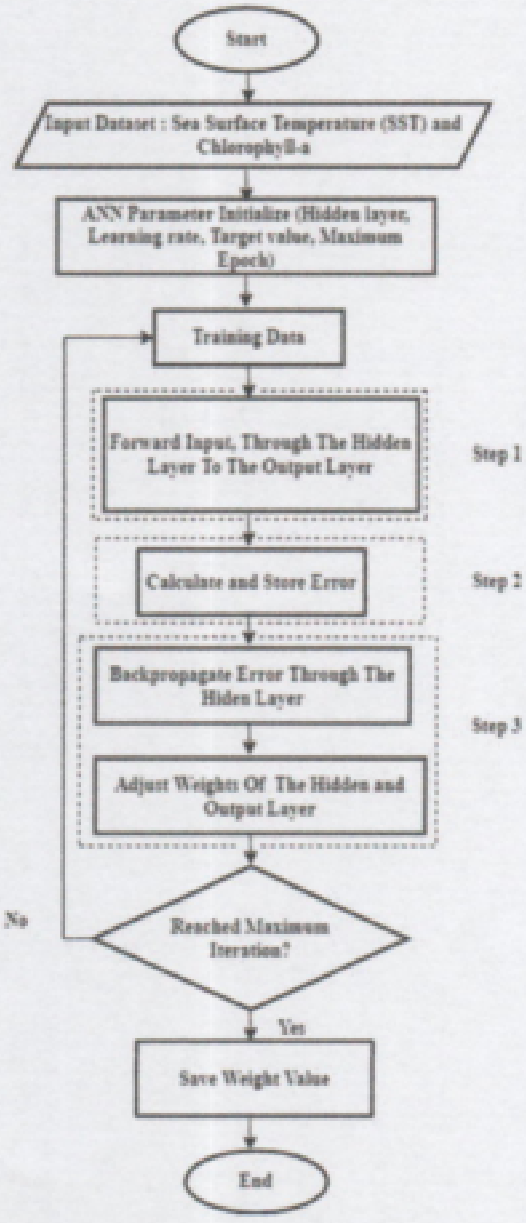


Fig. 4. Flowchart of training data

The backpropagation process includes 3 stages of training, starting with initializing the input weights and creating a random weights for each input unit (X_i,i= 1,....), followed by receiving the input signal x_i and spreading the signal throughout the hidden unit, and calculating all outputs in the hidden unit as in Fig. 4.

- Step 1

Forward propagation stage or commonly referred to as the "forward" calculation process from the input (x) until the output model (y) is obtained. The equation used at this stage is as follows:

$$y_j = \sum_{i=1}^{N} w_{ij} X_i + b_i \quad (1)$$

Where, w_{ij}: weight from input layer to first output value X_i : Input nodes, b_i: bias value

Sigmoid Activation Function:

$$\sigma(x) = \frac{1}{1+e^{-x}} \quad (2)$$

Where, x: sigma symbol in the activation function, e:constant value = 2.718.

- Step 2

Calculation of the error value, because the purpose of the ANN is to produce a predicted value that is as close as possible to the actual value. The equation used is as follows:

$$Error = \frac{1}{n}\sum_{i=1}^{n}(target - predicted)^2 \quad (3)$$

- Step 3

Improved error value with backpropagation. The main formula for correcting a w_ij weight based on the error value, namely:

$$W_{new} = W_{old} - \alpha \frac{\partial E}{\partial W} \quad (4)$$

Where, W_{new}: new weight value, W_old: current weight value, α: learning rate, $\frac{\partial E}{\partial W}$= partial derivative (E) of (w).

5) Testing and Result

The data testing process uses the weight values from the results of the data training process, resulting in the classification of potential and non-potential coordinate points.

This testing process is carried out on 8,700 data and then compared with the target value, if the weight value is met in accordance with the target value, the final result is potential, if it does not meet the target value the result is not potential. Fig. 5 depicts the flowchart of the data testing process.

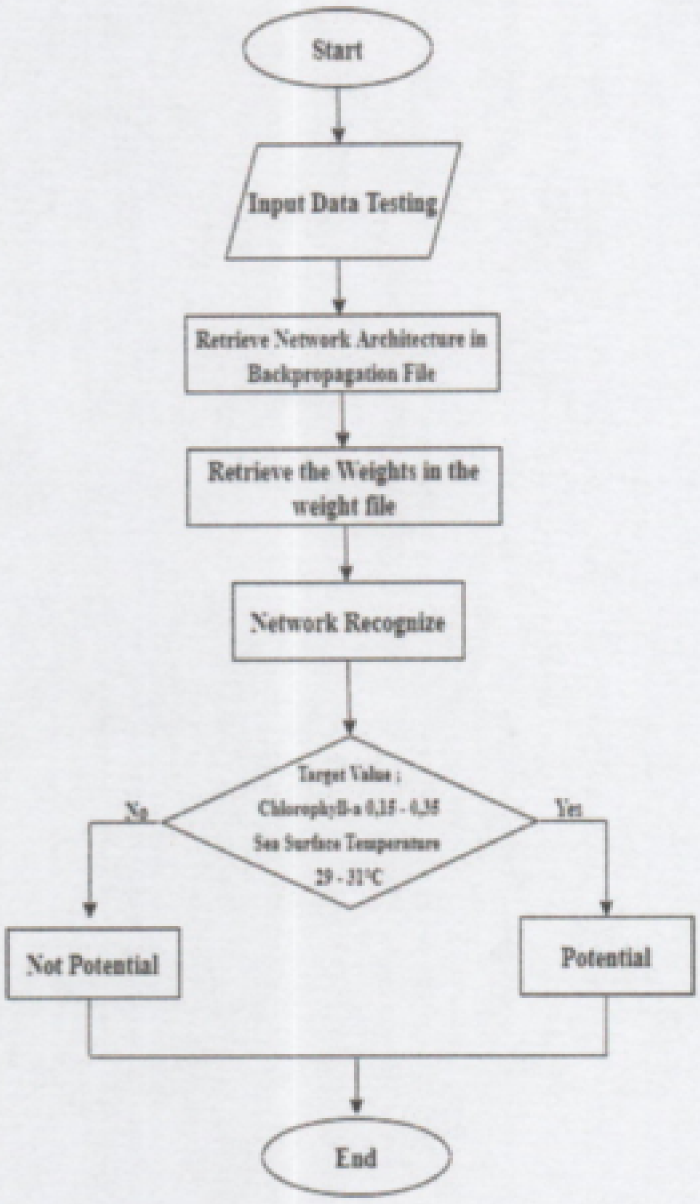


Fig. 5. Flowchart of testing data

B. Parameter Performance System

The developed system's performance is measured by evaluating the classification results using a confusion matrix, namely precision value, recall value, F1-score value, and accuracy value, as shown in equations (5-8).

$$Precision = \frac{TP}{TP+FP} * 100\% \tag{5}$$

$$Recall = \frac{TP}{TP+FN} * 100\% \tag{6}$$

$$F1-score = 2x\,\frac{Precision\ x\ Recall}{Precision+Recall} * 100\% \tag{7}$$

$$Accuracy = \frac{TP+TN}{N} * 100\% \tag{8}$$

in which:

- True Positive: predicts the positive and it is correct
- False Positive: predicts the positive but is incorrect.
- True Negative: predicts a negative outcome, which is correct.
- False Negative: predicts the negative and is incorrect.

As demonstrated by the formula (5), the precision value obtained by comparing the TP results with the volume of data is predicted to be positive, whereas the recall as stated in formula (6) value obtained by comparing the TP results with the volume of data is actually positive; The F1 score will then be calculated by averaging the precision and recall values, as stated in formula (7). The accuracy value is calculated by adding the TN and TP values, then dividing that result by the total quantity of data as stated in formula (8). The accuracy value is calculated by adding the TN and TP values, then dividing that result by the total quantity of data as stated in formula (8).

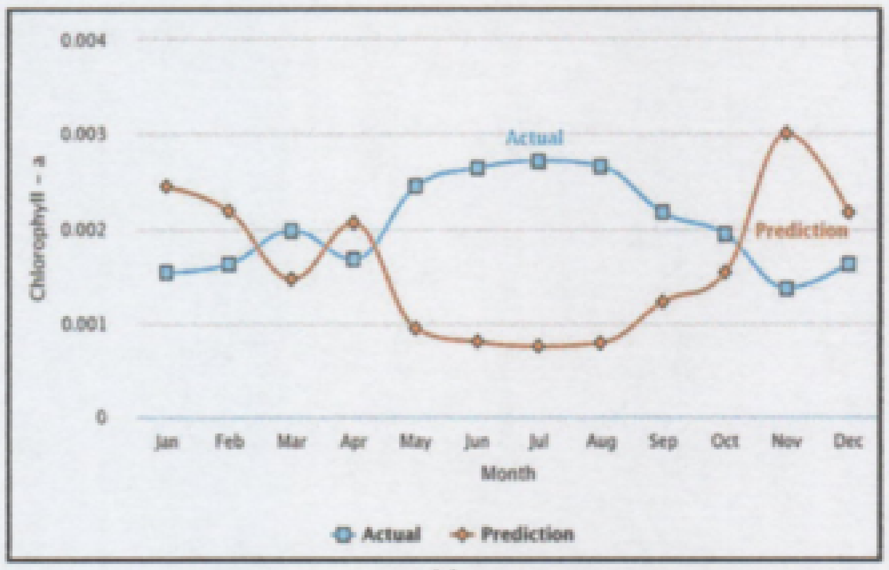
IV. Results And Discussion

Skipjack tuna distribution is dynamic and not fixed because it follows the physiological conditions and nutrients required by the fish, with a Sea Surface Temperature (SST) value of 29 - 31°C and a chlorophyll-a concentration of 0.15-0.35 mg/m^{-3}.

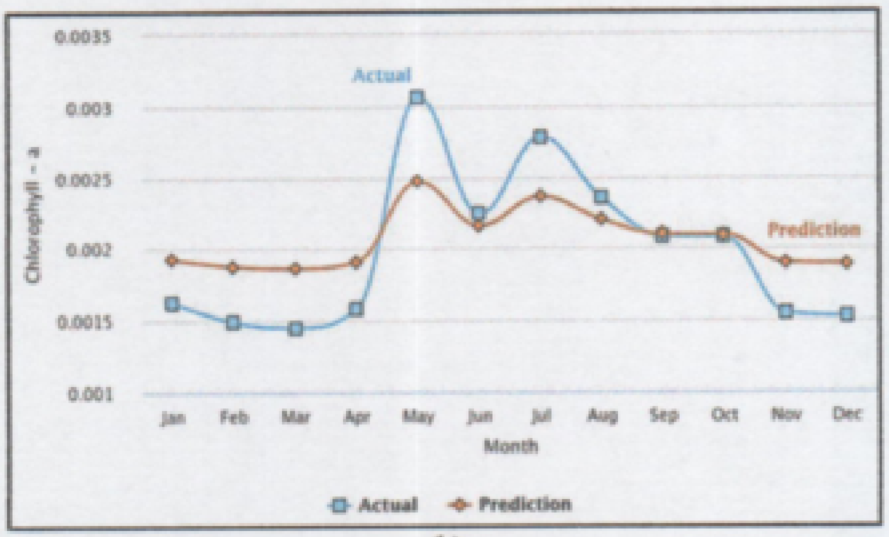
Based on previous research, skipjack fishing areas are still determined manually and not computerized thus, this study proposes a potential forecasting system for skipjack catching points based on oceanographic parameters, namely Chlorophyll-a and Sea Surface Temperature, using the backpropagation algorithm.

The training process is described in the Fig. 4. and the testing process is described in Fig. 5. Data analysis is carried out at each coordinate point in this process Backpropagation is designed and trained to recognize the value of chlorophyll-a and SST every month which consists of 34,800 training data and 8,700 test data.

Fig. 6 a, b, and c are the graph of chlorophyll-a training data analysis at coordinates -4.0208335 South Latitude, 121.02083 East Longitude (2018 - 2020).



(a)



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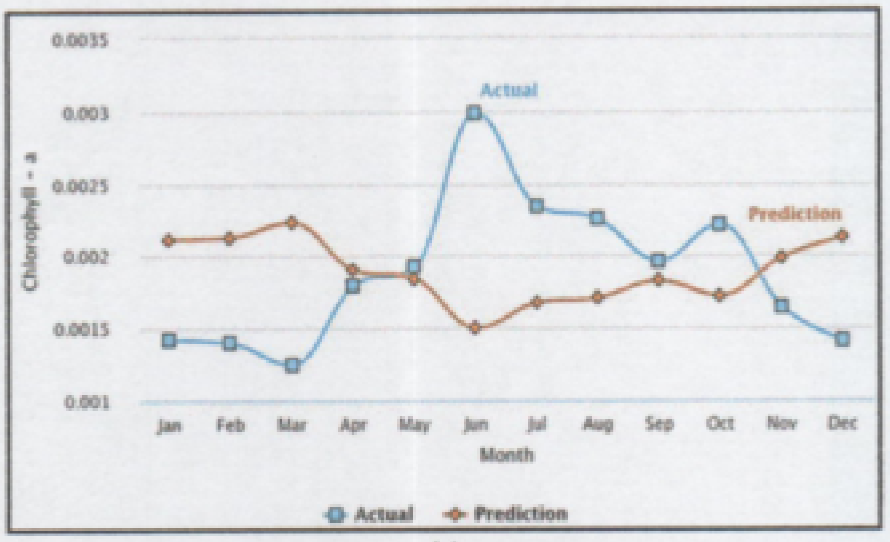
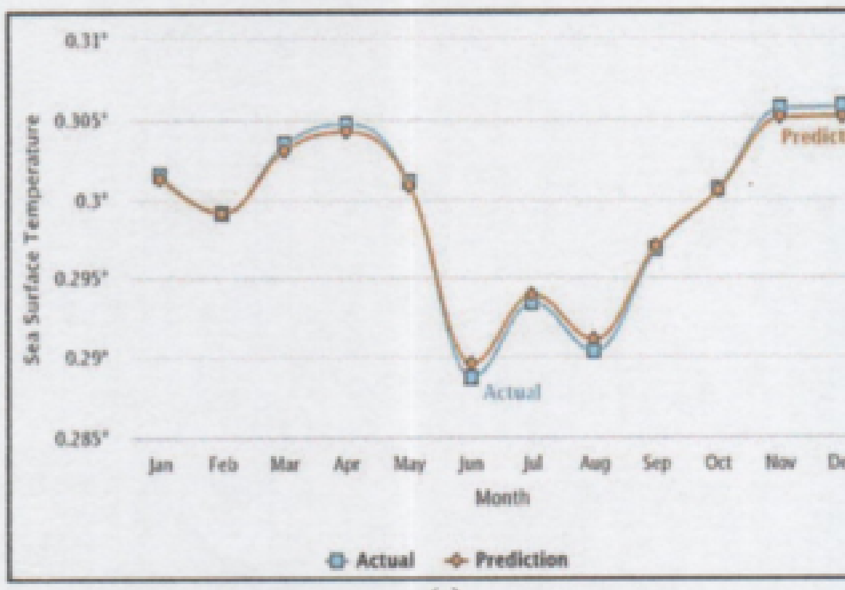


(c)

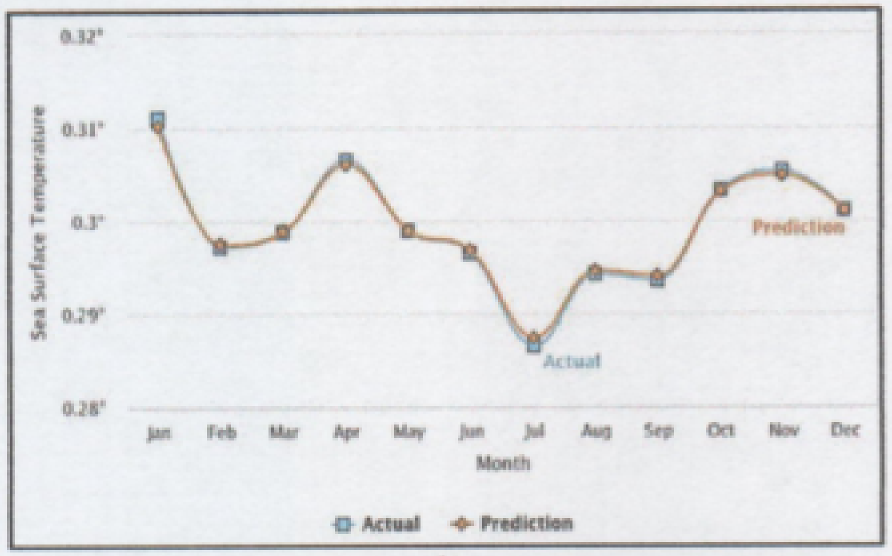
Fig. 6. Analysis of chlorophyll-a at point 4.0208335 South Latitude, 121.02083 East Longitude in 2018 (a), 2019 (b), 2020 (c)

In Fig. 6 a, b, c graph of training analysis of chlorophyll-a content in Bone waters, South Sulawesi, changes in the concentration of chlorophyll-a each year at the coordinates of 4.0208335 South Latitude, 121.02083 East Longitude, while the content of chlorophyll-a is not fixed or constant is influenced by natural factors, one of which is natural upwelling factors.

For the lower chlorophyll-a concentration in January-March where the number of nutrients is also less, the increase in chlorophyll-a content occurs in April-August, and in September-December tends to be normal where the amount of chlorophyll-a in that month is the amount chlorophyll-a which is preferred by skipjack tuna.



(a)



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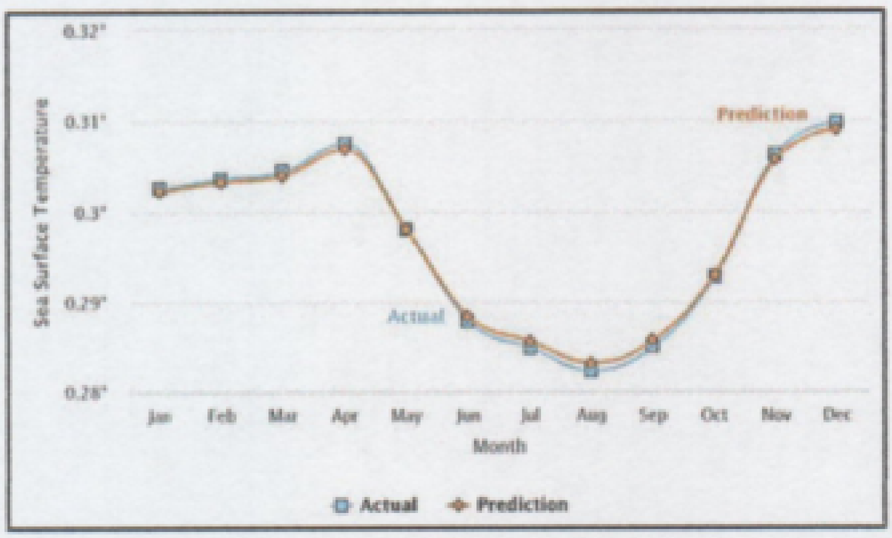
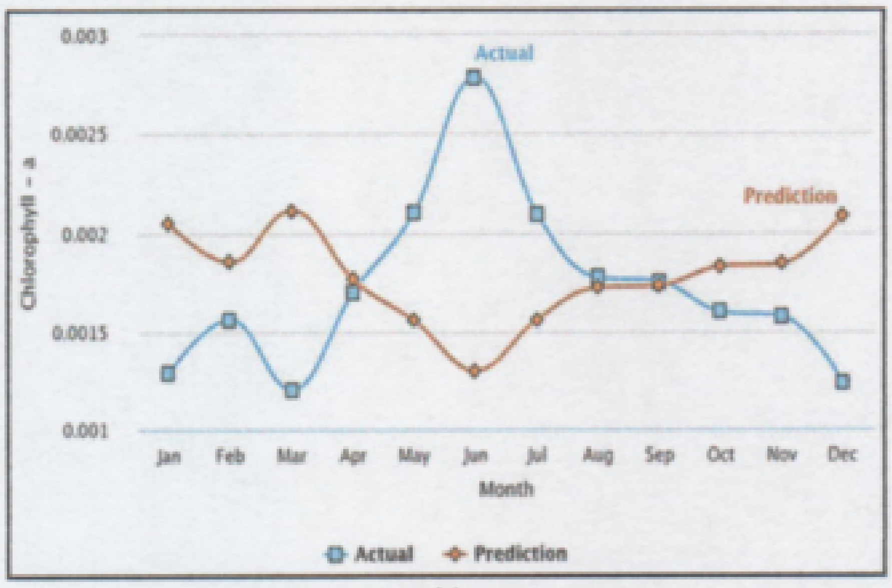


(c)

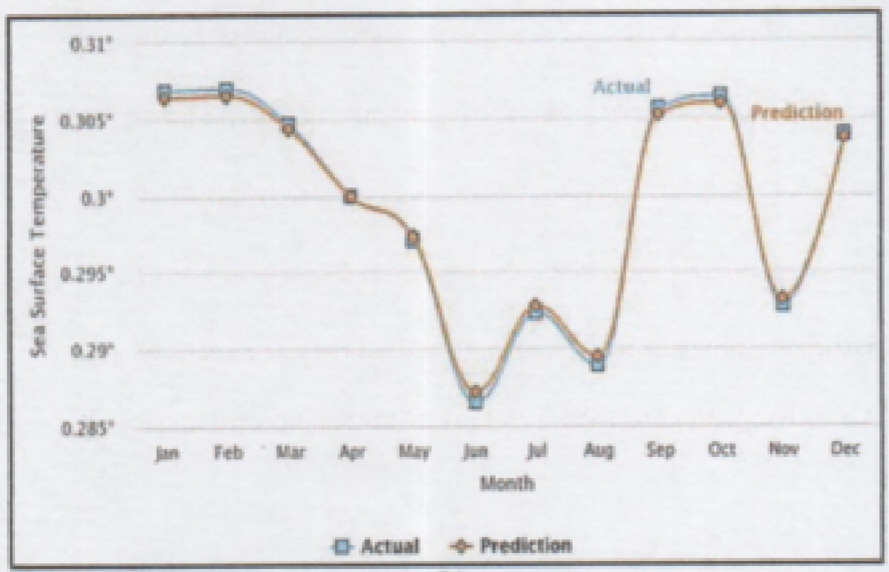
Fig. 7. Analysis of sea surface temperature (SST) at point 4.0208335 South Latitude, 121.02083 East Longitude in 2018 (a), 2019 (b), 2020 (c)

Analysis of the sea surface temperature (SST) training in Fi. 7. a, b, and c looks constant and does not see much change every year, the SST condition in Bone waters increases in February - April and decreases in May - September, then rises again in October - December.

After the training process, next is the testing process as described in Fig. 8. the weight value stored in the database is tested to find out whether the data can be recognized or not, which is adjusted to the actual value of the test results as shown in Fig. 6. a and b.



(a)



(b)

Fig. 8. Chlorophyll-a training at 4.0208335 South Latitude, 121.02083 East Longitude (a), Sea Surface Temperature Training (b)

After the training and test data process was carried out, the next step was to classify the coordinates of the potential (P) and non-potential (NP) points for skipjack fishing, Sea Surface Temperature (SST).

TABLE II. SAMPLE PREDICTION RESULT ON COORDINATE POINT 4.0208335 SOUTH LATITUDE, 121.02083 EAST LONGITUDE

Month	Coordinate Point	Prediction		Prediction Result
		SST (°C)	Chlorophyll-a (mg/m^{-3})	
1	4.0208335, 121.02083	30,30	0,24	P
2		30,50	0,22	P
3		30,50	0,20	P
4		30,30	0,30	P
5		29,90	0,10	NP
6		29,30	0,10	NP
7		28,80	0,10	NP
8		29,30	0,10	NP
9		29,00	0,13	NP
10		30,40	0,15	P
11		30,50	0,20	P
12		29,30	0,20	P

Table II describes predictions at one of the coordinate points, namely -4.0208335 South Latitude, 121.02083 East Longitude, for 12 months. Prediction results show that 4 months (January - April) at the beginning of the year and 3 months (November - December) at the end of the year are the potential time for skipjack catching, while 5 months (May - September) in the middle of the year are considered not to be potential for skipjack fishing, referring to oceanographic data, namely chlorophyll-a and Sea Surface Temperature (SST).

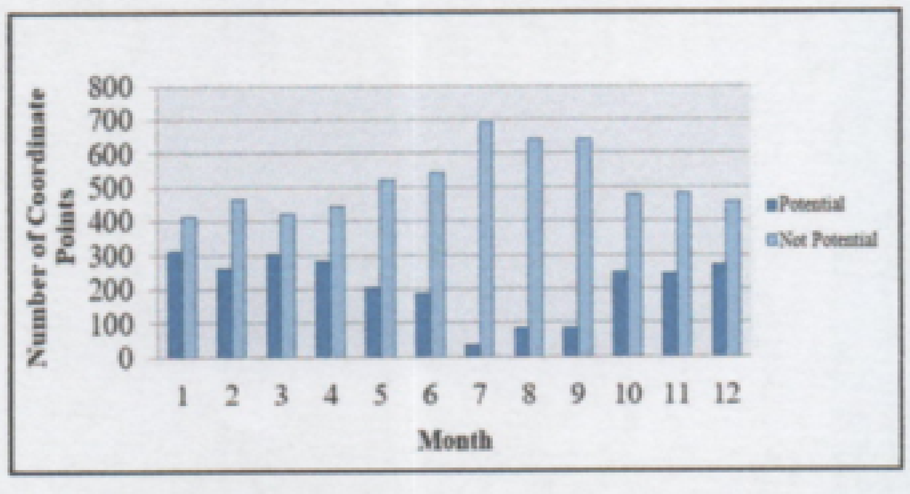


Fig. 9. Prediction number of potential and not potential in 2022

Fig. 9. explains that skipjack catches are considered good from January to May and October to December based on SST and Chlorophyll-a parameters which are by the physiological conditions and nutritional needs of skipjack tuna. Previous research suggests that fishing zones may form during the first transitional season, especially in May, and during the western season, especially in November. During these months, the specific SST is around 30°C, and the density of chlorophyll-a is 0.23 mg/m^{-3}. Most skipjack fishing areas have the potential to develop along with their oceanographic characteristics [13].

Applying this forecasting system is beneficial in temporarily determining the skipjack fishing calendar to increase the effectiveness and efficiency of costs, time and effort.

System performance was measured by evaluating the classification results using a confusion matrix, with a total data of 8,700, which was assessed based on precision, recall, F1-score and accuracy values.

TABLE III. CALCULATION RESULT OF CLASSIFICATION

	Confusion Matrix			
Month	TP	TN	FP	FN
1	328	363	30	4
2	269	407	28	21
3	333	347	43	2
4	321	358	44	2
5	227	447	51	0
6	175	505	45	0
7	16	692	17	0
8	52	661	1	11
9	71	630	24	0
10	252	444	29	0
11	287	396	42	0
12	259	415	51	0
Total	**2590**	**5665**	**405**	**40**

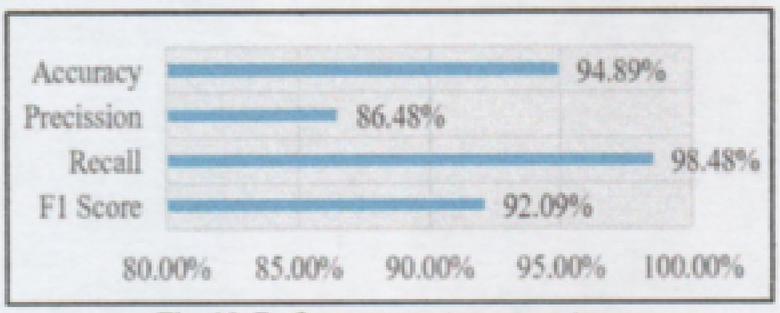


Fig. 10. Performance system percentage

V. CONCLUSION

This study proposed a forecasting system for the temporal distribution of skipjack potential points using the Artificial Neural Network algorithm, due to oceanographic satellite imagery data, namely density of chlorophyll-a and sea surface temperature, with a total of 8,700 data. The test results show that the best period for catching skipjack tuna is from January to May and October to December, which has a good association with the physiological condition and nutrient requirements of skipjack tuna.

Measurement of system performance utilized a confusion matrix. The measurement results revealed that precision value was of 86.48%, recall value was of 98.48%, F1-score was of 92.09% and the system accuracy was of 94.89%, respectively. This research is expected to contribute to the improvement of science and technology in the field of prediction of potential skipjack fishing areas using oceanographic variables.

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