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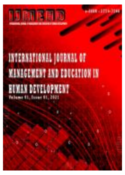

Water Mass Fingerprint Detection Using Machine Learning for the Sustainability of Capture Fisheries Economy in Southeast Sulawesi

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ABSTRACT

*Capture fisheries in Southeast Sulawesi play a strategic role in supporting regional food security and economic development. However, its utilization still faces challenges due to the limited availability of accurate and sustainable spatial data. This study aims to map the spatial distribution of fisheries potential in the waters of Southeast Sulawesi using a quantitative machine learning approach. The method employed is the Multi-Layer Perceptron (MLP) algorithm, trained using key oceanographic variables including sea surface temperature, chlorophyll-a, salinity, ocean currents, sea level height, seafloor topography, and vessel activity data from the Vessel Monitoring System (VMS)***.** *All datasets were extracted through Google Earth Engine (GEE)***,** *processed in Python (scikit-learn) through normalization, outlier handling, and minority class oversampling, and visualized as regional fingerprint maps in QGIS***.** *The results reveal a high degree of spatial heterogeneity, with the highest fisheries potential concentrated in the southern and southeastern parts of Southeast Sulawesi. The economic valuation analysis of six fisheries potential classes identified a total area of approximately 15.8 million hectares, with an estimated economic value of IDR 1.18 trillion. The highest class (Class 5) accounts for 44% of the total area and contributes about IDR 376.6. The integration of machine learning and spatial data provides a comprehensive understanding of the marine and fisheries potential distribution, serving as a strategic foundation for developing sustainable fisheries management policies in Southeast Sulawesi.*

Keywords: *Fisheries Potential, Machine Learning, Multi-Layer Perceptron*

I. INTRODUCTION

Southeast Sulawesi is an archipelagic province located at the heart of eastern Indonesian waters, with more than 70% of its area consisting of marine territory. The region spans two Fisheries Management Areas (WPP 713 and 714), covering the Bone Gulf, Tolo Gulf, Banda Sea, and Flores Sea, making it a strategic hub for national fish supply as well as a primary pillar of the regional marine economy. The agriculture, forestry, and fisheries sectors contribute nearly one-quarter of the Gross Regional Domestic Product (GRDP) of Southeast Sulawesi, highlighting their role as the backbone of the local economy (BPS, 2025). However, despite its vast potential, capture fisheries in Southeast Sulawesi face serious threats, particularly the loss of marine biodiversity. High fishing intensity often leads to bycatch, including juvenile fish and non-commercial species, which accelerates ecological pressure (Budiman et al., 2023).

In addition, one of the main challenges in fisheries management is the lack of knowledge regarding the spatial distribution of fisheries potential. Marine areas are not homogeneous; some zones exhibit high productivity, while others are relatively low. These variations are influenced by biophysical and oceanographic factors, such as chlorophyll-a concentration as an indicator of primary productivity, sea depth, current dynamics, salinity, sea surface temperature, and proximity to critical ecosystems such as coral reefs. Without a detailed spatial understanding, fisheries management risks becoming inefficient, exploitation zones may be misallocated, and marine economic potential may not be optimally utilized. This aligns with the findings of Rintaka and Susilo (2018), who demonstrated a strong relationship between oceanographic parameters and fish presence through fishing zone validation.

To address this need, the concept of water mass fingerprints is introduced as a method to identify the unique characteristics of each marine area. This approach integrates multiple environmental variables into a single spatial representation, enabling the classification of zones with high, medium, and low fisheries potential. With such fingerprinting, policymakers can establish more precise marine zoning, including intensive fishing zones, conservation areas, and transitional zones. This approach not only supports marine ecosystem sustainability but also promotes green economy-based regional development, as proper zoning maximizes economic value without degrading natural resources. The integration of environmental data and remote sensing has proven effective in identifying fish habitats and aggregation zones, thereby supporting spatial-based sustainable fisheries management (Belkin, 2021).

This approach is particularly important for fisheries management in Southeast Sulawesi. By understanding the spatial distribution of fisheries potential, local governments and stakeholders can determine priority fishing areas, optimize marine economic contributions, and implement appropriate conservation strategies. Such management enhances fish stock resilience and policy effectiveness amid environmental changes and exploitation pressures (Holsman et al., 2020). For instance, highly productive areas can be designated as primary fishing grounds with sustainable harvesting regulations, while low or transitional areas can be assigned as conservation or recovery zones to maintain ecosystem balance. Furthermore, integrating productivity data with economic valuation enables the formulation of policies that support green economy-based regional development, ensuring that economic growth aligns with environmental sustainability.

On the other hand, advancements in machine learning technology, particularly the Multi-Layer Perceptron (MLP) algorithm, enable more precise mapping of water mass fingerprints. MLP is capable of capturing complex non-linear relationships among oceanographic and ecological variables, producing accurate maps of fisheries potential distribution. These maps not only indicate fish locations but also reveal gradients of productivity from high- to low-index areas, forming a basis for spatial planning and economic valuation. The capability of machine learning approaches to extract complex patterns from image and environmental data is consistent with the findings of Buehler et al. (2019), who showed that computer vision techniques can automatically extract essential information from visual data to improve object identification accuracy in ecological studies.

Machine learning approaches have demonstrated high effectiveness in mapping potential fishing zones. Sivasankari et al. (2022) developed a satellite image-based HE-DFNETS architecture to detect Potential Fishing Zones (PFZ) in the Indian Ocean, achieving higher accuracy than conventional methods. Furthermore, Xie et al. (2024) adapted a modified U-Net model utilizing multi-layer environmental variables (such as sea surface temperature, salinity, and chlorophyll-a), significantly improving spatial prediction accuracy for fishing zones. These studies confirm that neural network-based modeling offers significant advantages in capturing complex non-linear patterns in fisheries data.

Therefore, this study positions the mapping of water mass fingerprints in Southeast Sulawesi using an MLP-based approach as a scientific foundation for fisheries management, marine zoning, and sustainable regional development. The resulting spatial distribution maps of fisheries potential will illustrate spatial variability, support economic valuation, and provide a basis for evidence-based policymaking. This approach not only addresses current fisheries management challenges but also opens opportunities for Southeast Sulawesi to optimize its marine resources sustainably, in line with blue and green economy principles.

II. LITERATURE REVIEW

2.1 Marine Fisheries Potential and Oceanographic Variability

Marine fisheries productivity is strongly influenced by oceanographic and ecological variability that determines fish distribution and abundance. Southeast Sulawesi, as an archipelagic region located within Fisheries Management Areas (WPP 713 and 714), exhibits high marine heterogeneity that contributes to variations in fisheries potential. According to Belkin (2021), ocean fronts derived from remote sensing data play a critical role in shaping marine ecosystems by enhancing nutrient availability and aggregating fish populations. These dynamic environmental conditions create spatially heterogeneous fishing grounds that require adaptive management approaches.

However, despite its high potential, fisheries resources in Indonesia face ecological pressures. Budiman et al. (2023) highlight that declining fish production is closely associated with overfishing intensity and ecosystem degradation, including the capture of juvenile and non-target species. Such pressures threaten long-term sustainability and emphasize the importance of spatially informed fisheries management. Furthermore, Holsman et al. (2020) emphasize that ecosystem-based fisheries management is essential to prevent climate-induced stock collapse and ensure long-term resilience of marine resources.

2.2 Remote Sensing and Spatial Fisheries Analysis

Advancements in remote sensing technology have significantly improved the ability to analyze marine environments at large spatial scales. Oceanographic variables such as chlorophyll-a, sea surface temperature, salinity, and current dynamics are widely used as indicators of marine productivity. These variables allow researchers to identify potential fishing zones and ecological hotspots with greater precision.

Rintaka and Susilo (2018) demonstrate that fishing zone validation shows a strong relationship between oceanographic parameters and fish presence, confirming the relevance of environmental variables in fisheries modeling. In addition, Belkin (2021) emphasizes that satellite-based ocean front detection is a powerful tool for identifying productive marine areas that support fish aggregation. These findings highlight the importance of integrating spatial data for effective fisheries resource assessment and management.

2.3 Machine Learning in Marine Resource Modeling

The application of machine learning in marine science has grown rapidly due to its ability to model complex, non-linear relationships in environmental systems. Neural network-based approaches such as the Multi-Layer Perceptron (MLP) have been widely used in environmental prediction and classification tasks.

Heddam (2016) demonstrates that MLP can accurately model phycocyanin pigment concentration in river systems, showing its capability in handling complex hydrological data. Similarly, Sarinah et al. (2019) apply MLP combined with Interval Type-2 Fuzzy Sets to map potential seaweed aquaculture areas, indicating its flexibility in managing environmental uncertainty. In fisheries applications, Sivasankari et al. (2022) developed a hybrid deep neural network model (HE-DFNETS) for detecting potential fishing zones, achieving higher accuracy compared to conventional methods. Furthermore, Xie et al. (2024) show that deep learning models incorporating multiple environmental variables significantly improve spatial prediction accuracy in fishing ground detection.

III. RESEARCH METHOD

3.1 Research Approach

This study adopts a quantitative approach based on machine learning, utilizing the Multi-Layer Perceptron (MLP) algorithm. As a type of artificial neural network, MLP is capable of identifying and disentangling multilayer relationships among marine environmental variables such as chlorophyll-a, salinity, sea surface temperature, and current velocity, which are often difficult to capture using classical statistical methods. Its effectiveness has been demonstrated in hydrological studies, such as the prediction of phycocyanin pigment concentrations in the Charles River, Massachusetts, where MLP achieved high accuracy using time-series datasets (Heddam, 2016). Furthermore, MLP has been applied to map potential seaweed aquaculture areas in combination with Interval Type-2 Fuzzy Sets, highlighting its flexibility in handling uncertainty in tropical aquatic environments (Sarinah et al., 2019).

The implementation of MLP modeling in this study is carried out through the integration of three main platforms: Python, QGIS, and Google Earth Engine (GEE). Python serves as the core programming environment for MLP implementation, including network architecture design, model training, and evaluation. GEE is utilized to efficiently access and extract high-resolution satellite data (such as chlorophyll-a and sea surface temperature) through Python-based scripts, enabling effective management of large-scale spatiotemporal datasets. QGIS is subsequently employed for more advanced spatial analysis, including spatial data processing and visualization of marine fingerprint maps. This integrated methodological framework aligns with current trends in marine science, where the integration of machine learning and satellite imagery through platforms such as GEE continues to grow rapidly, facilitating large-scale analytical applications in ocean forecasting (Heimbach et al., 2025).

3.2Data and Data Sources

This study utilizes a combination of oceanographic, ecological, and spatial data relevant to the development of a water mass fingerprint detection model. The data are obtained from various reliable sources, including remote sensing products and global oceanographic models, enabling the representation of the spatiotemporal conditions of Southeast Sulawesi waters. The selected variables are chosen based on their direct relationship with marine primary productivity, fish distribution, and aquatic environmental dynamics. The details of the data and their sources are presented in the following table.

Table 1. Data and Data Sources

No.	Data	Data Sources	Provider	Unit	Resolution
1.	Availability of Fishing Vessels	*Vessel Monitoring System* (VMS)	*Global Fishing Watch*	$hour/km^2$	1000 m
2.	Seafloor Topography (sft)	ETOPO 1: *Global 1 Arc-Minute Elevation*	NOAA	m	1855 m
3.	Sea Surface Temperature (sst)	*Ocean Color* SMI: *Standard Mapped Image MODIS Terra Data*	NOAA OB.DAAC at NASA Goddard Space Flight Center	^0C	4616 m
4.	Chlorophyll-a Concentration (chloro)	*Ocean Color* SMI: *Standard Mapped Image MODIS Terra Data*	NOAA OB.DAAC at NASA Goddard Space Flight Center	$mg/m^{‘3}$	4616 m
5,	Sea Surface Height (scu)	*HYCOM: Hybrid Coordinate Ocean Model, Sea Surface Elevation*	NOPP	m	8905.6 m
6.	Ocean Current Velocity (scv)	*HYCOM: Hybrid Coordinate Ocean Model, Water Velocity*	NOPP	m	8905.6 m
7.	Sea Water Salinity (sal)	*HYCOM: Hybrid Coordinate Ocean Model, Temperature, and Salinity*	NOPP	psu	8905.6 m

3.3 Data Processing

Data processing in this study is conducted through a series of systematic stages, including data extraction, raster data processing, pre-processing, feature engineering, and data splitting. The entire process integrates the use of Google Earth Engine (GEE) for satellite image extraction, Python for numerical data processing and machine learning, and QGIS for spatial analysis.

3.3.1 First Stage

The first stage involves data extraction. Oceanographic variables such as sea surface temperature and chlorophyll-a are obtained from the Ocean Color SMI (MODIS Terra) dataset through NOAA OB.DAAC – NASA Goddard Space Flight Center. These data have a spatial resolution of 4 km and are available in monthly raster format. Furthermore, salinity, current velocity, and sea surface height data are derived from the HYCOM (Hybrid Coordinate Ocean Model) numerical model, covering depths of 0 m, 100 m, and 200 m. Seafloor topography data are extracted from ETOPO 1 NOAA with a resolution of 1 arc-minute, while fishing vessel distribution data are obtained from the

Vessel Monitoring System (VMS) compiled by Global Fishing Watch. All datasets are downloaded in raster format and converted into a geographic coordinate system (WGS 84)

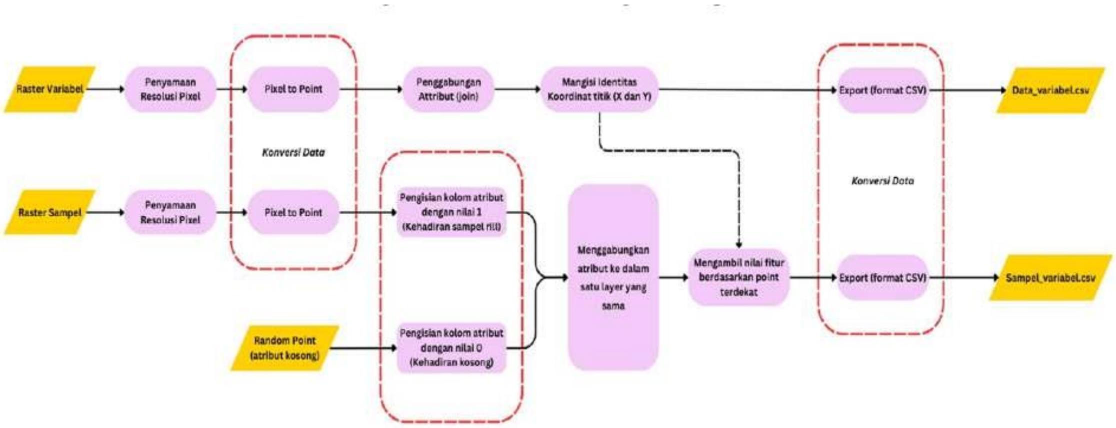
3.3.2 Second Stage

The second stage involves processing the extracted raster data. This process begins with standardizing the pixel resolution across all raster datasets, including both environmental variables and sample rasters, to produce a uniform spatial grid. The raster data are then converted into point data (pixel-to-point conversion) to obtain spatial coordinates (X, Y) along with attribute values for each pixel. In the sample dataset, the presence of fishing vessels is assigned an attribute value of 1 (label = 1), while randomly generated points representing the absence of fishing vessels are assigned a value of 0 (label = 0). These two types of points are then combined into a single layer to form a binary presence–absence dataset. Meanwhile, raster variable data that have been converted into points are joined with the sample layer through an attribute join process, ensuring that each sample point contains environmental variable values from the same or nearest location.

3.3.3 Third Stage

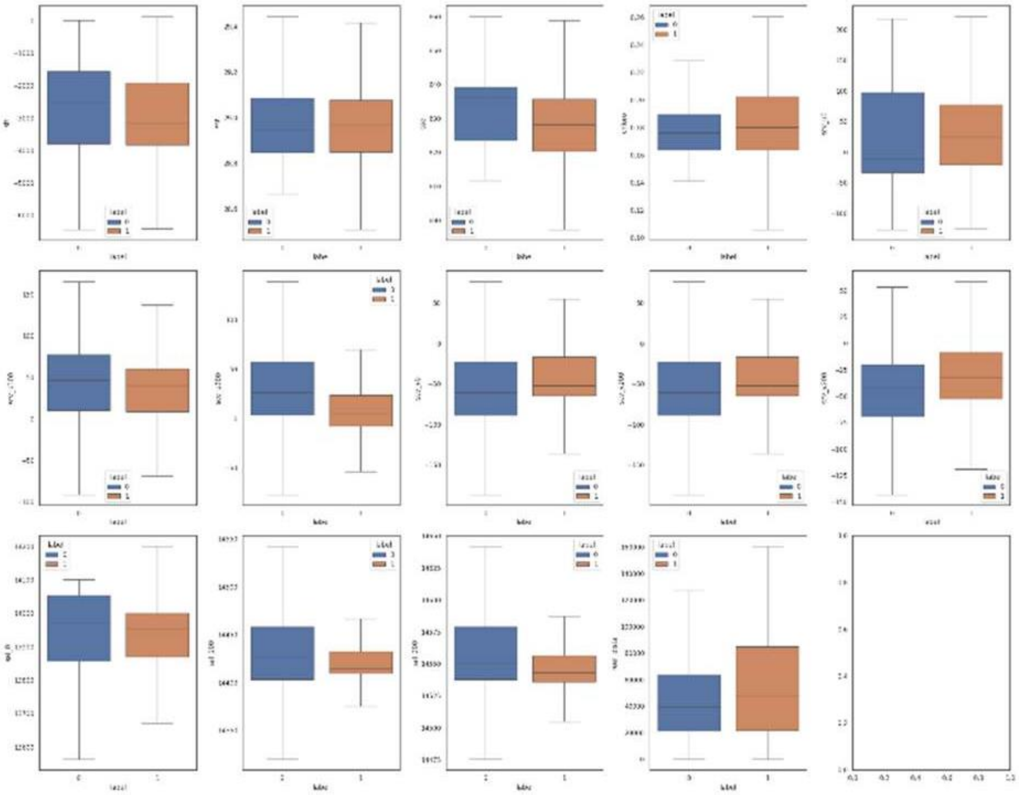
Before the data are used to train the model, several pre-processing steps are performed to ensure optimal data quality. The initial step involves handling outliers using a capping method based on the Interquartile Range (IQR) approach to identify and mitigate extreme values. This step is essential to prevent the model from being influenced by outliers, thereby improving the stability and reducing bias in the prediction results.

Figure 3.1. Data Processing Technique



Source: Data Processing, 2025

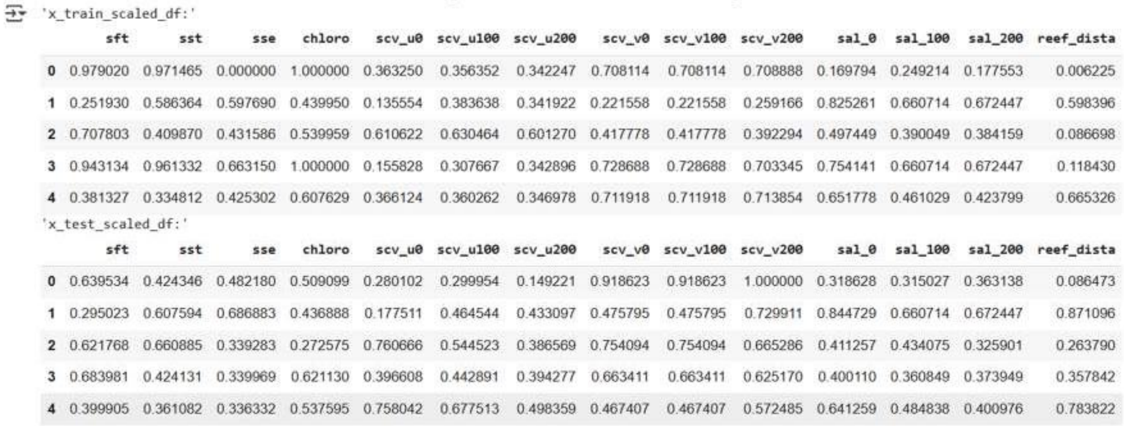
Figure 3.2. Outlier Analysis: Post-Preprocessing



Source: Analysis Results, 2025

The next step involves data normalization. All variables are normalized using the MinMaxScaler method into a range of [0–1]. This normalization aims to ensure that all features have a uniform scale, preventing variables with larger values from dominating the learning process. In addition, normalization helps accelerate the convergence of machine learning algorithms, including the Multi-Layer Perceptron (MLP).

Figure 3.3. Min–Max Scaling of Data



```
'x_train_scaled_df:'
        sft       sst       sse    chloro    scv_u0  scv_u100  scv_u200    scv_v0  scv_v100  scv_v200     sal_0   sal_100   sal_200  reef_dista
0  0.979020  0.971465  0.000000  1.000000  0.363250  0.356352  0.342247  0.708114  0.708114  0.708888  0.169794  0.249214  0.177553    0.006225
1  0.251930  0.586364  0.597690  0.439950  0.135554  0.383638  0.341922  0.221558  0.221558  0.259166  0.825261  0.660714  0.672447    0.598396
2  0.707803  0.409870  0.431586  0.539959  0.610622  0.630464  0.601270  0.417778  0.417778  0.392294  0.497449  0.390049  0.384159    0.086698
3  0.943134  0.961332  0.663150  1.000000  0.155828  0.307667  0.342896  0.728688  0.728688  0.703345  0.754141  0.660714  0.672447    0.118430
4  0.381327  0.334812  0.425302  0.607629  0.366124  0.360262  0.346978  0.711918  0.711918  0.713854  0.651778  0.461029  0.423799    0.665326
'x_test_scaled_df:'
        sft       sst       sse    chloro    scv_u0  scv_u100  scv_u200    scv_v0  scv_v100  scv_v200     sal_0   sal_100   sal_200  reef_dista
0  0.639534  0.424346  0.482180  0.509099  0.280102  0.299954  0.149221  0.918623  0.918623  1.000000  0.318628  0.315027  0.363138    0.086473
1  0.295023  0.607594  0.686883  0.436888  0.177511  0.464544  0.433097  0.475795  0.475795  0.729911  0.844729  0.660714  0.672447    0.871096
2  0.621768  0.660885  0.339283  0.272575  0.760666  0.544523  0.386569  0.754094  0.754094  0.665286  0.411257  0.434075  0.325901    0.263790
3  0.683981  0.424131  0.339969  0.621130  0.396608  0.442891  0.394277  0.663411  0.663411  0.625170  0.400110  0.360849  0.373949    0.357842
4  0.399905  0.361082  0.336332  0.537595  0.758042  0.677513  0.498359  0.467407  0.467407  0.572485  0.641259  0.484838  0.400976    0.783822
```

Source: Analysis Results, 2025

In addition, class imbalance handling is applied using the Synthetic Minority Over-sampling Technique (SMOTE). Class imbalance can cause the model to be biased toward the majority class, resulting in less fair classification performance.

3.3.4 Fourth Stage

The final stage involves data splitting. The cleaned and processed dataset is divided into two subsets: 75% for training (training set) and 25% for testing (testing set). This split is performed randomly while maintaining a balanced data distribution, ensuring that the Multi-Layer Perceptron (MLP) algorithm can be trained optimally and evaluated using previously unseen data.

3.4 Multi-Layer Perceptron (MLP) Modeling

The Multi-Layer Perceptron (MLP) is a machine learning algorithm based on artificial neural networks, designed to recognize complex patterns in data. Conceptually, MLP mimics the workings of the human brain, consisting of simple processing units (artificial neurons) interconnected through weights. In the hidden layers, each neuron performs a non-linear transformation using an activation function (σ), enabling the model to capture non- linear relationships among variables. Meanwhile, the output layer applies an activation function (f) to produce the final prediction according to the modeling objective.

The MLP training process is carried out using the backpropagation algorithm, which adjusts the network weights based on prediction error until the model achieves an optimal level of accuracy. Mathematically, the MLP model can be expressed as follows:

$$\mathrm{MLP}(X) = f\left(W^{(2)} \cdot \sigma\left(W^{(1)} \cdot X + b^{(1)}\right) + b^{(2)}\right)$$

where:

X = input vector (predictor variables),
$W^{(1)}, W^{(2)}$ = weight matrices for the hidden and output layers,
$b^{(1)}, b^{(2)}$ = bias vectors,
σ = activation function in the hidden layer,
f = activation function in the output layer.

3.5 Feature Engineering

At the feature engineering stage, derived variables are generated to enrich the information captured by the model. Several interaction features are constructed, such as *sst_chloro* (the product of sea surface temperature and chlorophyll-a) and sse*_sal0 (*sea surface elevation combined with surface salinity), which reflect the physical– biological relationships underlying marine productivity. In addition, critical zone indicators are developed, such as *hot_low_chloro* to detect high-temperature but low-productivity areas, and *stratified zone* to identify water masses characterized by high temperature and salinity, indicating stratification and low nutrient availability.

This process also includes the calculation of more representative variables, such as *scv_speed_0* for combined surface current velocity, and *delta_sal_0_200* to detect vertical stratification based on the difference between surface and subsurface salinity. Other features, such as *reef_low_chloro*, are used to identify areas near coral reefs with low productivity, indicating potentially stressed zones. With the inclusion of these features, the dataset becomes richer and better prepared for training the MLP model to identify water mass fingerprint patterns in Southeast Sulawesi.

3.6 Model Evaluation

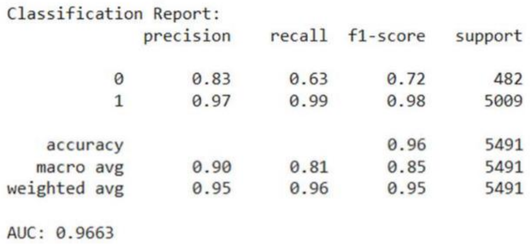
After the training process, the model is evaluated using the *evaluate_mlp* function, which measures performance using several key metrics, including the classification report (precision, recall, f1-score, and support), overall accuracy, and the Area Under the Curve (AUC). In addition, evaluation is conducted using 5-fold cross- validation to assess model stability and ensure that the results are not dependent on a specific data split. Thus, the evaluation provides a comprehensive overview of model performance in terms of both predictive accuracy and generalization capability.

The evaluation results indicate that the model performs well, achieving an overall accuracy of 96% and an AUC value of 0.9663, demonstrating a very high discriminative ability in distinguishing between positive and negative classes. For the majority class (label 1), the model achieves a precision of 0.97 and a recall of 0.99, resulting in an f1-score of 0.98, indicating that the model is highly reliable in identifying areas with fisheries potential with minimal misclassification. However, for the minority class (label 0), the model performance is relatively lower, with a precision of 0.83, recall of 0.63, and f1-score of 0.72. This suggests that although the model is fairly capable of identifying truly low-potential areas, there remains a tendency to misclassify some of these areas as high potential.

Overall, the macro-average f1-score of 0.85 and weighted-average f1-score of 0.95 indicate that the model is relatively balanced but still more influenced by the majority class, which should be carefully considered, particularly in decision-making contexts sensitive to minority class predictions.

Furthermore, the analysis of prediction distribution and visualization through the confusion matrix confirm that most classification errors occur in the minority class, especially in areas with ambiguous characteristics. This highlights that the model not only achieves high accuracy but also provides valuable insights into areas requiring additional attention in decision-making. With its combination of high accuracy, strong discriminative capability, and interpretability of error patterns, the MLP model proves to be a reliable tool for supporting fisheries potential identification, while also serving as a robust foundation for further improvements and mitigation strategies.

Figure 4. Evaluation Results of the Multi-Layer Perceptron Model



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Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.63      0.72       482
           1       0.97      0.99      0.98      5009

    accuracy                           0.96      5491
   macro avg       0.90      0.81      0.85      5491
weighted avg       0.95      0.96      0.95      5491

AUC: 0.9663
```

Source: Analysis Results, 2025

IV. RESEARCH RESULT AND DISCUSSION

4.1 Research Result

4.1.1 Water Mass Fingerprint Map of Southeast Sulawesi

The results of the Multi-Layer Perceptron (MLP) modeling produce a water mass fingerprint map that illustrates the spatial distribution of fisheries potential in the waters of Southeast Sulawesi. The map shows spatial variation through color gradients representing the fisheries potential index. Areas with high fisheries potential are indicated by red to orange colors, which are generally concentrated in the southern and southeastern waters of Southeast Sulawesi. These areas exhibit high primary productivity, as reflected by elevated chlorophyll-a concentrations, optimal sea depth, and current dynamics that support the accumulation of fish biomass. These zones have strong potential as primary fishing grounds; however, their management must adhere to sustainability principles to prevent overexploitation and maintain ecosystem balance.

Zones with moderate fisheries potential, represented by yellow to green colors, are distributed across the northeastern region and several parts of the waters surrounding smaller islands in the south. These areas function as transitional zones between high- and low-potential regions. Although their productivity is lower than that of high-potential zones, environmental factors such as salinity, seabed topography, and proximity to coral reefs still supportfish presence. These zones are suitable for more controlled fishing activities and can serve as ecological buffers that help maintain balance between high- and low-productivity areas.

Meanwhile, zones with low fisheries potential, indicated by blue to dark purple colors, are predominantly located near the main coastal areas of Southeast Sulawesi and parts of the southwestern region. The low fisheries potential index in these areas is likely influenced by a combination of oceanographic factors, such as suboptimal sea surface temperatures, low chlorophyll-a concentrations, or ecological pressure resulting from intensive fishing activities. These zones are more suitable to be designated as conservation or recovery areas to support fish stock regeneration and maintain ecosystem stability in surrounding waters.

When viewed in relation to administrative boundaries, high fisheries potential is largely concentrated around the Buton Archipelago. This presents significant opportunities for administrative regions such as Buton Regency, South Buton Regency, and Wakatobi to optimize fisheries management. However, this potential also necessitates the implementation of zoning-based regulations, such as the designation of conservation zones, limited fishing zones, and intensive fishing zones, to ensure that the distribution of fisheries potential supports long-term sustainability.

4.1.2 Economic Value

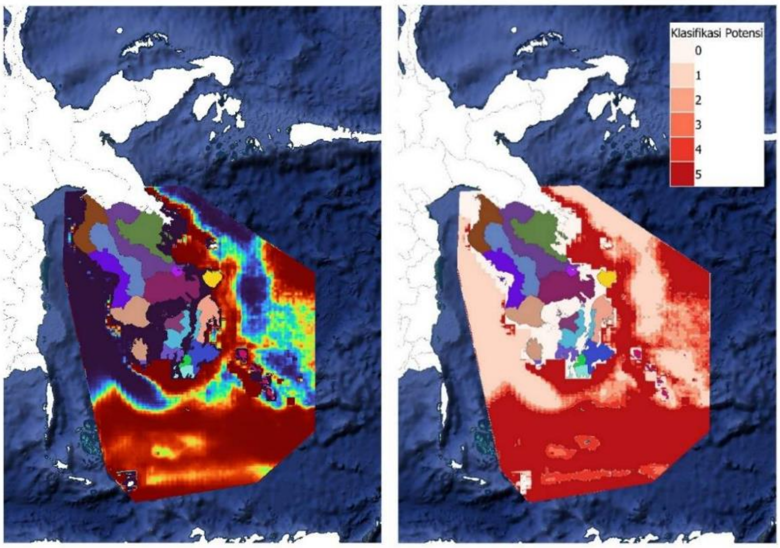
The classification of fisheries potential into six classes reveals variations in both spatial coverage and economic valuation. The total analyzed marine area reaches approximately 15.8 million hectares, with a cumulative economic value exceeding IDR 1.18 trillion. The highest potential class (Class 5, Value = 5) covers the largest area, approximately 6.96 million hectares or 44% of the total marine area, with an estimated economic value of IDR 376.6 billion. This dominant coverage indicates that a substantial portion of Southeast Sulawesi's waters exhibits relatively high fisheries productivity and can serve as the primary basis for capture fisheries activities.

On the other hand, the second-largest class (Class 1, Value = 1) generates an economic value of approximately IDR 439.4 billion. Although its spatial proportion is smaller than that of Class 5, its economic contribution remains highly significant due to its extensive coverage.

The moderate classes (Class 0, Value = 0 and Class 2, Value = 2) show differing contributions. Class 0 covers 1.78 million hectares (11%) with an economic valuation of IDR 690.4 billion, while Class 2 spans 1.03 million hectares (7%) with a similar valuation of IDR 690.4 billion. These figures indicate that despite having smaller spatial extents compared to Class 5, these classes maintain high economic value, suggesting the presence of high-potential areas within more limited spatial coverage.

The lower classes (Class 3 and Class 4) occupy relatively smaller areas, approximately 938 thousand hectares (6%) and 1.15 million hectares (7%), with economic values of IDR 439.3 billion and IDR 156.9 billion, respectively. This suggests that although their spatial contributions are less dominant, lower-class areas still provide meaningful economic value, albeit with more limited utilization potential.

Figure 4.1 Water Mass Fingerprint Map (left) and Classification of Fisheries Potential Levels in Southeast Sulawesi (right).



Source: Analysis Results, 2025

V. CONCLUSION AND SUGGESTIONS

5.1 Conclusion

Exhibit high heterogeneity in terms of fisheries potential. The spatial distribution of fish potential, as visualized through the water mass fingerprint map, shows that high-potential areas are concentrated in the southern and southeastern regions, particularly around the buton archipelago. These zones are characterized by favorable oceanographic conditions, such as high chlorophyll-a concentrations, suitable sea depth, and ocean current dynamics that facilitate the accumulation of fish biomass. In contrast, low-potential areas tend to be located near the main coastal regions of southeast sulawesi, likely influenced by ecological pressures and intensive fishing activities.

The economic valuation analysis reinforces these findings by showing that the two dominant classes (class 5 and class 1) account for nearly 70% of the total area and generate substantial economic value. Despite variations among classes, the economic value is relatively well distributed, indicating that all areas contribute to fisheries productivity. With a total analyzed area of approximately 15.8 million hectares and an economic valuation exceeding idr 1.18 trillion, these results highlight the importance of zoning-based fisheries management. The implementation of policies such as the designation of conservation zones, limited fishing zones, and intensive fishing zones is crucial to ensure that fisheries potential is utilized sustainably, balancing economic, social, and ecological interests. Furthermore, these findings provide a basis for local governments, fisheries managers, and other stakeholders to formulate more adaptive development strategies for the marine and fisheries sector. The resulting water mass fingerprint map serves not only as an analytical tool but also as a spatial planning instrument that can guide investment priorities, monitor fishing activities, and support the designation of conservation areas.

5.2 Suggestions

Based on the findings, it is recommended that fisheries management in Southeast Sulawesi adopts a spatially explicit, zoning-based approach supported by machine learning outputs. High-potential areas should be prioritized as regulated fishing grounds with strict sustainability measures, while moderate zones can function as controlled utilization areas and ecological buffers. Low-potential areas should be designated as conservation or recovery zones to support stock regeneration and ecosystem resilience. Furthermore, the integration of water mass fingerprint maps into regional planning systems is essential to guide investment decisions, improve monitoring and enforcement of fishing activities, and enhance adaptive policy responses to environmental changes. Strengthening data integration through satellite observations and continuous model refinement is also crucial to ensure the long-term effectiveness of fisheries governance aligned with blue and green economy principles.

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