Detecting Potential Fishing Zones Using Machine Learning

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ABSTRACT

Today, locating the right fishing spots is one of the most critical factors, especially in the fishing industry. Technically, a variety of tools have used the marine environment to forecast fishing spots, with others using different aquatic indicators to classify possible fishing zones. Our goal in this study is to provide better results when using SST, SSC, and SLP to determine fishing spots. The proposed method applies classification algorithms on oceanographic parameters of our dataset. The study uses Decision Tree, Random Forest, K-Nearest Neighbor, and Support Vector Machine for the prediction. Results shows that among the algorithms applied, Random Forest has an outstanding 96% accuracy rate, and declared to be the highest accuracy rate among classifying algorithms used. Also, the study was also compared with existing studies. Fortunately, our study has an improved accuracy score than these previous work applied. Hence, our study delivers an improved model in predicting potential fishing area considering oceanographic characteristics such as SST, SSC, and SLP.

Keywords

Machine Learning, Potential Fishing Zones, Oceanographic Data, SST, SSC, SLP, classification algorithms, Randomized Search.

1. INTRODUCTION

Today one of the most critical factors, especially in the fishing industry, is locating the right fishing spots. There are different kinds of techniques to find the right fishing spots. Some fishermen use [2] natural features such as flying seabirds, schools of dolphins, bubbles on the surface, wood, or other floating objects on the surface as a guide in locating the fishing area. On the other hand, some uses ocean condition maps (e.g., sea temperature maps) for deciding where to go fishing. They find specific structures of the ocean, such as warm water eddies, which would be highly related to good fishing spots [1]. According to Nurdin et al in 2015, traditional fishing methods based on repeated experience and the collection of knowledge from fellow fishermen are used to assess the fishing location. Jufri et al also discuss observing the conditions of the aquatic environment with its five senses is one of the traditional ways of evaluating a fishing area. However it is practically difficult to rely on it because of the limitation of five senses to address the different challenges of natural phenomenon. According to Semedi & Hadiyanto, the identification of fishing grounds depends not only on experience, but also on the knowledge of fish habitat. The ecosystem of fish is closely connected to certain oceanographic properties, such as the temperature of the sea surface and the chlorophyll-a of the sea surface. For this reason, a technological-based method is essential in optimizing of finding fishing ground in such area.

Many technologies used the marine environment in predicting fishing spots. [1] Since the marine environment is an important clue to estimate fishing spots in fisheries science, many attempts have been made to discover the mechanism of the ecology of fish. In the Philippines, [4] the researchers use nightly boat detection data, extracted by U.S. NOAA from the Visible Infrared Imaging Radiometer Suite (VIIRS), for the Philippines from 2012 to 2016, covering 1713 nights, to examine Spatio-temporal patterns of fishing activities in the country.

A study of Guyader et al. in 2018 [15] focuses on mapping dredge gear fishing grounds using fishing intensity estimates at the métier level based on automatic identification system (AIS) data. The capacity of the system to distinguish between fishing and non-fishing activities and error propagation through the methodological framework has been checked against established fishing positions. The testing was carried out in the Bay of Brest (France) in collaboration with a local fishermen's committee. With this, the study findings establish fishing grounds for dredging of big scallops (Pecten Maximus) in the western part of the Bay of Brest.

There are various of technologies and aquatic indicators to determine potential fishing zones. In this study, we used machine learning and oceanographic data such as sea surface temperature (SST), sea surface chlorophyll (SSC), and sea level pressure (SLP) to find the right fishing spots. Oceanographic parameters like SST and SSC are essential for fishing ground. These parameters show a strong correlation with specific aquatic environments [3]. The goal of this research is to provide better results in determining fishing spots using SST, SSC, and SLP. There are various methods to identify PFZ in a specific location by utilizing the characteristics derived from remote sensing data [3]. This research focuses on oceanographic factors (SST, SSC, SLP) to estimate the potential fishing zone. Then we apply different kinds of classification techniques to find the best model in our study. Finally, result analysis is then described.

2. REVIEW OF RELATED LITERATURE

This chapter presents various studies and literature regarding the detecting of potential fishing zones, and the aquatic parameters to be used in our study.

2.1 Related Works Concerning Potential Fishing Zones

Many attempts of using different techniques to address this problem. Mudliar et al. in 2019, studied the Seasonal

Autoregressive Integrated Moving Average (SARIMA) to obtain the two parameters, dissolved oxygen, and salinity. This study is to utilize the Indian fishing vessel track dataset together with dissolved oxygen and salinity to do the prediction. [5] The results show that these two parameters enable the detection of potential fishing zones and help fishermen for a better catch.

In the study of Geronimo et al. in 2019, Satellite images were used during the night to detect fishing grounds in the Philippines for fishing gear that uses powerful lights to attract pelagic coastal fish. The researchers [4] used nightly boat detection data, extracted by U.S. NOAA from the Visible Infrared Imaging Radiometer Suite (VIIRS), for the Philippines from 2012 to 2016, covering 1713 nights, to examine Spatio-temporal patterns of fishing activities in the country. The result shows 134 core fishing areas (CFAS) were identified within the Philippines' maritime zones. [5] This case study highlights nighttime satellite images as a useful source of spatial fishing effort information for fisheries, especially in Southeast Asia.

Another study by Roy et al. in 2018, uses oceanographic data and classification techniques to predict potential fishing zones. [3] The researchers procured spatiotemporal images from Copernicus Online Data Access (CODA) and then extracted characteristics, Sea Surface Temperature (SST) and Sea Surface Chlorophyll (SSC) with the help of Sentinel Application Platform (SNAP). Results show that these two parameters have a strong correlation and deliver a prediction model of the potential fishing area.

In the same year, the study of Iiyama et al. [1] presents a new machine-learning method for uncovering oceanographic patterns related to good fishing spots. The method utilizes the input of a sea temperature chart, extracts sea temperature patterns from arbitrary points on the map, and assesses if the patterns correspond to good fishing spots. The result shows that this study enables the detection of potential fishing spots with the aid of oceanographic patterns.

2.2 Sea Surface Temperature

Sea surface temperature (SST) is a strong indicator of productivity, pollution, and global climate change, and this can be measured using thermal infrared (IR) bands from optical satellites [6]. SST offers fundamental knowledge on the climate system, it contributes to abundance transitions, food chains, etc., that may have an impact on composition and value. [12] Sea surface temperature can be used as an indicator to determine the existence of a species of fish in waters. Each fish species has a tolerance of a certain temperature range which is favored for its survival so that it influences the presence and spread of fish in the waters.

The study of J. Wang et al. in 2015, uses SST as one of the parameters in detecting fishing ground for O. bartramii. [9] Many studies showed that optimal SSTs for squid varied with fishing months and areas; it appeared that the optimal SST gradually decreased from west to east. The researchers stated that in the development of fishing grounds, the SST was the most significant environmental factor and had the greatest impact on the prediction model, indicating that the SST could be used as a predictor to explore the PFZ.

The study of Nugraha et al. in 2020, stated that [12] determination of the fishing ground can be expected from the oceanographic parameters that are the habitat of a species. SST is one of the indicators to determine the circumstance of a fish species. In this study, sea surface temperatures are an important oceanographic parameter to determine the effect of the length and size of Katsuwonus pelamis and promote the study of possible fishing areas. The result shows that the majority of the catches of K. Pelamis can be located in the 29-30°C temperature range. This demonstrates that the temperature for capturing K. Pelamis is 29-30 ° C sufficient in the Banda Sea. However, [12] Sea surface temperature has no significant effect on the number and size of caught K. Pelamis in the Banda Sea.

Another study of Apriliani et al. aims to improve the effectiveness of catches by identifying potential fishing zones for hairtail fishing in Pangandaran, West Java, Indonesia. The study stated that different factors that determine the success of fishing operations help the optimization of fishing activities. The discovery of fishing grounds is one of the deciding factors. [14] This fishing ground has certain parameters such as sea surface chlorophyll-a, sea surface temperature, and sea surface salinity which can be utilized for efficient and optimum fishing operation. Based on study findings it can be concluded that there are 7 potential fishing grounds for hairtail in the Pangandaran Regency. These potential fishing grounds were determined with the help of the said oceanographic factors.

In our study, we utilized SST as one of our parameters in detecting PFZ. SST is an important variable especially in weather forecasting and atmosphere model simulations and is also essential for the observation of aquatic ecosystems.

2.3 Sea Surface Chlorophyll

Chlorophyll is recognized as the most important oceanographic factor impacting the marine environment and the natural habitat of fish species [13]. It is a primary form of chlorophyll used in photosynthesis. It absorbs light energy from wavelengths of violet-blue and orange-red light, and it reflects green/yellow light, thus resulting in the observed green color of most plants [6]. [14] Chlorophyll-a in a water is closely related to the food chain, where high chlorophyll-a content will increase zooplankton productivity, thus creating a food chain supporting fish productivity in water.

SSC was also used as input data to generate potential fishing zones for skipjack in the study of Mukti Zainuddin. The ranges SSC of 0.15-0.40 mg mg^{-3} represent the oceanographic range particularly from May to June. This range can be viewed as an initial indicator of the area most likely to detect skipjack tuna in Bone Bay. Study shows SSC provides a good indicator in detecting potential fishing spots for Skipjack Tuna in Bone Bay.

Once more the study of Wang et al. stated [5] chl-a concentration is a good indicator of the food availability for squid. Large concentrations of chl-a create good feeding conditions, providing higher phytoplankton and zooplankton nutrient quantities, as well as dissolved organic materials correlated with food density and availability for the O. bartramii.

In the study of Daqamesh et al. in 2019, [13] a multi-linear regression model for potential fishing zone (PFZ) mapping along the Saudi Arabian Red Sea coasts of Yanbu' al Bahr and Jeddah was developed, using Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data derived parameters, such as sea surface salinity (SSS), sea surface temperature (SST), and chlorophyll-a (Chl-a). MODIS data was also used to validate the model. The results suggest that the model developed during the project may be of great benefit to fisheries in the Red Sea region, and likely even to fisheries in other areas around the world.

2.4 Sea Level Pressure

Sea level pressure is the pressure within the atmosphere of Earth. Pressure in the ocean increases about one atmosphere for every 10 meters of water depth. With these, SLP brings an impact to fish species. The lower the pressure, the less fish will appear in that area. [11] The possible range to determine a suitable for fishing is from 1005.8 - 1029.5.

The study of Zamorov et al. in 2018, stated that one of the most significant variables influencing fish activity is sea-level pressure. The researchers examined the effect of sea-level pressure together with a water temperature of round Roby, Neogobius melanostomus on the study area of coastal water of the Black sea. [10] The result shows that increasing the atmospheric pressure at temperatures 10–24°C influenced the activity of round goby, which then stabilized within one hour. Fish activity then decreased till it matches the level observed before experimental pressure changes. Changes in atmospheric pressure did not influence fish activity at higher temperatures of 26–28°C. In conclusion, the study was intended to determine the effect of sea-level pressure and water temperature of the round Roby. The relation between these two parameters shows a potential mechanism driving the round roby migration.

Another study of Carassou et al. in 2011 [11] conducted in the river-dominated coastal system of the north-central Gulf of Mexico, the researchers investigated the impact of climatic and environmental factors on interannual variability in juvenile abundances of marine fish. Among the factors that we're used in this study is sea-level pressure. The result shows that juvenile fringed flounder abundances were positively correlated with sea-level pressure during summer and fall. Another marine fish, juvenile abundances of southern kingfish were highly associated with sea-level pressure during summer and fall. And lastly, juvenile abundances of hogchokers were strongly correlated with sea-level pressure during summer and fall. In conclusion, this study offers the first study of environmental effects on juvenile fish dynamics in the north-central Gulf of Mexico using a multi-species and multivariable approach.

3. METHODOLOGY

From the discussion mentioned above, we came up with a procedure in utilizing oceanographic parameters in order to determine PFZ. Below are the steps included, which are dataset preparation, data preprocessing, dataset splitting, modeling, model evaluation, and testing. Figure 1 shows the overall methodology of the study.

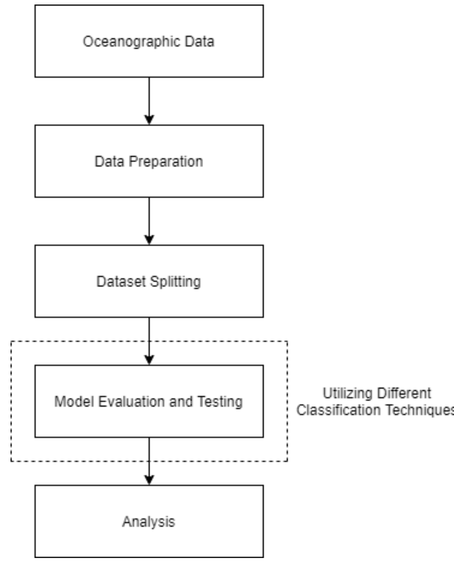

Figure 1. Methodology for detecting PFZs.

3.1 Oceanographic Data

There are various characteristics in determining potential fishing spots. In our study, we utilized SSC, SST, and SLP as a parameter in detecting fishing spots. [3] Oceanographic parameters like Sea Surface Temperature (SST) and Sea Surface Chlorophyll (SSC) are important for fishing ground. Although SST temperature depends on every region, this factor is widely used in determining fishing spots. The primary development of phytoplankton, the first food chain of pelagic animals, has a clear connection with the SSC [3]. In other words, the SSC content can also indicate the degree of fertility in an aquatic environment. And lastly, SLP also affect the aquatic environment for it's changed of temperature brings an influenced to some fishes.

3.2 Data Preparation

The dataset contains year, month, oceanographic parameters such as SSC, SST, SLP and the last is Label (for potential and non-potential fishing zones) and is obtained from Kaggle.com. These data are recorded monthly from year 2007 to 2017. In labeling the data, potential and non-potential fishing zones were defined by expert researchers.

In preparing the dataset, year and month are removed since this has nothing to benefit in feeding the model, the remaining data are SSC, SST, SLP, and label. After that, we utilized normalization on all the attributes in the dataset except for the label. Normalization is a method of rescaling to the range of 0 to 1 for each attributes. It helps to get an overall understanding of how our dataset is distributed.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (1)$$

3.3 Dataset Splitting

The dataset should be partitioned into two subsets: 80% train dataset and 20% test dataset. The training dataset is to fit the model while the test dataset acts as an input element to the model, then produces predictions and compared to the expected values. Figure 2 below represents the train-test split of the study.

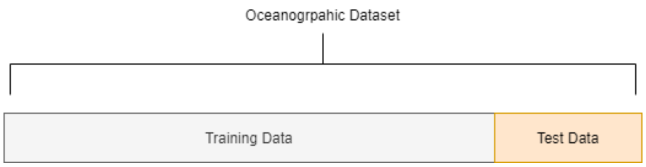

Figure 2. Train-test split scenario.

3.4 Model Evaluation and Testing

This phase is to train several models to define which of them offers the most accurate prediction. The study is composed of supervised machine learning, respectable, we chose 4 different learning algorithms that are under supervised machine learning. The algorithms that we used are Decision Tree, Random Forest, K- Nearest Neighbor, and Support Vector Machine. For various classifications, these algorithms are good and they have their own properties and results. And for the implementation of the study, we utilized Anaconda for implementation of the study and Python 3 as our programming language.

Decision Tree. Decision tree is the most widely used tool for decision making [7]. This learning algorithms can be used in various ways, such as to compare data statistically. It can also be used in classifying or extracting texts. In our study, we utilized this learning algorithm as classifying a potential and non-potential fishing zones.

Random Forest. Random Forest is a regression technique that combines the performance of numerous Decision Tree algorithms to classify or predict the value of a variable [19]. The output is achieved by picking the highest vote among all the individual trees.

K- Nearest Neighbor. K-nearest Neighbor is to classify unlabeled observations by assigning them to the most comparable labeled class [20]. When an unknown variable is to be classified, its nearest k neighbor are identified and the variable are now labeled. KNN are used in several approach, this can be utilized in predicting wind speed, classifying breast cancer, and many others.

Support Vector Machine. Support Vector machine primarily builds a boundary between two categories to determine different classes. This algorithm are applied on both linear and non-linear classification data and have been used for two-class classification. Here in our study, we utilize this algorithm to determine the classes (PFZ, NPFZ) in detecting potential fishing spots with the help of linear SVC.

To estimate the performance of each machine learning algorithms, we utilized Randomized Search Cross-Validation and Confusion Matrix. To train the model and score, Random Search set up a grid of hyperparameter values and choose random combinations. It allows you to control the number of parameter combinations, unlike Grid Search. Random Search fits in our study instead of Grid Search because of computational cost. Grid search spends so much time evaluating the hyperparameter search space's regions because it has to test every single combination in the grid. Random search, on the other hand, does a great job of exploring the search space and can thus typically find a successful hyperparameter combination in far fewer iterations. Figure 3 shows the process of Random Search.

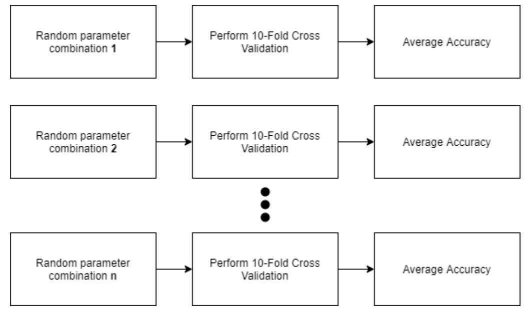

Figure 3. Working of Random Search Cross-Validation.

The study applies K-Fold Cross-validation in evaluating the machine learning techniques. With that, in every given random parameter generated by Random search, k-fold cross-validation is set. K refers to the number of classes that will be split into a given training dataset. In our case, we label our K as 10, which means it splits the training data into 10 folds. Figure 4 represents the scenario of 10-Fold cross-validation.

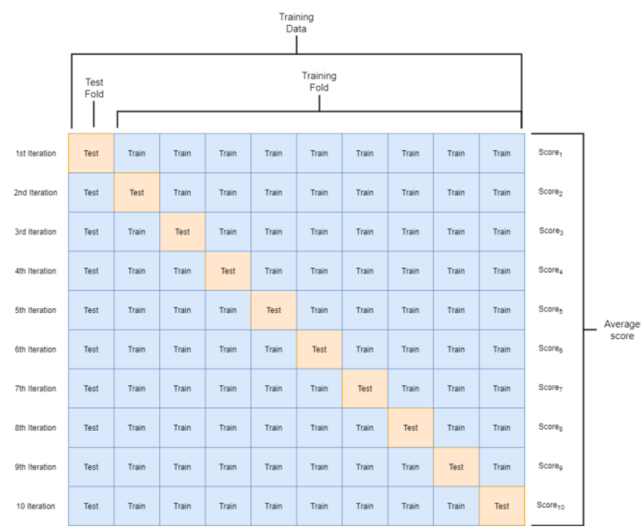

Figure 4. 10-Fold cross-validation.

Figure 5 shows the process of comparing these four classification algorithms namely: Decision Tree, Random Forest, K-nearest neighbor, and Support Vector Machine to determine the fitted model of the study. In this process, there four classification algorithm to compare. In determining the best fitted model for this study, first, is assigning random parameter combinations given by Random search. The number of iteration used in this study is 100. Next is assigning of number of fold to iterate. After assigning the number of fold is the parting of assignments which is the training and test set. In segmenting the data, it will be determined based on the number of fold assigned. The training data will then now feed the assigned classification model following the testing process. The testing process now examines the result and evaluates. After that, it will now increment the K-fold and repeat the same process until the statement has been carried out.

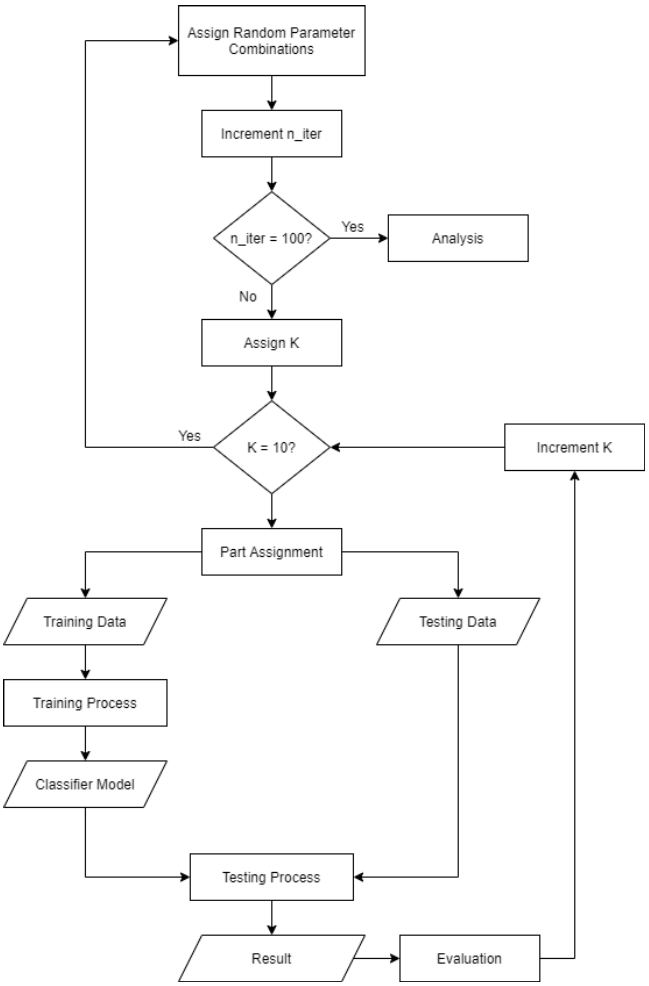

Figure 5. Model Classification Process.

Next, we utilized confusion matrix in visualizing the accuracy of each model. Figure below shows the visualization of the performance of an algorithm.

		Detected	
		Potential	Non-potential
Actual Data	Potential	A	B
	Non-potential	C	D

Table 1. Confusion Matrix

This table is used to define the output of a classification model on a collection of test data that are considered to be true values. To understand the table, here, A is true positive, B is false negative, C is false positive, and D is true negative. A explains that these are the type in which it is predicted to be a potential and actually it is a potential spot. On the other hand, B describes that is it predicted to be a non-potential but clearly it is a potential fishing spots. Furthermore, C represents a detected potential fishing zones but distinctly it is a non-potential fishing spot. Lastly, D label as a detected non-potential fishing spots and clearly it is a non-potential fishing spots.

4. RESULTS AND DISCUSSION

Several studies are still in the development of automated approaches in determining potential fishing zones. The aim of this study is to build a classification model that could produce an improved accuracy compared to previous studies in this area. Here, we compared most of the machine learning algorithms in determining the best model in the study. Figure 6 shows the accuracy comparison between algorithms. These algorithms were evaluated in our dataset. Decision Tree was tested first, it gives a satisfying 95% accuracy rate. Then Random Forest is next to be tested with an achieving 96.52% accuracy rate. Thirdly, K-Nearest Neighbor was performed next to observe further improvement of the result. It achieved an accuracy of 73%, far from the accuracy gained by Random Forest. Lastly, Support Vector Machine was performed garnered an underperforming accuracy of 56.9% or nearly 57%.

Among the algorithms tested in the study, it can be confirmed that Random Forest achieved the highest accuracy rate and performs better than the rest of the algorithms used. So, it can be concluded that RF is a best model to be used in this study.

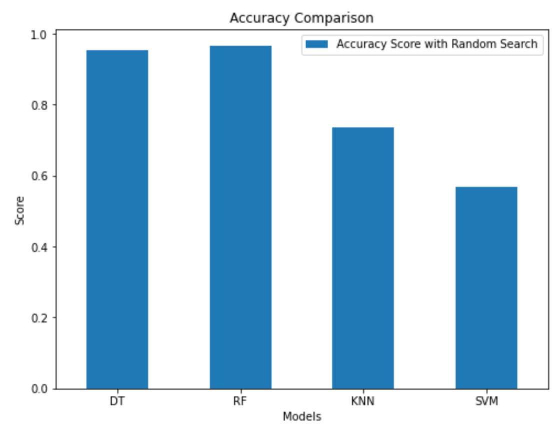

Figure 6. Accuracy Comparison.

References	Accuracy Score
Wang, J., Yu, W., Chen, X., Lei, L., & Chen, Y.[8]	80%
Devi Fitrianah, Remmy A.M. Zen, and Nursidik Heru Praptono. [21]	92.75%
Zhu, J., Xu, J., Zhang, C., & Gao, Y. [22]	80.7%
Proposed Study	96.52%

Table 2. Performance of the proposed study with existing work.

After acquiring the accuracy result, the study is then compared with existing works. The table above shows the comparison between previous studies in terms of accuracy score. In particular, our model was able to achieve a substantially higher accuracy than the rest. It can be declared that our proposed study can detect PFZ's well than these previous studies.

5. CONCLUSION

This goal of this study was to provide improve results in determining potential fishing zones. Several algorithms were used to discover a best model in the study. Then, each model is applied to the field of PFZ Prediction. Results shows that among the algorithms applied, Random Forest has an outstanding 96% accuracy rate, and declared to be the highest accuracy rate among classifying algorithms used. Also, the study was also compared with existing studies. Fortunately, our study has an improved accuracy score than these previous work applied. Hence, our study delivers an improved model in predicting potential fishing area considering oceanographic characteristics such as SST, SSC, and SLP. For future PFZ prediction, new oceanographic parameters may be added. To improve efficiency, other prediction methods can also be implemented.

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