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Machine Learning XGBoost Method for Detecting Mangrove Cover Using Unmanned Aerial Vehicle Imagery

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ABSTRACT

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The mangrove ecosystem can be understood as a unique and different type of ecosystem that can benefit the surrounding ecosystem from the socio-economic and ecological perspective. The purpose of this study is to classify mangrove cover in Tanjung Lapin Beach, about 18.3 hectares, North Rupat District Bengkalis Regency, Riau Province, by applying machine learning XGBoost methods of UAV images by producing interpretations of mangrove cover in the research area. The use of machine learning with a high level of accuracy resulting from the XGBoost method is expected to help the availability of spatial data in identifying better mangrove forest cover. The data obtained from the orthomosaic results from the 3,500 tiles image is used as a reference for making sample points for the analysis process using the XGBoost method, with 224 sample points of mangrove objects visually recognized as training data. Regarding training data, the XGBoost method's iteration result obtained 99% overall accuracy and Kappa accuracy of about 0.98. It means the analysis process continues to the mangrove object cover detection stage. Based on the detection results, it was obtained about 11.9 hectares of mangrove forest cover (64% of the total study area). It has 68 sample points as test data used as an accuracy test tool from the detection results of mangrove objects, where an overall accuracy of 87% and kappa accuracy of 0.82 were obtained. This shows the successful use of the XGBoost method in identifying the mangrove's cover.

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1. INTRODUCTION

The mangrove forest ecosystem can be interpreted as a unique and distinctive form of the ecosystem, so it can bring many benefits to the surrounding ecosystem, starting from a socio-economic and ecological perspective (Rahmat Maulana et al., 2021). Amidst the vast expanse of Southeast Asia lies a crucial ecosystem known as mangrove forests, sustaining the livelihoods of millions. However, the unfortunate reality persists as these vital coastal habitats rapidly decline. Between 2000 and 2012, these irreplaceable mangrove forests were lost at an average annual rate of 0.18%, putting the well-being of nature and the people who depend on it at risk (Richards & Friess, 2016). Without substantial intervention in the brackish water aquaculture sectors and palm oil plantations, the current business-as-usual policy approach paints a grim picture for mangrove forests. Over the next two decades, a staggering 700,000 hectares of these vital ecosystems are at risk of being lost, with the majority converted into fish and shrimp ponds. Urgent action is needed to avert this impending catastrophe and safeguard the future of our precious mangrove forests (Ilman et al., 2016). At the Asian level, the area of Indonesian mangrove forests is around 49% of the total area of mangrove forests in Asia, followed by Malaysia (10%) and Myanmar (9%)

(Schaduw, 2019). The area tends to decrease from year to year. In 25 years (1980-2005), Indonesia lost 30.1% or 1.3 million hectares of mangroves. Efforts to protect and manage mangrove ecosystems require serious attention from various parties. Fast and accurate mapping techniques are needed to monitor and manage mangrove resources effectively (Rosmasita et al., 2018).

Research on classification in the field of remote sensing is increasing along with technological developments. Using satellite imagery, humans can interpret an area being or will be studied. The development of technology presents remote sensing facilities that are more practical and easier to implement, namely the Unmanned Aerial Vehicle (UAV) (Fitriawan et al., 2020). Making spatial information based on aerial photo data using drones provides excellent potential for developing remote sensing technology, such as classifying an area (Timisela et al., 2020). This study uses a method in machine learning, namely the XGBoost method. XGBoost has better convergence and generalization capabilities than its predecessors, such as gradient boosting (Jiang et al., 2019). This is evident from the highly accurate accuracy performance metrics. In addition, XGBoost has a good ability to handle unbalanced data. XGBoost can distinguish the most essential features in data (Siringoringo et al., 2022). The XGBoost method is developed using the Gradient Boosting Decision Tree algorithm (Friedman, 2001). The XGBoost is one such library machine learning that can predict or classify decision tree-based (Jiang et al., 2019). Algorithm, it is possible to do optimization ten times faster compared to other Gradient Boosting methods (Chen & Guestrin, 2016). Whereas for produces the value of the accuracy of the classification results depending on which parameters are used. XGBoost and random forest are algorithms composed of several decision trees. Unlike random forest, which uses bagging, XGBoost uses a boosting technique to prepare the algorithm (Syukron et al., 2020). Previous research obtained results using XGBoost classification of air pollution levels getting an average accuracy of 98%, a precision value of 79%, recall value of 79% (Nababan et al., 2023).

The purpose of this study is to classify mangrove cover in the Tanjung Lapin Beach area, North Rupat District Bengkalis Regency, Riau Province, by applying machine learning XGBoost methods of UAV images by producing interpretations of mangrove cover in the research area. The use of machine learning with a high level of accuracy resulting from the XGBoost method is expected to be able to help the availability of spatial data in identifying better mangrove forest cover, and the information obtained can be used as a reference for decision-making, planning, and implementation of mangrove forest management.

2. METHOD

2.1. Location

The research was conducted in December 2021 and is located in the Tanjung Lapin Beach area (Figure 1), North Rupat Island, Bengkalis Regency, Riau Province, with mangrove forest areas scattered almost along the coastal area of about 18.3 hectares. The material used in this study is spatial data in the form of Multispectral UAV Imagery of the Mangrove Forest Area of Tanjung Lapin Beach (direct data collection at the research site in 2021) with a UAV flight altitude of 100 meters and field survey data (direct data collection in 2021).

The data collection stage tends to facilitate the classification process. The data type is divided into two parts: spatial data and field survey data. Spatial data is data in the form of multispectral UAV imagery, while field survey data is data obtained through direct field surveys to see the diversity of existing land cover. The first stage before conducting a direct survey is to determine the real-time position differently using phase data which provides real-time data using the Real Time Kinematic (RTK) tool. RTK is positioning with the method of positioning and obtaining coordinates at a moment's notice while moving around (Hafiz et al., 2014). A survey with GPS Real Time Kinematic (RTK) has the advantage of being faster and easier than the total station (Safrel et al., 2018). The use of GPS RTK in this research to assist UAV images is a common method of improving the accuracy and precision of georeferenced information in real-time, making it invaluable for various applications, including mapping using UAVs and terrestrial surveys.

Data taken is in the form of observational data regarding the land cover around the research area, and the data taken is also in the form of aerial photographs taken by UAVs with multispectral sensors in the mangrove forest area (Tanjung Lapin Beach). After the data preparation, the next

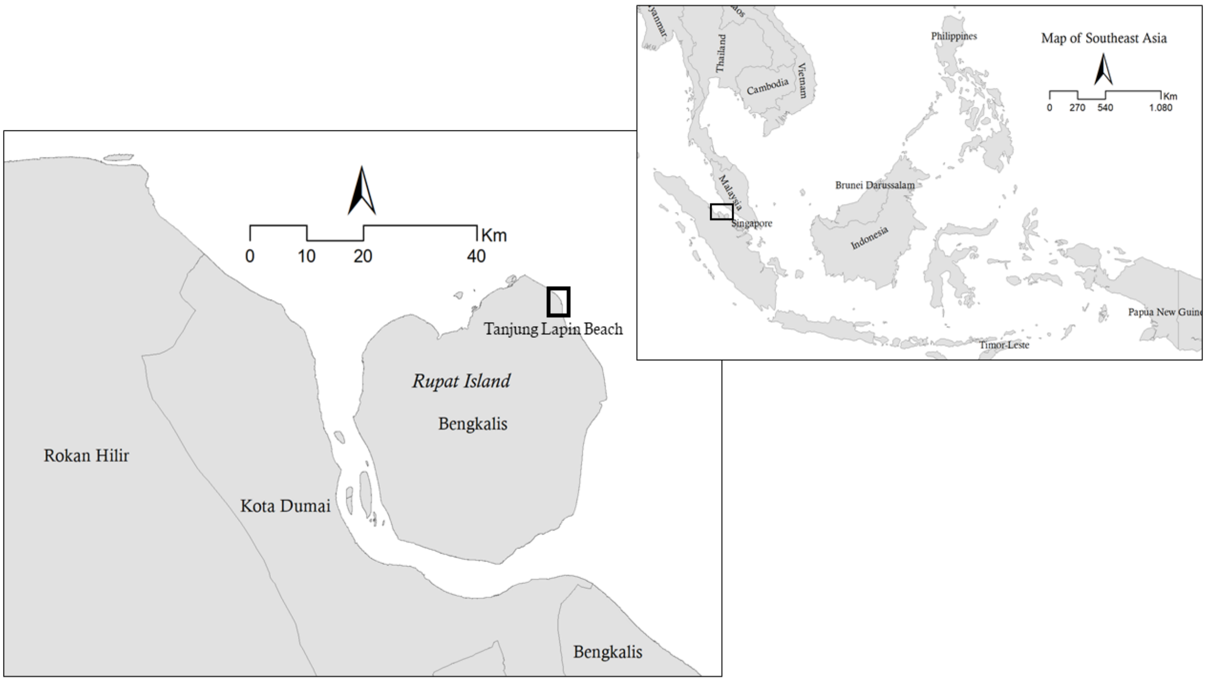

Figure 1. Research location

step is to perform data analysis on the Rstudio software. Source Code is written using the R programming language and the XGBoost method for the calcification process, and the code is run in R-studio.

The ortho-mosaic data had integrated with mangrove object sample points using conversion from raster format to vector format. The following analysis is to train 224 sample points data of mangrove objects onto ortho mosaic data to get an adequate level of accuracy by dividing the original dataset into (70%), namely as many as 156 sample points as training data and (30%) as many as 68 sample points as test data. The model uses training data to learn patterns owned by the data. It helps us understand our model working in actual conditions using the XGBoost model with 200 iterations. The overall flow of this research is described simply in Figure 2.

2.2. Equation

XGBoost is a boosting method, a collection of decision trees whose construction of the next tree will depend on the previous tree. The first tree in XGboost will be weak in classification, with the initialization probability determined by the researcher. Then it will update the weights on each tree built to produce a collection of strong classification trees. Prediction is made by summing up all the weights in each tree and then entering the value into the logistic function (Syukron et al., 2020). XGBoost is a boosted tree model that integrates many tree models to form a robust classifier model. The algorithm applied by XGBoost is an improvement of the gradient descent tree. The core idea is to learn a new function each time to fit the residuals of the last prediction and calculate the score corresponding to each node based on the characteristics of the sample (Xu et al., 2022). The XGBoost is almost faster than other benchmark implementations of R, Python Spark, and H2O and faster when compared to other algorithms (Chen & Guestrin, 2016).

XGBoost dominates structured or tabular data sets on classification and regression predictive modeling problems. The following are the steps for implementing the XGBoost for classification in R: 1) Loading the required libraries; 2) Load data into R; 3) Prepare training data; 4) Read the data set and explore the data; 5) Train and Test data; 6) Start parallelizing for model fitting; 7) Setting parameters for Tree Booster; 8) Train the XGBoost model; 9) Making predictions and confusion matrices on data sets; 10) Make predictions on grid locations; 11) Convert data to raster; 12) Perform plots on the predicted raster map.

2.3. Image Processing

The research method used in this research is the analysis method and the system design method in collecting and analyzing data regarding the use of UAV imagery for land cover classification

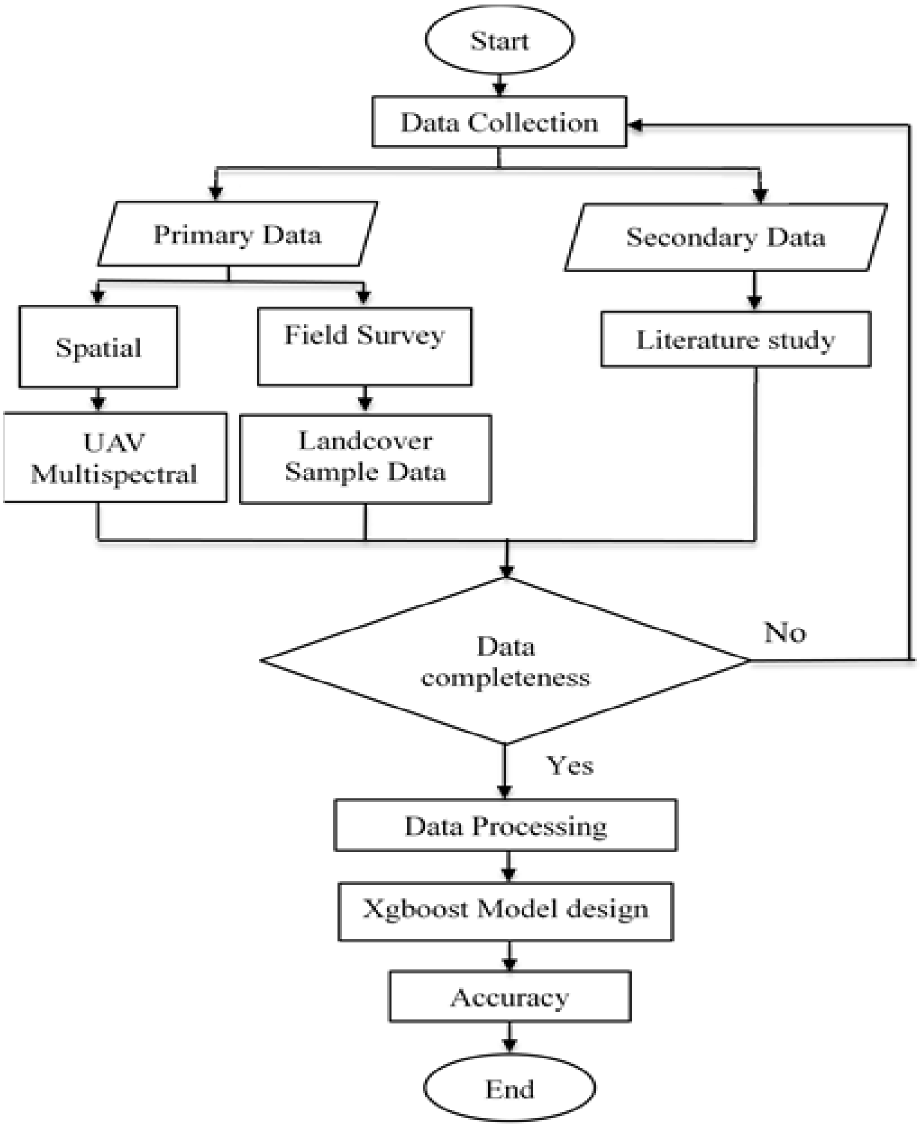

Figure 2. Research flowchart

using the XGBoost method. The process of collecting data first stage that is carried out is data preparation, which is the process of finding and collecting data related to research. The data collection stage is carried out to facilitate the classification process. The data type is divided into two parts: spatial data and field survey data. Spatial data is data in the form of UAV imagery taken using a multispectral sensor, while field survey data is data obtained through direct field surveys to see the diversity of existing land cover.

The stage continues with data processing using photogrammetry software to create ortho-mosaic maps and spatial analysis software to create sample points for training and testing sample data. The result of multispectral UAV imageries is to create an ortho-mosaic map, which produces a single image resulting from a combination of the previous images. Furthermore, the creation of sample points is carried out based on the image results from the ortho-mosaic. Sample points were made into five classes based on ortho-mosaic imagery results: roads, bodies of water, open fields, built-up land, and mangrove forests. This data will be used in the analysis process using the R programming language on Rstudio through a classification process using the XGBoost method.

2.4. Accuracy Assessment

It can mathematically find the value of the producer's accuracy, the user's overall accuracy, and Kappa accuracy through the confusion matrix. Accuracy that can be calculated consists of the producer's, user, and overall accuracy. Mathematically the formula for accuracy can be stated as follows:

$$\text{User Accuracy } = \frac{xii}{x+i}\ 100\% \tag{1}$$

$$\text{Producer Accuracy } = \frac{xii}{xi+}\ 100\% \tag{2}$$

$$\text{Overall Accuracy } = \frac{\sum_{i=1}^{r}}{\mathrm{N}}\ 100\% \tag{3}$$

This accuracy is often referred to as the kappa index, and mathematically the kappa accuracy is presented as follows:

$$\frac{\mathrm{N}\sum_{\mathrm{i=1}}^{\mathrm{r}} \mathrm{X_{ii}} - \sum_{\mathrm{i=1}}^{\mathrm{r}} \mathrm{X_{i+}X_{+i}}}{\mathrm{N}^2 - \sum \mathrm{X_{i+}X_{+i}}}\ \mathrm{x}\ 100 \tag{4}$$

Where: Xii is the Diagonal value of the contingency matrix i-th row and i-column; X+I is The number of pixels in the i-th column; Xi+ is The number of pixels in the i-th row; N is The number of pixels in the example.

The Kappa coefficient value ranges from 0 to 1. In the land cover classification/mapping process, the acceptable accuracy value is 85% or 0.85.

3. RESULTS AND DISCUSSION

3.1. Data Processing

The result of the sample tile image obtained from UAV and made into an ortho-mosaic (Figure 3) data from 3,500 tiles image. The data obtained from the ortho-mosaic result is used as a reference for making sample points for the analysis process using the XGBoost method, as shown in Figure 4. Sample points are created using the GIS software by creating a new point shapefile from the various sampled areas and creating labels. After generating ortho-mosaic data, the next step is to determine about 224 sample points of mangrove objects that are visually recognized. These sample points are useful to help the XGBoost method in identifying mangrove objects and performing image classification. With data samples, the data processing that is carried out next is to analyze the data and classify it using the XGBoost method.

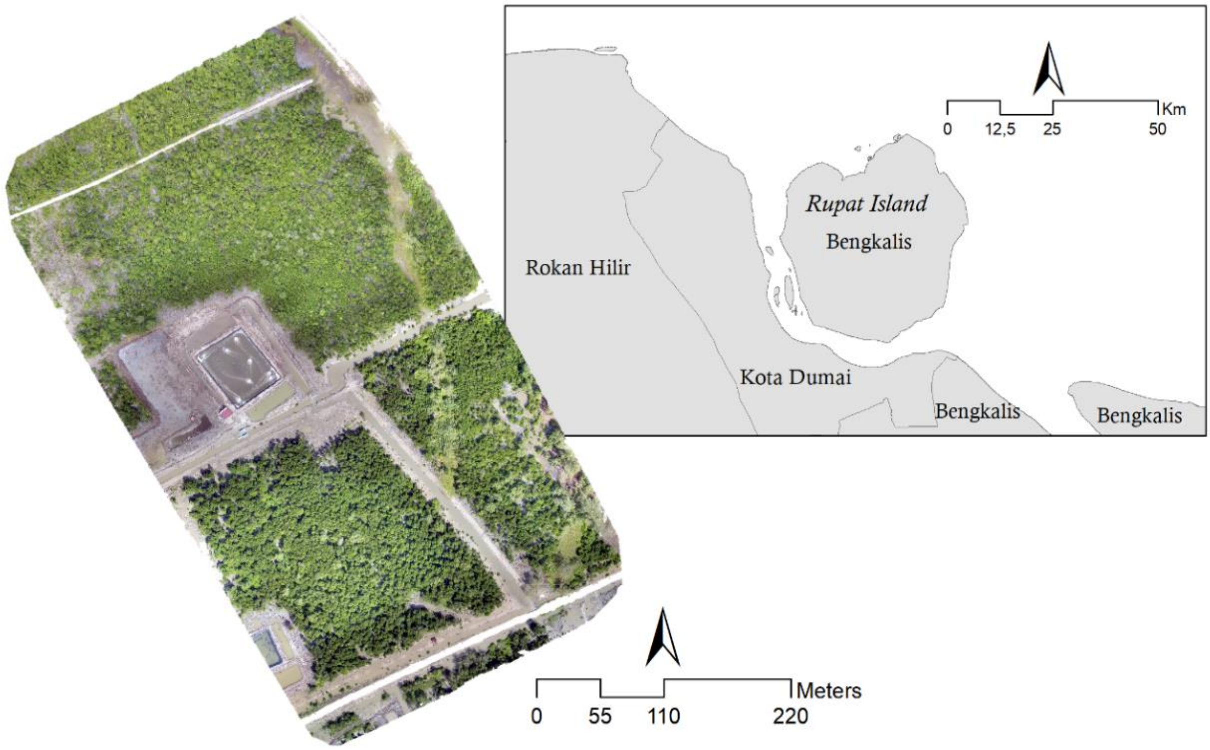

Figure 3. Tanjung Lapin orthomosaic image

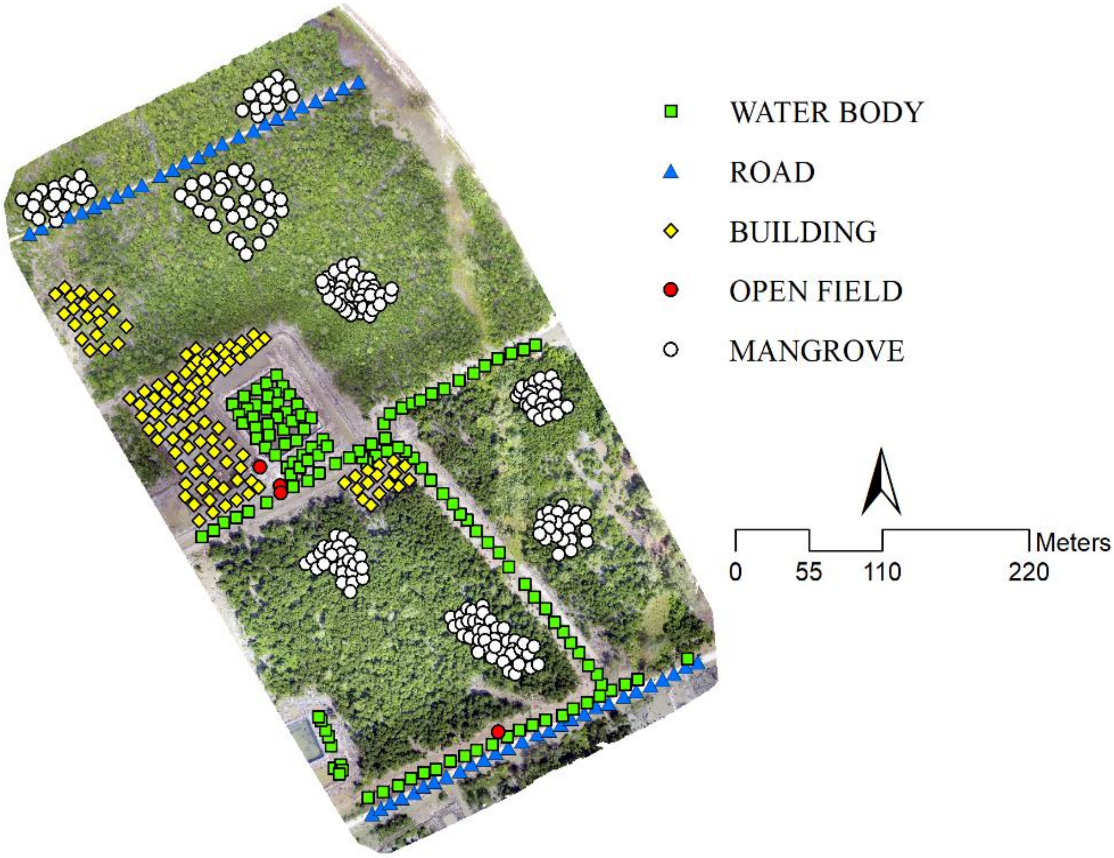

Figure 4. Mangrove's cover sample points

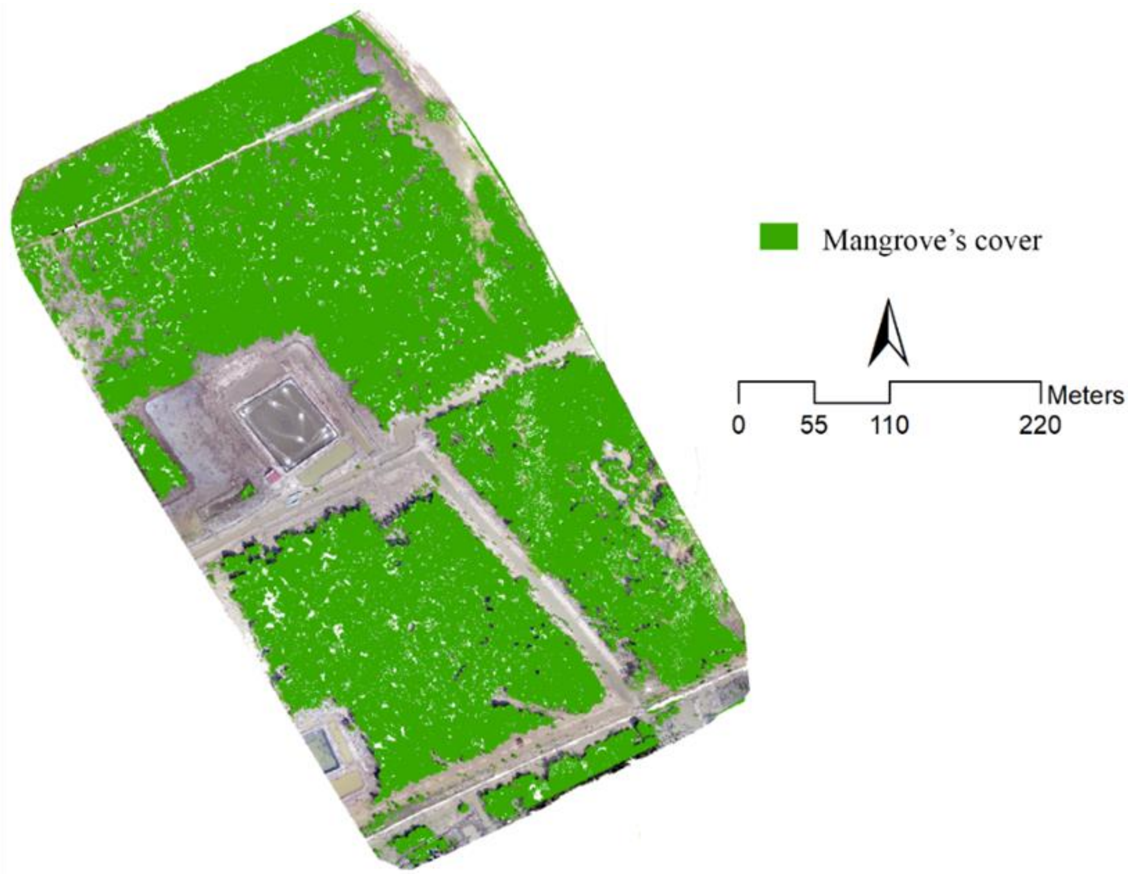

Figure 5. Classification Results

The boosting algorithm, also known as adaptive boosting, is a powerful technique utilized in machine learning. It adapts to each instance by assigning higher weights to those instances that have been erroneously categorized. This approach proves highly effective in supervised learning, as it minimizes bias and variation, ultimately leading to more accurate and robust models. By leveraging boosting, machine learning systems can make better-informed decisions and achieve higher performance levels in various tasks and applications (Al-Mistarehi et al., 2022). The analysis was carried out using R-studio software with the R programming language. The application of R-studio software for statistical computing is methodologically adequate (Knez et al., 2022).

3.2. Data Analysis

Figure 5 shows the results of the classification using the XGBoost method. Regarding training data, the XGBoost method's iteration result obtained 99% overall accuracy and Kappa accuracy of about 0.98. It means the analysis process continues to the mangrove object cover detection stage. Based on the detection results, it was obtained about 11.9 hectares of mangrove forest cover (64% of the total study area).

Almost 68 sample points as test data were used as an accuracy test tool from the detection results of mangrove objects, where an overall accuracy of 87% and kappa accuracy of 0.82 were obtained. This shows the successful use of the XGBoost method in identifying the mangrove's cover (Table 1).

From the prediction results, it can be seen that 156 objects in the testing data, 137 objects, are correctly detected according to predetermined classes. The results of testing the Confusion Matrix data obtained an accuracy of 0.87% and a kappa of 0.8243 with the following mathematical calculations:

1. Producer's Accuracy: The producer's accuracy results in water at about 78%, road at about 93%, vacant land at about 76%, build-up land at about 0%, and mangrove at about 98%.
2. User's Accuracy: The result of the user's accuracy is water at about 85%, road at about 83%, vacant land at about 81%, build-up land at about 0%, and mangrove at about 92%.
3. Overall Accuracy: Overall accuracy is about 87%.
4. Kappa Accuracy: The Calculation of kappa accuracy is about 0.8243, where the diagonal value of the contingency matrix is about 7.463. In our research, namely the detection of mangrove cover, an overall accuracy of 87% was obtained using the XGBoost method. Another study using Sentinel-2B Imagery in Liong River, Bengkalis, Riau Province, obtained overall accuracy results of 78.7% and 70.9% in the classification of mangrove land cover using object-based classification methods (Rosmasita et al., 2018).

The Confusion matrix was applied to the algorithm with the highest overall accuracy to assess the relationship between correctly and wrongly classified data in the confusion matrix table. By conducting these statistical tests, we gain valuable insights into the strength of the associations between the algorithm's predictions and the actual outcomes. This analysis allows us to understand better the algorithm's performance and evaluate its ability to distinguish between correct and incorrect classifications, providing crucial information for refining and optimizing the model's predictive capabilities (Nooni et al., 2014). The kappa coefficients and the total number of isolated pixels derived from all classifiers, including individual classifiers, were analyzed using the

Table 1. Confusion matrix of accuracy assessment result

Class/Labels	Waterbody	Road	Open field	Building	Mangrove	Total	*User's accuracy*
Waterbody	30	0	6	0	2	38	85%
Road	1	15	0	0	0	16	83%
Open field	3	3	26	0	2	34	81%
Building	0	0	0	0	1	1	0%
Mangrove	1	0	0	0	66	67	92%
Total	35	18	32	0	71	156	
Producer Accuracy	78%	93%	76%	0%	98%		
Overall accuracy = 87 %; Kappa =0.82							

correlation coefficient. This analytical approach aimed to establish and verify the relationship between classification accuracy and the occurrence of isolated pixels. By examining these correlations, we can gain valuable insights into how the classifiers' performance is affected by the presence of isolated pixels in the classification results. This investigation provides a comprehensive understanding of the impact of isolated pixels on classification accuracy. It helps devise strategies to enhance the classifiers' overall performance and reduce the occurrence of isolated pixels (Hirayama et al., 2019).

Based on the analysis above, the XGBoost method can be applied in detecting mangrove land cover. The accuracy results show that the XGBoost method can detect several land covers, namely water bodies with 85% detection accuracy, roads with 83% detection accuracy, open land with 81% detection accuracy, and mangroves with 92% detection accuracy. Related parties can use the results of this research to monitor, manage, inventory, and interpret mangrove resources.

The XGBoost operates by iteratively constructing new decision trees that target the reduction of residuals between actual and predicted values. With each iteration, the algorithm identifies the shortcomings in its previous predictions and creates new decision trees to better fit these residual errors. This process is repeated until the model converges, resulting in highly accurate and refined predictions that significantly minimize the discrepancies between the actual and predicted values. Through this adaptive approach, XGBoost consistently improves performance and achieves remarkable predictive accuracy in various applications (Hengl et al., 2017). The XGBoost algorithm is an innovative development that integrates two powerful learning methods: boosting and bagging. Building upon the boosting method, XGBoost combines the strengths of the bagging method during its evolution process. XGBoost achieves enhanced performance and robustness in learning by harnessing the best of both worlds (Zhao et al., 2022).

Currently, the focus of existing algorithms for data classification primarily revolves around classifying a single class at a time. However, in the future, further efforts will be devoted to advancing these algorithms to achieve an optimal solution that allows for the classification of multiple classes simultaneously. Researchers and developers will continue to explore and innovate in this field to enhance the efficiency and effectiveness of data classification techniques, enabling more robust and comprehensive solutions for complex real-world problems. As technology progresses, we can look forward to more sophisticated algorithms that can handle diverse and intricate datasets with improved accuracy and versatility (Kumar et al., 2019).

4. CONCLUSIONS

Based on the analysis results, it can be concluded that using UAV imagery can provide a visual image of mangrove objects. The use of the XGBoost method in detecting mangrove cover is quite suitable with an adequate level of accuracy. Using the XGBoost method on mangrove objects in different places should be considered, especially in coastal areas with similar environmental conditions as the Tanjung Lapin beach. Due to hardware limitations, this study could not construct the XGBoost method. However, despite this constraint, the accuracy achieved using the XGBoost method for detecting mangroves has been remarkable. The XGBoost algorithm has demonstrated its potential in distinguishing mangrove objects from other image datasets. To further enhance the classification accuracy, the authors propose increasing the number of sample points and the number of feature classes in the convolutional layers. Additionally, they plan to include more features in the input layer and improve the XGBoost architecture to achieve higher accuracy when working with larger image datasets containing more classes. These advancements are expected to contribute significantly to the mangrove detection and classification field, enabling more robust and accurate analysis in the future.

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