UNIVERSITAS
LAMBUNG MANGKURAT

Novitasari Novitasari <novitasari@ulm.ac.id>

Fwd: Submit article

NOVITASARI <novitasari@ulm.ac.id>   Tue, Jan 10, 2023 at 1:48 PM
Date: 10 Jan 2023 21.20.44 GMT+8
To: ijetae@gmail.com, editor@ijetae.com
Subject: Submit article

Dear Editor's IJETAE,
I are writing to submit our manuscript entitled, "Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model" for consideration for publication in IJETAE.
Thank you for your attention. I'am waiting for your feedback.

Novitasari

Faculty of Engineering, Universitas Lambung Mangkurat (ULM)

Gedung Fakultas Teknik ULM, Jl. Brig. Hasan Basry Kayutangi

Banjarmasin 70123 Kalsel, Indonesia

Mobile: +62 817442724. Telp/fax: +62 (511) 4773858 / 4773868

---

2 attachments

📄 **Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model.pdf**
563K

📄 **Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model.doc**
12337K

International Journal of Emerging Technology and Advanced Engineering Paper Template Format

First Author[1], Second Author[2], Third Author[3]

[1]First Author Affiliation & Address
[2]Second Author Affiliation & Address
[3]Third Author Affiliation & Address

```
¹first.author@first.edu
²second.author@second.com
³third.author@third.edu
```

Abstract— **This document gives formatting guidelines for authors preparing papers for publication in the International Journal of Emerging Technology and Advanced Engineering The authors must follow the instructions given in the document for the papers to be published.**

Keywords—**Keyword are your own designated keyword which can be used for easy location of the manuscript using any search engines. It includes at least 5 keywords or phrases in alphabetical order separated by comma.**

I. INTRODUCTION

This document is template. We ask that authors follow some simple guidelines. In essence, we ask you to make your paper look exactly like this document. The easiest way to do this is simply to download the template, and replace(copy-paste) the content with your own material.

II. PAGE LAYOUT

An easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it.

Page Layout

The margins must be set as follows:
- Top = 1.7cm
- Bottom = 1.7cm
- Left = 1.7cm
- Right = 1.7cm

Your paper must be in two column format with a space of 1.27 cm between columns.

III. PAGE STYLE

All paragraphs must be indented. All paragraphs must be justified, i.e. both left-justified and right-justified.

A. Text Font of Entire Document

The entire document should be in Times New Roman or Times font. Type 3 fonts must not be used. Other font types may be used if needed for special purposes.

Recommended font sizes are shown in Table 1.

B. Title and Author Details

Title must be in 20 pt Times New Roman font. Author name must be in 11 pt Regular font. Author affiliation must be in 10 pt Italic. Email address must be in 9 pt Courier Regular font.

TABLE I
FONT SIZES FOR PAPERS

Font Size	I. Appearance (in Time New Roman or Times)		
	Regular	Bold	Italic
8	table caption (in Small Caps), figure caption, reference item		reference item (partial)
9	author email address (in Courier), cell in a table	abstract body	abstract heading (also in Bold)
10	level-1 heading (in Small Caps), paragraph		level-2 heading, level-3 heading, author affiliation

11	author name		
20	title		

All title and author details must be in single-column format and must be centered. Every word in a title must be capitalized. Email address is compulsory for the corresponding author.

C. Section Headings

No more than 3 levels of headings should be used. All headings must be in 10pt font. Every word in a heading must be capitalized except for short minor words as listed in Section III-B.

Level-1 Heading: A level-1 heading must be in Small Caps, centered and numbered using uppercase Roman numerals. For example, see heading "III. Page Style" of this document. The two level-1 headings which must not be numbered are "Acknowledgment" and "References".

Level-2 Heading: A level-2 heading must be in Italic, left-justified and numbered using an uppercase alphabetic letter followed by a period. For example, see heading "C. Section Headings" above.

Level-3 Heading: A level-3 heading must be indented, in Italic and numbered with an Arabic numeral followed by a right parenthesis. The level-3 heading must end with a colon. The body of the level-3 section immediately follows the level-3 heading in the same paragraph. For example, this paragraph begins with a level-3 heading.

D. Figures and Tables

Figures and tables must be centered in the column. Large figures and tables may span across both columns. Any table or figure that takes up more than 1 column width must be positioned either at the top or at the bottom of the page.

E. Figure Captions

Figures must be numbered using Arabic numerals. Figure captions must be in 8 pt Regular font. Captions of a single line must be centered whereas multi-line captions must be justified. Captions with figure numbers must be placed after their associated figures

F. Table Captions

Tables must be numbered using uppercase Roman numerals. Table captions must be centred and in 8 pt Regular font with Small Caps. Every word in a table caption must be capitalized except for short minor words as listed in Section III-B. Captions with table numbers must be placed before their associated tables, as shown in Table 1.

G. Page Numbers, Headers and Footers

Page numbers, headers and footers must not be used.

H. Links and Bookmarks

All hypertext links and section bookmarks will be removed from papers during the processing of papers for publication. If you need to refer to an Internet email address or URL in your paper, you must type out the address or URL fully in Regular font.

References

The heading of the References section must not be numbered. All reference items must be in 8 pt font. Please use Regular and Italic styles to distinguish different fields as shown in the References section. Number the reference items consecutively in square brackets (e.g. [1]).

[1] Bowman, M., Debray, S. K., and Peterson, L. L. 1993. Reasoning about naming systems. .

[2] Ding, W. and Marchionini, G. 1997 A Study on Video Browsing Strategies. Technical Report. University of Maryland at College Park.

[3] Fröhlich, B. and Plate, J. 2000. The cubic mouse: a new device for three-dimensional input. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems

[4] Tavel, P. 2007 Modeling and Simulation Design. AK Peters Ltd.

[5] Sannella, M. J. 1994 Constraint Satisfaction and Debugging for Interactive User Interfaces. Doctoral Thesis. UMI Order Number: UMI Order No. GAX95-09398., University of Washington.

[6] Forman, G. 2003. An extensive empirical study of feature selection metrics for text classification. J. Mach. Learn. Res. 3 (Mar. 2003), 1289-1305.

[7] Brown, L. D., Hua, H., and Gao, C. 2003. A widget framework for augmented interaction in SCAPE.

[8] Y.T. Yu, M.F. Lau, "A comparison of MC/DC, MUMCUT and several other coverage criteria for logical decisions", Journal of Systems and Software, 2005, in press.

[9] Spector, A. Z. 1989. Achieving application requirements. In Distributed Systems, S. Mullende

UNIVERSITAS
LAMBUNG MANGKURAT

Novitasari Novitasari <novitasari@ulm.ac.id>

IJETAE :Paper Status Notification - 001

EDITOR IJETAE <ijetae@gmail.com>   Tue, Feb 7, 2023 at 2:19 AM
To: novitasari@ulm.ac.id

Dear Researcher

Season's Greeting for Your Good Health and Happiness.

This is to inform you that your paper has been selected for publication in the International Journal of Emerging Technology and Advanced Engineering, An ISO 9001:2008 Certified International Journal, please follow paper template below.

You have to complete all before 21 FEB 2023.

In case of any query, feel free to contact us at editor@ijetae.com, ijetae@gmail.com

Hope for Cooperation from Your End.

Regards

Editor In Chief
International Journal of Emerging Technology & Advanced Engineering
An ISO 9001:2008 Certified, ISSN 2250–2459(ONLINE)
Website: http://www.ijetae.com/

2 attachments

IJETAE_COPYRIGHT_FORM.doc
35K

IJETAE_PAPER_TEMPLATE.doc
56K

Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model.pdf
2627K

Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model.pdf
2627K

Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model

Novitasari Novitasari[1], Yuslena Sari[2], Yudi Firmanul Arifin[3], Mohammad Reza Faisal[4],

Andreyan Rizky Baskara[2], Rian Ridhani[2]

[1]*Department of Civil Engineering, Universitas Lambung Mangkurat, Banjarbaru, Indonesia*
[2]*Department of Information Technology, Universitas Lambung Mangkurat, Jl. Brig. Hasan Basri, Banjarmasin, Indonesia*
[3]Faculty of Forestry, Universitas Lambung Mangkurat, *Banjarbaru, Indonesia*
[4]*Department of Computer Science, Universitas Lambung Mangkurat, Banjarbaru, Indonesia*
[5]*Department of Information Technology, Universitas Lambung Mangkurat, Jl. Brig. Hasan Basri, Banjarmasin, Indonesia*
[5]*Department of Information Technology, Universitas Lambung Mangkurat, Jl. Brig. Hasan Basri, Banjarmasin, Indonesia*
[1]novitasari@ulm.ac.id
[2]yuzlena@ulm.ac.id
[3]yudifirmanul@ulm.ac.id
[4]andreyan.baskara@ulm.ac.id
[5]1710817210014@ulm.ac.id

Abstract— **Land cover is the appearance of the earth's surface covered by biological and non-biological diversity. Land cover can provide important information for modeling and understanding natural phenomena that occur on the earth's sur-face. Supervising land cover change is useful for designing and managing better actions to prevent or ameliorate loss-es resulting from land cover change activities. Types of land cover based on the ministry of environment and forestry and S.N.I. In the Liang Anggang protected forest area are primary swamp forest, secondary swamp forest, open swamp, wet bush, pure dry agriculture, mixed dry agriculture, open water, transmigration areas, plantation forest, and vacant land. The type of land cover in the Liang Anggang protected forest area can be classified into 3 types, namely bare, softly, and heavily. Land cover classification can be done from two types of data, namely satellite data and unmanned aerial vehicle (UAV). This research will use UAV data for better image detail. The model used is YOLOv5. The results of this study obtained mAP@.5 74.8%, mAP@.95 31.3%, precision 81.7%, recall 66.4% for bare class. mAP@.5 81.1%, mAP@.95 45.7%, precision 80.1%, recall 78.6% for "softly" class. mAP@.5 40.1%, mAP@.95 21.9%, precision 49.5%, recall 36.9% for "heavily" class. mAP@.25 72.8%, mAP@.5 65.6%, mAP@.75 53.6%, mAP@.95 33%, precision 70.4%, recall 60.7%, and accuracy 60% for all class.**
*Keywords—*Classification, Land Cover, YOLOv5, UAV

I. Introduction

Land cover is the appearance of the earth's surface covered by biological and non-biological diversity. Land cover can provide important information for modelling and understanding natural phenomena that occur on the earth's surface. Land cover data can also be used to study climate change and understand the relationship between human activities and global change [1]. One type of land cover in South Kalimantan is peat land. One of the peatland areas in South Kalimantan is the Liang Anggang protected forest, Banjarbaru block 1 area which has an area of 494 hectares and is filled with land such as agriculture, plantations, roads, settlements, and shrubs. Apart from the fact that the location is peatland, the location in block 1 fulfils the characteristics and suitability of the needs in collecting data for the classification of peatland cover. So as the selection of this research location is in accordance with the data requirements.

Destructive changes in land use including on peatlands are the main cause of loss of biodiversity, damage to ecosystems and drastic climate change. Monitoring land cover change is useful for designing and managing better regulations to prevent or remedy losses arising from land cover change activities. Monitoring land cover changes can help in predicting and avoiding natural disasters or other hazardous events [1]–[3]. Monitoring and analysis of land

cover can be carried out by classifying land cover, according to the

Ministry of Environment and Forestry and the National Standardization Agency, especially the Indonesian National Standard, land cover is classified into 23 classes, consisting of 6 forest classes, 16 non-forest classes, and 1 rehabilitation forest class [4]. The types of land cover based on the ministry of environment and forestry and the Indonesian National Standard (S.N.I) found in the Liang Anggang protected forest area are primary swamp forest, secondary swamp forest, open swamp, wet shrub, pure dry agriculture, mixed dry agriculture, open water, transmigration areas, plantation forests, and bare ground. The types of land cover in the Liang Anggang protected forest area can be classified into 3 types, namely bare (surface that has no vegetation at all), Softly (surface covered with medium and high vegetation), and Heavily (surface covered with moderate vegetation). The data collection technique is carried out using the Unmanned Aeiral Vehicle (UAV) which can take pictures from a lower altitude so that the spatial resolution obtained is 1cm, more detailed than the satellite (30cm). And also, the UAV can take pictures in cloudy weather conditions because the UAV's height is lower than the clouds [5]–[8].

The technique that is highly favoured for classification is Machine Learning. Machine Learning is continually evolving and producing new fields such as Deep Learning. Deep Learning is popular in image analysis and intelligent image processing [9]–[12]. One of the popular models used in Deep Learning is You Only Look Once (YOLO).

The YOLO model is well-known for its use in object detection [13]. Several studies have used YOLOv5 for research purposes, such as Jun-Hwa Kim et al., who conducted a study on maritime object classification and optimized the Singapore Maritime Dataset (SMD) [14]. Nidhi et al. conducted a study on seed classification and quality using YOLOv5 and K-Means [15]. Linfeng et al. detected traffic signs using SSD300, Faster RCNN, YOLOv3, YOLOv4, and YOLOv5 to compare the accuracy of these models [16]. Daniel Padilla Carrasco et al. detected small vehicles in parking lots using YOLOv5 to manage parking spaces efficiently and achieve the goal of a smart city [17]. Tian-Hao Wu et al. used YOLOv5 to detect vehicles and their distances in real-time in a virtual environment to optimize autonomous vehicle technology [18]. Lastly, How Yong Chen et al. used YOLOv5 to detect defects in glove production [19].

II. LITERATURE REVIEW

A. Land Cover

Land cover refers to the surface features of the Earth that are covered by biotic and abiotic elements. Land cover provides important information for modeling and understanding natural phenomena occurring on the Earth's surface. Land cover data can also be used to study climate change and understand the relationship between human activities and global changes. Accurate land cover information is one of the determining factors in improving the performance of ecosystem, hydrology, and atmospheric models. One type of land cover found in South Kalimantan is peatland. Peatland is a water-saturated land composed of organic material (>12%) that occurs due to the accumulation of decomposing plant remains and tissues with a thickness of more than 50 cm. The accumulation is caused by the slow rate of decomposition compared to the rate of organic material accumulation inundated by water over a long period of time [1]–[3].

B. Peatland

Peatland is a water-saturated land composed of organic material (>12%). Peatland is formed by the accumulation of plant residues and decomposed plant tissues with a thickness of more than 50 cm. The accumulation is due to the slow rate of decomposition compared to the rate of organic material accumulation that is inundated with water for a long period of time [1]. Peat is classified as marginal land and is vulnerable to disturbances, so any increase in the productivity of peatland must be accompanied by efforts to prevent ecosystem damage. Peatland damage is caused by tree felling and forest conversion, fires, and reclamation. Peat can be considered a renewable resource only on a geological time scale. Peat growth estimates vary between 0.5 to 1 mm per year, and the subsidence rate of drained peatland is between 1.5 to 3 cm per year. Because the subsidence rate is 15-30 times that of the growth rate, peatland cannot be categorized as a renewable resource.

Several types of land cover based on the ministry of environment and forestry and S.N.I. located in the Liang Anggang area include:

1. Primary swamp forest: Forests growing in wet habitats include mangroves, sago, and peatlands.
2. Secondary swamp forest: Forests growing in wet habitats include mangroves, sago, and peat, often with human interventions such as logging and agriculture.
3. Open swamp: Open swamp with little vegetation.
4. Wet shrub: Wet area filled with shrubs.

5. Mixed dry agriculture: Areas used for agricultural activities and still have wild plants such as shrubs and trees scattered in the agricultural area.
6. Open water: Open water areas such as rivers and lakes.
7. Transmigration areas: The area surrounding the forest that is related to human activities such as houses, parks, and huts.
8. Pure dry agriculture: Areas used for agricultural activities.
9. Plantation forest: An area that has been planted with vegetation as part of forest rehabilitation efforts.
10. Bare ground: An area of empty land without vegetation.

Pictures of land cover types in the Liang Anggang protected forest can be seen in Table 1.

TABLE I
TYPES OF LAND COVER IN THE LIANG ANGGANG PROTECTED FOREST

Land Image	Land Type	Land Image	Land Type
	Primary Swamp Forest		*Wet Shrub*
	Secondary Swamp Forest		*Mixed Dry Agriculture*
	Open Swamp		*Open Water*
	Plantation Forest		*Transmigration Area*
	Pure Dry Agriculture		*Bare Ground*

C. Image Classification

Image classification is the process of arranging or grouping pixels into several classes based on object categories or certain criteria. Each pixel in each class is assumed to have homogenous characteristics. The goal of classification is to extract spectral patterns found within the image [20]–[22].

III. RESEARCH METHODOLOGY

A. Problem Identification

The first stage of this research is to identify the problem. Problem identification is carried out qualitatively by focusing on in-depth observation to discover a problem. The problem identified is the importance of classifying land cover using a reliable model to produce accurate land cover types with good accuracy results. The solution to this problem is to use the best object detection model for land cover classification and then observe the accuracy results of using the model. Good accuracy results in using the model can be a recommendation for the next researchers in land cover classification and object detection in general. And land cover classification information can be a further action by researchers or agencies related to land cover.

B. Image Acquisition

Image acquisition is carried out to collect the necessary data and to determine the digital image recording model to be used [23]. Land images were taken using a DJI Mavic Pro drone in November - December 2021 and July - August 2022. The drone is automatically controlled using the DroneDeploy application. The drone follows a predetermined path on DroneDeploy but can still be manually controlled with a remote. Image capture is done in clear or slightly cloudy weather conditions. The drone is set to fly at a height of 20 meters from the surface. Image capture is done between 8 am and 12 pm.

Because the Liang Anggang protected forest is located near the Syamsudin Noor airport, some areas cannot be captured with a drone because they are in a restricted fly zone with a maximum height of 60 meters in yellow areas and not allowed to fly at all in blue areas. Therefore, the area to be captured is located within a maximum of 60 meters with a drone capture height of 20 meters so that the drone can still capture images with sufficient coverage. The

restricted fly zone in the Liang Anggang protected forest can be seen in Figure 1.

Figure 1. Restricted Fly Zone Around Liang Anggang Protection Forest

IV. RESULT

A. Image Capture Process

The first stage of taking images with a drone is determining the area to be photographed. Area capture settings are made in the Google Earth Pro application to determine the area to be captured. After the area marking has been completed, the results will be exported into a file with the .KML format. Then the file will be imported into the DroneDeploy application. From the DroneDeploy application, drones can be set to take pictures automatically according to the area that has been marked.

UAV image data obtained from the results of drone capture conducted in July - August 2022 collected 7437 images with an area of 22.6 hectares. The total image data collected after being combined with data taken in November - December 2021 collected 17,674 images with an area of 40.6 hectares. Areas that have been taken using drones are marked in orange which can be seen in Figure 2.

Figure 2. Territory That Has Been Taken by Drones

1. *Labelling*

   Labelling process is carried out to label objects in the image that will be detected. The label will assist the trained model to identify the objects to be detected.

   After all images have been preprocessed, the dataset construction is carried out to divide the dataset according to its usage in each stage. The dataset is divided into three folders, namely train, val, and test.

   The complete structure of the dataset can be seen in Figure 3.

Figure 3. Complete Structure of Dataset

B. Training Model

Training is conducted using the Google Colab platform. The training stage in the YOLOv5 model is divided into 3 stages, namely the training, validation, and testing stages.

1. Training

   At the training model stage, the first step is to run the code to download the YOLOv5 file into the Google Colab project. After the download process is complete, the project will display the YOLOv5 folder. Then the next step is to connect the project with the dataset that has been stored on Google Drive and determine the location of the dataset from the coco128.yaml file.

   Model training is carried out by conducting training several times with different batch and epoch values to find out the optimal setting values to get the best precision, recall, and mAP values. The training results from the YOLOv5 training model for land classification for all classes obtained values of

mAP@.25 0.728, mAP@.5 0.656, mAP@.75 0.536, mAP@.95 0.33, precision 0.704, recall 0.607. Complete values of training results for 100 epochs and 5 batches can be seen in table 2.

TABLE III
TRAINING RESULT VALUE

Class	Precission	Recall	mAP @.25	mAP @.5	mAP @.75	mAP @.95
All	0.704	0.607	0.728	0.656	0.536	0.33
Bare	0.817	0.664	0.688	0.748	0.418	0.313
Softly	0.801	0.786	0.841	0.811	0.661	0.457
Heavily	0.495	0.369	0.656	0.41	0.528	0.219

2. Validation

After the training process is complete, the validation stage is carried out. The validation results of the YOLOv5 model for land classification for all classes obtained values of mAP@.25 0.728, mAP@.5 0.661, mAP@.25 0.536, mAP@.95 0.326, precision 0.696, recall 0.614. the complete value of the validation calculation can be seen in Table 3.

TABLE IIIII
VALIDATION VALUE

Class	Precission	Recall	mAP @.25	mAP @.5	mAP @.75	mAP @.95
All	0.696	0.614	0.728	0.661	0.536	0.326
Bare	0.798	0.676	0.688	0.75	0.418	0.309
Softly	0.798	0.79	0.841	0.815	0.661	0.455
Heavily	0.492	0.376	0.656	0.418	0.528	0.213

3. Testing

The last stage is testing the model that has been trained in detecting objects. The mAP@.5 value of 0.65 indicates that the model can detect Softly land cover types quite well. However, it struggles to detect bare and heavily land cover types, as well as photos with more than one land cover type. Some test results can be seen in Figure 4.

Figure 4. Testing Result Image Examples

V. ANALYSIS

A. Training and Validation Result Analysis

Based on the precision-recall curve and the values of mAP, precision, and recall result can be seen in Figure 5 and Table 4.
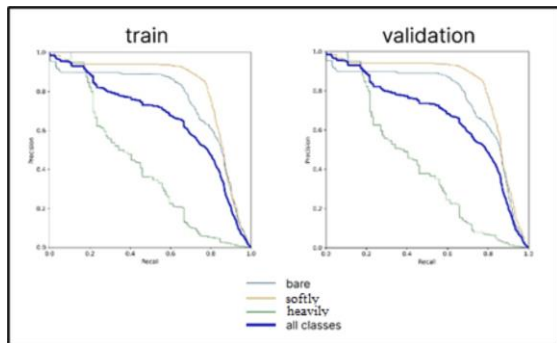

Figure 5. Precision-Recall Curve on Training and Validation

TABLE VI
COMPARISON OF MAP VALUE ON TRAINING AND VALIDATION

mAP / Stage	All	Bare	Softly	Heavily
Train	65.6%	74.8%	81.1%	41%
Validation	66.1%	75%	81.5%	41.8%
Difference	0.5%	0.2%	0.4%	0.8%

The identical and quite good precision-recall graph and mAP values are above 70% and have a difference of less than 1% for the bare and Softly land cover types indicating the model's best fitting. However, the low precision-recall graph and mAP values below 70% for the Heavily land cover type indicate an underfitting model for that land cover type. The low value of the Heavily land cover type results in a low total mAP value for all classes, which is 65%, so it can be concluded that the model is underfitting.

B. Accuracy Analysis

The accuracy calculation was done using land photos that were not used in training the model and was calculated using Microsoft Excel. The resulting image for the accuracy calculation can be seen in Figure 6.

Figure 4. Example Used in Accuracy Calculation

The accuracy calculation was done using formula (5), Microsoft Excel, and images outside the training dataset to avoid bias with the training phase. The result of the calculation yielded an accuracy value of 0.6 or 60%. Based on the very small difference in values between the train and validation phases, below 1% (0.5% for all classes, 0.2% for the bare class, 0.4% for the Softly class, and 0.8% for the Heavily class), but having an mAP value below 70%, which is 65.6%, it can be concluded that the model is underfitting to classify land cover types.

C. Model Performance Comparison

This research will also use another deep learning model, YOLOv4, to compare its performance with the currently used YOLOv5 model. The comparison results between the performance of YOLOv4 and YOLOv5 can be seen in Table 5.

TABLE V
PERFORMANCE COMPARISON OF YOLOv4 AND YOLOv5 MODEL

Model / Value	YOLOv4	YOLOv5
mAP@.5	43.45%	65.6%
mAP@.95	0.0041%	33%
Precision	66%	70.4%
Recall	31%	60.7%

From the table above it can be seen that the performance of the YOLOv4 model is lower than that of the YOLOv5 model.

VI. CONCLUSIONS

A. Accuracy Analysis

The conclusions based on the research that has been done are as follows:

1. The YOLOv5 model obtained an mAP@.5 score of 75% and 81.5% for classifying bare and Softly land covers, but obtained a low mAP@.5 score of 41.8% for classifying Heavily land cover, indicating that YOLOv5 is good at classifying bare and Softly land covers but not as good for classifying Heavily land cover.

2. The YOLOv5 model obtained a precision of 70.4%, recall of 60.7%, mAP@.25 of 72.8%, mAP@.5 of 65.6%, mAP@.75 of 53.6%, mAP@.95 of 33%, and an accuracy of 60% for all classes.

B. Recommendation

The recommendations given in this study are as follows:

1. Using the pro version of the Google Colab account so that the training process on Google Colab becomes more effective.

2. Using special drones for industrial use, mapping, inspection and surveys so that the process of taking land images becomes more effective.

3. Using a dataset that has Heavily image quality and a larger number, especially for Heavily land cover

types, so that the classification results, especially for Heavily land cover types, are better.

4. The YOLOv5 model gets a mAP@.5 value of 65.6% which is categorized as unfavorable. Therefore, the authors suggest using a model with a better architecture so that the value of the classification results becomes higher.

References

[1] K. A. Hapsari *et al.*, "Resilience of a peatland in Central Sumatra, Indonesia to past anthropogenic disturbance: Improving conservation and restoration designs using palaeoecology," *J. Ecol.*, vol. 106, no. 6, pp. 2473–2490, 2018, doi: 10.1111/1365-2745.13000.

[2] A. Vali, S. Comai, and M. Matteucci, "Deep learning for land use and land cover classification based on hyperspectral and multispectral earth observation data: A review," *Remote Sens.*, vol. 12, no. 15, 2020, doi: 10.3390/RS12152495.

[3] Akhbar, I. Arianingsih, Misrah, and Naharuddin, "Application of the AR4 model image of landsat 8 on land cover classification in central sulawesi grand forest park," *Int. J. Appl. Eng. Res.*, vol. 12, no. 20, pp. 9405–9412, 2017.

[4] S. M. A. Letsoin, D. Herak, F. Rahmawan, and R. C. Purwestri, "Land cover changes from 1990 to 2019 in Papua, Indonesia: Results of the remote sensing imagery," *Sustain.*, vol. 12, no. 16, pp. 1–18, 2020, doi: 10.3390/su12166623.

[5] N. F. H. Jumaat, B. Ahmad, and H. S. Dutsenwai, "Land cover change mapping using high resolution satellites and unmanned aerial vehicle," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 169, no. 1, 2018, doi: 10.1088/1755-1315/169/1/012076.

[6] B. Prayudha *et al.*, "The application of Landsat imageries and mangrove vegetation index for monitoring mangrove community in Segara Anakan Lagoon, Cilacap, Central Java," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 944, no. 1, 2021, doi: 10.1088/1755-1315/944/1/012039.

[7] Y. Sari, Y. F. Arifin, N. Novitasari, and M. R. Faisal, "Effect of Feature Engineering Technique for Determining Vegetation Density," *Int. J. Adv. Comput. Sci. Appl.*, vol. 13, no. 7, pp. 655–661, 2022, doi: 10.14569/IJACSA.2022.0130776.

[8] Y. Sari, Y. Arifin, Novitasari, and M. Faisal, "Implementation of Deep Learning Based Semantic Segmentation Method To Determine Vegetation Density," *Eastern-European J. Enterp. Technol.*, vol. 5, no. 2–119, pp. 42–54, 2022, doi: 10.15587/1729-4061.2022.265807.

[9] Y. Heryadi and E. Miranda, *Land cover classification based on sentinel-2 satellite imagery using convolutional neural network model: A case study in Semarang Area, Indonesia*, vol. 830, no. January. Springer International Publishing, 2020.

[10] Y. Sari, M. Alkaff, and M. Maulida, "Classification of Rice Leaf using Fuzzy Logic and Hue Saturation Value (HSV) to Determine Fertilizer Dosage," 2020, doi: 10.1109/ICIC50835.2020.9288585.

[11] Y. Sari, M. Alkaff, and R. A. Pramunendar, "Iris recognition based

on distance similarity and PCA," *AIP Conf. Proc.*, vol. 1977, no. August 2019, 2018, doi: 10.1063/1.5042900.

[12] M. Alkaff, H. Khatimi, W. Puspita, and Y. Sari, "Modelling and predicting wetland rice production using support vector regression," *Telkomnika (Telecommunication Comput. Electron. Control.*, vol. 17, no. 2, pp. 819–825, 2019, doi: 10.12928/TELKOMNIKA.V17I2.10145.

[13] L. Jiang, H. Liu, H. Zhu, and G. Zhang, "Improved YOLO v5 with balanced feature pyramid and attention module for traffic sign detection," *MATEC Web Conf.*, vol. 355, p. 03023, 2022, doi: 10.1051/matecconf/202235503023.

[14] J. H. Kim, N. Kim, Y. W. Park, and C. S. Won, "Object Detection and Classification Based on YOLO-V5 with Improved Maritime Dataset," *J. Mar. Sci. Eng.*, vol. 10, no. 3, 2022, doi: 10.3390/jmse10030377.

[15] N. Kundu, G. Rani, and V. S. Dhaka, "Seeds Classification and Quality Testing Using Deep Learning and YOLO v5," *ACM Int. Conf. Proceeding Ser.*, no. August, pp. 153–160, 2021, doi: 10.1145/3484824.3484913.

[16] P. Jiang, D. Ergu, F. Liu, Y. Cai, and B. Ma, "A Review of Yolo Algorithm Developments," *Procedia Comput. Sci.*, vol. 199, pp. 1066–1073, 2021, doi: 10.1016/j.procs.2022.01.135.

[17] D. P. Carrasco, H. A. Rashwan, M. A. Garcia, and D. Puig, "T-YOLO: Tiny vehicle detection based on YOLO and multi-scale convolutional neural networks," *IEEE Access*, vol. 11, no. December 2021, 2021, doi: 10.1109/ACCESS.2021.3137638.

[18] M. Krishnaveni, S. K. P. Kumar, E. A. Muthusamy, J. Kowshick, and K. G. Arunya, "Real-time Monitoring of Water Level and Storage Dynamics of Irrigation Tank Using IoT," *H2Open J*, vol. 3, no. 1, pp. 392–400, 2020, doi: 10.2166/h2oj.2020.123.

[19] Y. C. How, A. F. Ab. Nasir, K. F. Muhammad, A. P. P. Abdul Majeed, M. A. Mohd Razman, and M. A. Zakaria, "Glove Defect Detection Via YOLO V5," *Mekatronika*, vol. 3, no. 2, pp. 25–30, 2022, doi: 10.15282/mekatronika.v3i2.7342.

[20] F. A. P, H. Segah, N. S. Yusuf, and R. M. Sukarna, "Analysis Of Changes In Mangrove Cover Using Landsat Imagery In Seruyan District," vol. 2, no. 12, pp. 2717–2733, 2022.

[21] Y. Sari and P. B. Prakoso, "Detection of Moving Vehicle using Adaptive Threshold Algorithm in Varied Lighting," *Proceeding - 2018 5th Int. Conf. Electr. Veh. Technol. ICEVT 2018*, no. 1, pp. 136–141, 2019, doi: 10.1109/ICEVT.2018.8628398.

[22] Y. Sari, A. R. Baskara, and R. Wahyuni, "Classification of Chili Leaf Disease Using the Gray Level Co-occurrence Matrix (GLCM) and the Support Vector Machine (SVM) Methods," *2021 6th Int. Conf. Informatics Comput. ICIC 2021*, 2021, doi: 10.1109/ICIC54025.2021.9632920.

[23] A. Sharifara, M. S. M. Rahim, H. Sayyadi, and F. Navabifar, "Search space optimization and false alarm rejection face detection framework," *J. Theor. Appl. Inf. Technol.*, vol. 79, no. 3, pp. 370–379, 2015.

UNIVERSITAS LAMBUNG MANGKURAT

Novitasari Novitasari <novitasari@ulm.ac.id>

IJETAE :Paper Status Notification – 002

EDITOR IJETAE <ijetae@gmail.com>   Tue, March 7, 2023 at 2:19 AM

To: novitasari@ulm.ac.id

Dear Researcher

Season's Greeting for Your Good Health and Happiness.

This is to inform you that your paper has been selected for publication in the International Journal of Emerging Technology and Advanced Engineering, An ISO 9001:2008 Certified International Journal, with a **MINOR Revision** below.

Please do theory and analysis corrections in the marked sections in manuscript below before **28 March 2023**.

Hope for Cooperation from Your End.

Regards

Editor In Chief
International Journal of Emerging Technology & Advanced Engineering
An ISO 9001:2008 Certified, ISSN 2250–2459(ONLINE)
Website: http://www.ijetae.com/

---

1 attachments

Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model.pdf
563K

📄 **Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model.pdf**
2627K

📄 **Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model.pdf**
2627K

UNIVERSITAS
LAMBUNG MANGKURAT

Novitasari Novitasari <novitasari@ulm.ac.id>

IJETAE :Paper Status Notification 1

EDITOR IJETAE <ijetae@gmail.com>   Tue, Apr 4, 2023 at 3:19 AM
To: novitasari@ulm.ac.id

Dear Researcher

Season's Greeting for Your Good Health and Happiness.

This is to inform you that your paper has been selected for publication in the International Journal of Emerging Technology and Advanced Engineering, An ISO 9001:2008 Certified International Journal, typo and image errors.

After completion of all formalities your paper will be published on **24 APR 2023.** In

In case of any query, feel free to contact us at editor@ijetae.com, ijetae@gmail.com

Hope for Cooperation from Your End.

Regards

Editor In Chief
International Journal of Emerging Technology & Advanced Engineering
An ISO 9001:2008 Certified, ISSN 2250–2459(ONLINE)
Website: http://www.ijetae.com/

---

1 attachments

📄 **Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model.pdf**
563K

Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model

by Yuslena Sari

Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model

Novitasari Novitasari[1], Yuslena Sari[2], Yudi Firmanul Arifin[3], Mohammad Reza Faisal[4],

Andreyan Rizky Baskara[2], Rian Ridhani[2]

[1]Department of Civil Engineering, Universitas Lambung Mangkurat, Banjarbaru, Indonesia
[2]Department of Information Technology, Universitas Lambung Mangkurat, Jl. Brig. Hasan Basri, Banjarmasin, Indonesia
[3]Faculty of Forestry, Universitas Lambung Mangkurat, Banjarbaru, Indonesia
[4]Department of Computer Science, Universitas Lambung Mangkurat, Banjarbaru, Indonesia
[5]Department of Information Technology, Universitas Lambung Mangkurat, Jl. Brig. Hasan Basri, Banjarmasin, Indonesia
[5]Department of Information Technology, Universitas Lambung Mangkurat, Jl. Brig. Hasan Basri, Banjarmasin, Indonesia

[1]novitasari@ulm.ac.id
[2]yuzlena@ulm.ac.id
[3]yudifirmanul@ulm.ac.id
[4]andreyan.baskara@ulm.ac.id
[5]1710817210014@ulm.ac.id

Abstract— **Land cover is the appearance of the earth's surface covered by biological and non-biological diversity. Land cover can provide important information for modeling and understanding natural phenomena that occur on the earth's sur-face. Supervising land cover change is useful for designing and managing better actions to prevent or ameliorate loss-es result from land cover change activities. Types of land cover based on the ministry of environment and forestry and S.N.I. In the Liang Anggang protected forest area are primary swamp forest, secondary swamp forest, open swamp, wet bush, pure dry agriculture, mixed dry agriculture, open water, transmigration areas plantation forest, and vacant land. The type of land cover in the Liang Anggang protected forest area can be classified into 3 types, namely bare, softly, and heavily. Land cover classification can be done from two types of data, namely satellite data and unmanned aerial vehicle (UAV). This research will use UAV data for better image detail. The model used is YOLOv5. The results of this study obtained mAP@.5 74.8%, mAP@.95 31.3%, precision 81.7%, recall 66.4% for bare class. mAP@.5 81.1%, mAP@.95 45.7%, precision 80.1%, recall 78.6% for "softly" class. mAP@.5 40.1%, mAP@.95 21.9%, precision 49.5%, recall 36.9% for "heavily" class. mAP@.25 72.8%, mAP@.5 65.6%, mAP@.75 53.6%, mAP@.95 33%, precision 70.4%, recall 60.7%, and accuracy 60% for all class.**

Keywords—**Classification, Land Cover, YOLOv5, UAV**

I. INTRODUCTION

Land cover is the appearance of the earth's surface covered by biological and non-biological diversity. Land cover can provide important information for modelling and understanding natural phenomena that occur on the earth's surface. Land cover data can also be used to study climate change and understand the relationship between human activities and global change [1]. One type of land cover in South Kalimantan is peat land. One of the peatland areas in South Kalimantan is the Liang Anggang protected forest, Banjarbaru block 1 area which has an area of 494 hectares and is filled with land such as agriculture, plantations, roads, settlements, and shrubs. Apart from the fact that the location is peatland, the location in block 1 fulfils the characteristics and suitability of the needs in collecting data for the classification of peatland cover. So as the selection of this research location is in accordance with the data requirements.

Destructive changes in land use including on peatlands are the main cause of loss of biodiversity, damage to ecosystems and drastic climate change. Monitoring land cover change is useful for designing and managing better regulations to prevent or remedy losses arising from land cover change activities. Monitoring land cover changes can help in predicting and avoiding natural disasters or other hazardous events [1]–[3]. Monitoring and analysis of land cover can be carried out by classifying land cover, according to the

Ministry of Environment and Forestry and the National Standardization Agency, especially the Indonesian National Standard, land cover is classified into 23 classes, consisting of 6 forest classes, 16 non-forest classes, and 1 rehabilitation forest class [4]. The types of land cover based on the ministry of environment and forestry and the Indonesian National Standard (S.N.I) found in the Liang Anggang protected forest area are primary swamp forest, secondary swamp forest, open swamp, wet shrub, pure dry agriculture, mixed dry agriculture, open water, transmigration areas, plantation forests, and bare ground. The types of land cover in the Liang Anggang protected forest area can be classified into 3 types, namely bare (surface that has no vegetation at all), Softly (surface covered with medium and high vegetation), and Heavily (surface covered with moderate vegetation). The data collection technique is carried out using the Unmanned Aeiral Vehicle (UAV) which can take pictures from a lower altitude so that the spatial resolution obtained is 1cm, more detailed than the satellite (30cm). And also, the UAV

can take pictures in cloudy weather conditions because the UAV's height is lower than the clouds [5]–[8].

The technique that is highly favoured for classification is Machine Learning. Machine Learning is continually evolving and producing new fields such as Deep Learning. Deep Learning is popular in image analysis and intelligent image processing [9]–[12]. One of the popular models used in Deep Learning is You Only Look Once (YOLO).

The YOLO model is well-known for its use in object detection [13]. Several studies have used YOLOv5 for research purposes, such as Jun-Hwa Kim et al., who conducted a study on maritime object classification and optimized the Singapore Maritime Dataset (SMD) [14]. Nidhi et al. conducted a study on seed classification and quality using YOLOv5 and K-Means [15]. Linfeng et al. detected traffic signs using SSD300, Faster RCNN, YOLOv3, YOLOv4, and YOLOv5 to compare the accuracy of these models [16]. Daniel Padilla Carrasco et al. detected small vehicles in parking lots using YOLOv5 to manage parking spaces efficiently and achieve the goal of a smart city [17]. Tian-Hao Wu et al. used YOLOv5 to detect vehicles and their distances in real-time in a virtual environment to optimize autonomous vehicle technology [18]. Lastly, How Yong Chen et al. used YOLOv5 to detect defects in glove production [19].

II. Literature Review

A. Land Cover

Land cover refers to the surface features of the Earth that are covered by biotic and abiotic elements. Land cover provides important information for modeling and understanding natural phenomena occurring on the Earth's surface. Land cover data can also be used to study climate change and understand the relationship between human activities and global changes. Accurate land cover information is one of the determining factors in improving the performance of ecosystem, hydrology, and atmospheric models. One type of land cover found in South Kalimantan is peatland. Peatland is a water-saturated land composed of organic material (>12%) that occurs due to the accumulation of decomposing plant remains and tissues with a thickness of more than 50 cm. The accumulation is caused by the slow rate of decomposition compared to the rate of organic material accumulation inundated by water over a long period of time [1]–[3].

B. Peatland

Peatland is a water-saturated land composed of organic material (>12%). Peatland is formed by the accumulation of plant residues and decomposed plant tissues with a thickness of more than 50 cm. The accumulation is due to the slow rate of decomposition compared to the rate of organic material accumulation that is inundated with water for a long period of time [1]. Peat is classified as marginal land and is vulnerable to disturbances, so any increase in the productivity of peatland must be accompanied by

efforts to prevent ecosystem damage. Peatland damage is caused by tree felling and forest conversion, fires, and reclamation. Peat can be considered a renewable resource only on a geological time scale. Peat growth estimates vary between 0.5 to 1 mm per year, and the subsidence rate of drained peatland is between 1.5 to 3 cm per year. Because the subsidence rate is 15-30 times that of the growth rate, peatland cannot be categorized as a renewable resource.

Several types of land cover based on the ministry of environment and forestry and S.N.I. located in the Liang Anggang area include:

1. Primary swamp forest: Forests growing in wet habitats include mangroves, sago, and peatlands.
2. Secondary swamp forest: Forests growing in wet habitats include mangroves, sago, and peat, often with human interventions such as logging and agriculture.
3. Open swamp: Open swamp with little vegetation.
4. Wet shrub: Wet area filled with shrubs.
5. Mixed dry agriculture: Areas used for agricultural activities and still have wild plants such as shrubs and trees scattered in the agricultural area.
6. Open water: Open water areas such as rivers and lakes.
7. Transmigration areas: The area surrounding the forest that is related to human activities such as houses, parks, and huts.
8. Pure dry agriculture: Areas used for agricultural activities.
9. Plantation forest: An area that has been planted with vegetation as part of forest rehabilitation efforts.
10. Bare ground: An area of empty land without vegetation.

Pictures of land cover types in the Liang Anggang protected forest can be seen in Table 1.

TABLE I
TYPES OF LAND COVER IN THE LIANG ANGGANG PROTECTED FOREST

2

Land Image	Land Type	Land Image	Land Type
	Primary Swamp Forest		Wet Shrub
	Secondary Swamp Forest		*Mixed Dry Agriculture*
	Open Swamp		Open Water
	Plantation Forest		Transmigration Area
	Pure Dry Agriculture		Bare Ground

C. Image Classification

Image classification is the process of arranging or grouping pixels into several classes based on object categories or certain criteria. Each pixel in each class is assumed to have homogenous characteristics. The goal of classification is to extract spectral patterns found within the image [20]–[22].

III. RESEARCH METHODOLOGY

A. Problem Identification

The first stage of this research is to identify the problem. Problem identification is carried out qualitatively by focusing on in-depth observation to discover a problem. The problem identified is the importance of classifying land cover using a reliable model to produce accurate land cover types with good accuracy results. The solution to this problem is to use the best object detection model for land cover classification and then observe the accuracy results of using the model. Good accuracy results in using the model can be a recommendation for the next researchers in land cover classification and object detection in general.

And land cover classification information can be a further action by researchers or agencies related to land cover.

B. Image Acquisition

Image acquisition is carried out to collect the necessary data and to determine the digital image recording model to be used [23]. Land images were taken using a DJI Mavic Pro drone in November - December 2021 and July - August 2022. The drone is automatically controlled using the DroneDeploy application. The drone follows a predetermined path on DroneDeploy but can still be manually controlled with a remote. Image capture is done in clear or slightly cloudy weather conditions. The drone is set to fly at a height of 20 meters from the surface. Image capture is done between 8 am and 12 pm.

Because the Liang Anggang protected forest is located near the Syamsudin Noor airport, some areas cannot be captured with a drone because they are in a restricted fly zone with a maximum height of 60 meters in yellow areas and not allowed to fly at all in blue areas. Therefore, the area to be captured is located within a maximum of 60 meters with a drone capture height of 20 meters so that the drone can still capture images with sufficient coverage. The restricted fly zone in the Liang Anggang protected forest can be seen in Figure 1.

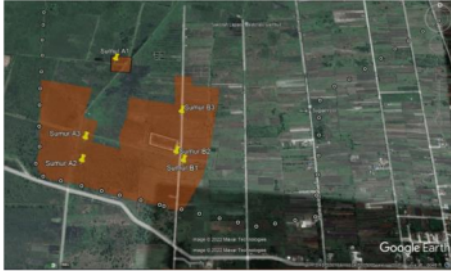Figure 1. Restricted Fly Zone Around Liang Anggang Protection Forest

IV. RESULT

A. Image Capture Process

The first stage of taking images with a drone is determining the area to be photographed. Area capture settings are made in the Google Earth Pro application to determine the area to be captured. After the area marking has been completed, the results will be exported into a file with the .KML format. Then the file will be imported into the DroneDeploy application. From the DroneDeploy application, drones can be set to take pictures automatically according to the area that has been marked.

UAV image data obtained from the results of drone capture conducted in July - August 2022 collected 7437

images with an area of 22.6 hectares. The total image data collected after being combined with data taken in November - December 2021 collected 17,674 images with an area of 40.6 hectares. Areas that have been taken using drones are marked in orange which can be seen in Figure 2.

Class	Precission	Recall	mAP @.25	mAP @.5	mAP @.75	mAP @.95
All	0.704	0.607	0.728	0.656	0.536	0.33
Bare	0.817	0.664	0.688	0.748	0.418	0.313
Softly	0.801	0.786	0.841	0.811	0.661	0.457
Heavily	0.495	0.369	0.656	0.41	0.528	0.219

Figure 2. Territory That Has Been Taken by Drones

1. *Labelling*

Labelling process is carried out to label objects in the image that will be detected. The label will assist the trained model to identify the objects to be detected.

After all images have been preprocessed, the dataset construction is carried out to divide the dataset according to its usage in each stage. The dataset is divided into three folders, namely train, val, and test.

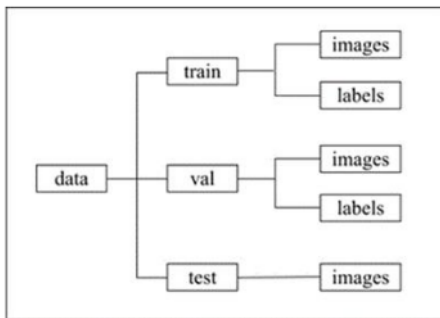The complete structure of the dataset can be seen in Figure 3.

4

Figure 3. Complete Structure of Dataset

B. *Training Model*

Training is conducted using the Google Colab platform. The training stage 15 the YOLOv5 model is divided into 3 stages, namely the training, validation, and testing stages.

1. Training

At the training model stage, the first step is to run the code to download the YOLOv5 file into the Google Colab project. After the download process is complete, the project will display the YOLOv5 folder. Then the next step is to connect the project with the dataset that has been stored on Google Drive and determine the location of the dataset from the coco128.yaml file.

Model training is carried out by conducting training several times with different batch and epoch values to find out the optimal setting values to get the best precision, recall, and mAP values. The training results from the YOLOv5 training model for land classification for all classes obtained values of mAP@.25 0.728, mAP@.5 0.656, mAP@.75 0.536, mAP@.95 0.33, precision 0.704, recall 0.607. Complete values of training results for 100 epochs and 5 batches can be seen in table 2.

TABLE III
TRAINING RESULT VALUE

2. Validation

After the training process is complete, the validation stage is carried out. The validation results of the YOLOv5 model for land classification for all classes obtained values of mAP@.25 0.728, mAP@.5 0.661, mAP@.25 0.536, mAP@.95 0.326, precision 0.696, recall 0.614. the complete value of the validation calculation can be seen in Table 3.
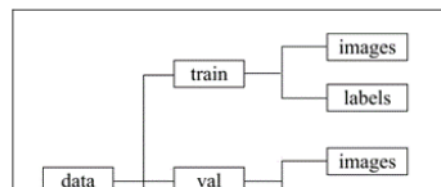
TABLE VI
COMPARISON OF MAP VALUE ON TRAINING AND VALIDATION

mAP / Stage	All	Bare	Softly	Heavily
Class	Precission	Recall	mAP@.25	mAP@.5	mAP@.75	mAP@.95
All	0.696	0.614	0.728	0.661	0.536	0.326
Bare	0.798	0.676	0.688	0.75	0.418	0.309
Softly	0.798	0.79	0.841	0.815	0.661	0.455
Heavily	0.492	0.376	0.656	0.418	0.528	0.213
Train		65.6%	74.8%	81.1%	41%	
Validation		66.1%	75%	81.5%	41.8%	
Difference		0.5%	0.2%	0.4%	0.8%	

The identical and quite good precision-recall graph and mAP values are above 70% and have a difference of less than 1% for the bare and Softly land cover types indicating the model's best fitting. However, the low precision-recall graph and mAP values below 70% for the Heavily land cover type indicate an underfitting model for that land cover type. The low value of the Heavily land cover type results in a low total mAP value for all classes, which is 65%, so it can be concluded that the model is underfitting.

TABLE IIIII
VALIDATION VALUE

3. Testing

The last stage is testing the model that has been trained in detecting objects. The mAP@.5 value of 0.65 indicates that the model can detect Softly land cover types quite well. However, it struggles to detect bare and heavily land cover types, as well as photos with more than one land cover type. Some test results can be seen in Figure 4.
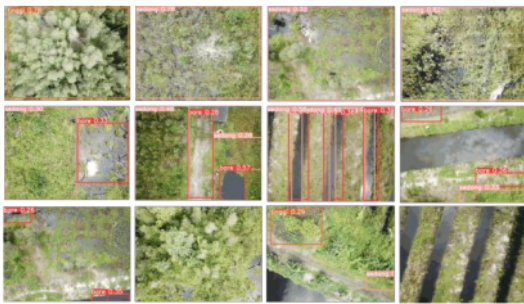

Figure 4. Testing Result Image Examples

V. ANALYSIS

A. Training and Validation Result Analysis

Based on the precision-recall curve and the values of mAP, precision, and recall result can be seen in Figure 5 and Table 4.
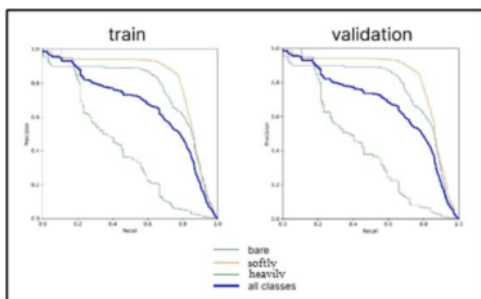

B. Accuracy Analysis

The accuracy calculation was done using land photos that were not used in training the model and was calculated using Microsoft Excel. The resulting image for the accuracy calculation can be seen in Figure 6.

Figure 4. Example Used in Accuracy Calculation

The accuracy calculation was done using formula (5), Microsoft Excel, and images outside the training dataset to avoid bias with the training phase. The result of the calculation yielded an accuracy value of 0.6 or 60%. Based on the very small difference in values between the train and validation phases, below 1% (0.5% for all classes, 0.2% for the bare class, 0.4% for the Softly class, and 0.8% for the Heavily class), but having an mAP value below 70%, which is 65.6%, it can be concluded that the model is underfitting to classify land cover types.

C. Model Performance Comparison

This research will also use another deep learning model, YOLOv4, to compare its performance with the currently used YOLOv5 model. The comparison results between the performance of YOLOv4 and YOLOv5 can be seen in Table 5.

TABLE V
PERFORMANCE COMPARISON OF YOLOv4 AND YOLOv5 MODEL

Model / Value	YOLOv4	YOLOv5
mAP@.5	43.45%	65.6%
mAP@.95	0.0041%	33%
Precision	66%	70.4%
Recall	31%	60.7%

From the table above it can be seen that the performance of the YOLOv4 model is lower than that of the YOLOv5 model.

VI. CONCLUSIONS

A. Accuracy Analysis

The conclusions based on the research that has been done are as follows:

1. The YOLOv5 model obtained an mAP@.5 score of 75% and 81.5% for classifying bare and Softly land covers, but obtained a low mAP@.5 score of 41.8% for classifying Heavily land cover, indicating that YOLOv5 is good at classifying bare and Softly land covers but not as good for classifying Heavily land cover.

2. The YOLOv5 model obtained a precision of 70.4%, recall of 60.7%, mAP@.25 of 72.8%, mAP@.5 of 65.6%, mAP@.75 of 53.6%, mAP@.95 of 33%, and an accuracy of 60% for all classes.

B. Recommendation

The recommendations given in this study are as follows:

1. Using the pro version of the Google Colab account so that the training process on Google Colab becomes more effective.
2. Using special drones for industrial use, mapping, inspection and surveys so that the process of taking land images becomes more effective.
3. Using a dataset that has Heavily image quality and a larger number, especially for Heavily land cover types, so that the classification results, especially for Heavily land cover types, are better.
4. The YOLOv5 model gets a mAP@.5 value of 65.6% which is categorized as unfavorable. Therefore, the authors suggest using a model with a better architecture so that the value of the classification results becomes higher.

References

[1] K. A. Hapsari *et al.*, "Resilience of a peatland in Central Sumatra, Indonesia to past anthropogenic disturbance: Improving conservation and restoration designs using palaeoecology," *J. Ecol.*, vol. 106, no. 6, pp. 2473–2490, 2018, doi: 10.1111/1365-2745.13000.
[2] A. Vali, S. Comai, and M. Matteucci, "Deep learning for land use and land cover classification based on hyperspectral and multispectral earth observation data: A review," *Remote Sens.*, vol. 12, no. 15, 2020, doi: 10.3390/RS12152495.
[3] Akhbar, I. Arianingsih, Misrah, and Naharuddin, "Application of the AR4 model image of landsat 8 on land cover classification in central sulawesi grand forest park," *Int. J. Appl. Eng. Res.*, vol. 12, no. 20, pp. 9405–9412, 2017.

6

[4] S. M. A. Letsoin, D. Herak, F. Rahmawan, and R. C. Purwestri, "Land cover changes from 1990 to 2019 in Papua, Indonesia: Results of the remote sensing imagery," *Sustain.*, vol. 12, no. 16, pp. 1–18, 2020, doi: 10.3390/su12166623.

[5] N. F. H. Jumaat, B. Ahmad, and H. S. Dutsenwai, "Land cover change mapping using high resolution satellites and unmanned aerial vehicle," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 169, no. 1, 2018, doi: 10.1088/1755-1315/169/1/012076.

[6] B. Prayudha *et al.*, "The application of Landsat imageries and mangrove vegetation index for monitoring mangrove community in Segara Anakan Lagoon, Cilacap, Central Java," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 944, no. 1, 2021, doi: 10.1088/1755-1315/944/1/012039.

[7] Y. Sari, Y. F. Arifin, N. Novitasari, and M. R. Faisal, "Effect of Feature Engineering Technique for Determining Vegetation Density," *Int. J. Adv. Comput. Sci. Appl.*, vol. 13, no. 7, pp. 655–661, 2022, doi: 10.14569/IJACSA.2022.0130776.

[8] Y. Sari, Y. Arifin, Novitasari, and M. Faisal, "Implementation of Deep Learning Based Semantic Segmentation Method To Determine Vegetation Density," *Eastern-European J. Enterp. Technol.*, vol. 5, no. 2–119, pp. 42–54, 2022, doi: 10.15587/1729-4061.2022.265807.

[9] Y. Heryadi and E. Miranda, *Land cover classification based on sentinel-2 satellite imagery using convolutional neural network model: A case study in Semarang Area, Indonesia*, vol. 830, no. January. Springer International Publishing, 2020.

[10] Y. Sari, M. Alkaff, and M. Maulida, "Classification of Rice Leaf using Fuzzy Logic and Hue Saturation Value (HSV) to Determine Fertilizer Dosage," 2020, doi: 10.1109/ICIC50835.2020.9288585.

[11] Y. Sari, M. Alkaff, and R. A. Pramunendar, "Iris recognition based on distance similarity and PCA," *AIP Conf. Proc.*, vol. 1977, no. August 2019, 2018, doi: 10.1063/1.5042900.

[12] M. Alkaff, H. Khatimi, W. Puspita, and Y. Sari, "Modelling and predicting wetland rice production using support vector regression," *Telkomnika (Telecommunication Comput. Electron. Control.*, vol. 17, no. 2, pp. 819–825, 2019, doi: 10.12928/TELKOMNIKA.V17I2.10145.

[13] L. Jiang, H. Liu, H. Zhu, and G. Zhang, "Improved YOLO v5 with balanced feature pyramid and attention module for traffic sign detection," *MATEC Web Conf.*, vol. 355, p. 03023, 2022, doi: 10.1051/matecconf/202235503023.

[14] J. H. Kim, N. Kim, Y. W. Park, and C. S. Won, "Object Detection and Classification Based on YOLO-V5 with Improved Maritime Dataset," *J. Mar. Sci. Eng.*, vol. 10, no. 3, 2022, doi: 10.3390/jmse10030377.

[15] N. Kundu, G. Rani, and V. S. Dhaka, "Seeds Classification and Quality Testing Using Deep Learning and YOLO v5," *ACM Int. Conf. Proceeding Ser.*, no. August, pp. 153–160, 2021, doi: 10.1145/3484824.3484913.

[16] P. Jiang, D. Ergu, F. Liu, Y. Cai, and B. Ma, "A Review of Yolo Algorithm Developments," *Procedia Comput. Sci.*, vol. 199, pp. 1066–1073, 2021, doi: 10.1016/j.procs.2022.01.135.

[17] D. P. Carrasco, H. A. Rashwan, M. A. Garcia, and D. Puig, "T-YOLO: Tiny vehicle detection based on YOLO and multi-scale convolutional neural networks," *IEEE Access*, vol. 11, no. December 2021, 2021, doi: 10.1109/ACCESS.2021.3137638.

[18] M. Krishnaveni, S. K. P. Kumar, E. A. Muthusamy, J. Kowshick, and K. G. Arunya, "Real-time Monitoring of Water Level and Storage Dynamics of Irrigation Tank Using IoT," *H2Open J*, vol. 3, no. 1, pp. 392–400, 2020, doi: 10.2166/h2oj.2020.123.

[19] Y. C. How, A. F. Ab. Nasir, K. F. Muhammad, A. P. P. Abdul Majeed, M. A. Mohd Razman, and M. A. Zakaria, "Glove Defect Detection Via YOLO V5," *Mekatronika*, vol. 3, no. 2, pp. 25–30, 2022, doi: 10.15282/mekatronika.v3i2.7342.

[20] F. A. P, H. Segah, N. S. Yusuf, and R. M. Sukarna, "Analysis Of Changes In Mangrove Cover Using Landsat Imagery In Seruyan District," vol. 2, no. 12, pp. 2717–2733, 2022.

[21] Y. Sari and P. B. Prakoso, "Detection of Moving Vehicle using Adaptive Threshold Algorithm in Varied Lighting," *Proceeding - 2018 5th Int. Conf. Electr. Veh. Technol. ICEVT 2018*, no. 1, pp. 136–141, 2019, doi: 10.1109/ICEVT.2018.8628398.

[22] Y. Sari, A. R. Baskara, and R. Wahyuni, "Classification of Chili Leaf Disease Using the Gray Level Co-occurrence Matrix (GLCM) and the Support Vector Machine (SVM) Methods," *2021 6th Int. Conf. Informatics Comput. ICIC 2021*, 2021, doi: 10.1109/ICIC54025.2021.9632920.

[23] A. Sharifara, M. S. M. Rahim, H. Sayyadi, and F. Navabifar, "Search space optimization and false alarm rejection face detection framework," *J. Theor. Appl. Inf. Technol.*, vol. 79, no. 3, pp. 370–379, 2015.

Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model

Papua, Indonesia: Results of the Remote Sensing Imagery", Sustainability, 2020
Publication

5   www.ijisae.org   1 %
     Internet Source

6   Submitted to Coventry University   1 %
     Student Paper

7   jurnal.iaii.or.id   1 %
     Internet Source

8   www.e3s-conferences.org   1 %
     Internet Source

9   Juhriyansyah Dalle, Muhammad Tamjidi,   1 %
     Syarif Yusirwan Syafruddin. "Implementation
     of Water Debit Measurement Using
     Microcontroller-Connected Flow Meters", TEM
     Journal, 2020
     Publication

10   www.researchgate.net   <1 %
     Internet Source

11   Submitted to Universitas Pancasila   <1 %
     Student Paper

12   Nisa Novita, Nurul Silva Lestari, Mega Lugina,   <1 %
     Tatang Tiryana, Imam Basuki, Joni Jupesta.
     "Geographic Setting and Groundwater Table
     Control Carbon Emission from Indonesian
     Peatland: A Meta-Analysis", Forests, 2021

Publication

13 Ava Vali, Sara Comai, Matteo Matteucci. "Deep Learning for Land Use and Land Cover Classification Based on Hyperspectral and Multispectral Earth Observation Data: A Review", Remote Sensing, 2020
Publication
<1 %

14 Eka Setya Wijaya, Andy Mizwar, Achmad Mujaddid Islami, Yuslena Sari, Erika Maulidiya, Irham Maulani Abdul Gani. "Garbage Classification Using CNN Architecture ShuffleNet v2", 2022 Seventh International Conference on Informatics and Computing (ICIC), 2022
Publication
<1 %

15 Hakki Soy. "chapter 9 Edge AI-Based Crowd Counting Application for Public Transport Stops", IGI Global, 2022
Publication
<1 %

16 cdn.undiksha.ac.id
Internet Source
<1 %

17 repo.ikippgribali.ac.id
Internet Source
<1 %

18 www.mdpi.com
Internet Source
<1 %

19 Yuslena Sari, Andreyan Rizky Baskara, Khair Zuniar Rahman, Puguh Budi Prakoso.
<1 %

"Counting the Number of Moving Vehicles by Its Type Based on Computer Vision", 2021 4th International Conference of Computer and Informatics Engineering (IC2IE), 2021
Publication

20   A G Salim, B H Narendra, Y Lisnawati, H H Rachmat. "Hydro-physical properties of agriculturally used peatlands in Liang Anggang Protected Forest, South Kalimantan, Indonesia", IOP Conference Series: Earth and Environmental Science, 2021
Publication

<1 %

21   Yuslena Sari, Mutia Maulida, Razak Maulana, Johan Wahyudi, Ahmad Shalludin. "Detection of Corn Leaves Nutrient Deficiency Using Support Vector Machine (SVM)", 2021 4th International Conference of Computer and Informatics Engineering (IC2IE), 2021
Publication

<1 %

UNIVERSITAS
LAMBUNG MANGKURAT

Novitasari Novitasari <novitasari@ulm.ac.id>

IJETAE :Paper Status Notification for Volume 13, Issue 5, May 2023.

EDITOR IJETAE <ijetae@gmail.com>   Tue, May 9, 2023 at 2:19 AM
To:novitasari@ulm.ac.id

Dear Researcher

Season's Greeting for Your Good Health and Happiness.

This is to inform you that your paper has been selected for publication in the International Journal of Emerging Technology and Advanced Engineering, An ISO 9001:2008 Certified International Journal, Volume 13, Issue 5, May 2023.

Please find attached your Paper Acceptance Letter, Copyright Form and Publication Fee details.

You are requested to fill the Copyright form (attached here with) in your own handwriting and revert it to editor@ijetae.com, ijetae@gmail.com .

Also, please send **MS Word (DOC)** format of Camera Ready Paper (Final Version of Paper) as per the IJETAE Template. Please highlight the modifications in the Camera Ready Paper as per the Reviewers Comments. **Please provide author(s)/co author(s) ORCID ID** (16 digits, please visit www.orcid.org).

Please note that your paper will be provided Crossref DOI (Digital Object Identifier) after publishing. This will include your paper in 14000+ Digital Library Database.

You have to complete all format on or before 26 May 2023.

After completion of all formalities your paper will be published on **29 May 2023.**

In case of any query, feel free to contact us at editor@ijetae.com, ijetae@gmail.com

Hope for Cooperation from Your End.

Regards

Editor In Chief
International Journal of Emerging Technology & Advanced Engineering
An ISO 9001:2008 Certified, ISSN 2250–2459(ONLINE)
Website: http://www.ijetae.com/

---

5 attachments

📄 **IJETAE_COPYRIGHT_FORM.doc**
35K

📄 **IJETAE_PAPER_TEMPLATE.doc**
56K

📄 **Publication_Fee_ IJETAE.pdf**
113K

📄 **IJETAE_0523_677_Acceptance_Letter.pdf**
152K

Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model.pdf
2627K

Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model.pdf
2627K

Date: **22 May, 2023**

Acceptance Letter

Author's Name	Novitasari Novitasari, Yuslena Sari, Yudi Firmanul Arifin, Mohammad Reza Faisal, Andreyan Rizky Baskara, Rian Ridhani
Paper ID:	IJETAE_0523_677
Paper Title	Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model

Dear Author

This is to inform you that your paper submitted for publishing in IJETAE has been provisionally accepted based on the recommendations provided by the Technical Review Committee. IJETAE Team would like to request you to go through the correction/changes as specified by the reviewers in order to increase your paper quality.

Please analyze the following Reviewer's Comments and make changes in the Camera Ready Copy (Final Version of your manuscript).

Paper Status:	Accepted	Accepted After Minor Modifications	Rejected
1) The authors must do an English grammar check on the entire paper to correct the grammatical errors. The authors can use any online tool to correct English and Grammar. 2) The abstract is looking like an introduction section. It should describe the problem and high-level solution details. Include the technical content as needed.			

You have to complete all formalities (Camera Ready, Copyright and Publication Fee Submission) on or before May 26, 2023.

Your Manuscript will be published on May 29, 2023 if you complete all paper publishing formalities.

Also, you can opt for next upcoming issue.

IJETAE Team congratulates you for this achievement.

Regards

Editor in Chief
International Journal of Emerging Technology and Advanced Engineering
Website: www.ijetae.com
ISSN 2250-2459 (Online), ISO 9001:2008 Certified,
Email: editor@ijetae.com, ijetae@gmail.com

International Journal of Emerging Technology and Advanced Engineering
Website: www.ijetae.com (ISSN 2250-2459, ISO 9001:2008 Certified Journal)
COPYRIGHT FORM

Please complete and sign the form and send it with the final version of your manuscript. It is required to obtain written confirmation from authors in order to acquire copyrights for papers published in the journal so as to index them to various repositories.

Title of the Paper:

_____

Name of the Author:

_____

The undersigned hereby transfer any and all rights in and to the paper including without limitation all copyrights to the International Journal of Emerging Technology and Advanced Engineering. The undersigned hereby represents and warrants that the paper is original and that he/she is the author of the paper, except for material that is clearly identified as to its original source, with permission notices from the copyright owners where required. The undersigned is responsible for all disputes/claims from original author if his/her paper is having any plagiarism in its contents/tables/charts/figures. Also, the undersigned represents that he/she has the power and authority to make and execute this assignment.

This agreement is to be signed by at least one of the authors who have obtained the assent of the co-author(s) where applicable.

_____

(1) Signature and date

_____

(1) Author's Name and Title (Designation)

_____

Please scan and paste your Photo/Signature Identity Proof (PAN Card/ Voter Identity Card/ College or University Identity Card/Driving License).

(1)Institution/Organization or company seal (if appropriate)

After completion of this form, please email the scanned file of original signed form to editor@ijetae.com, ijetae@gmail.com .

PUBLICATION   FEE   FORM

Please print this form, fill in the required information in your own handwriting , and return it together with your payment details or/and mail scanned copy of Sealed Bank Deposit/Transaction ID as proof of payment.

Name of Author:_____

Deposit Bank Branch/Transaction ID_____

City _____**Province/State**_____

Country _____**Postal/Zip Code**_____

Author Telephone _____ **Mobile**_____

E-mail _____ **Paper ID:** _____

Paper Title: _____

Payment Details for Authors:

	Publication Fee	Deposited Money Details
Publication fee up to 20 pages	**520 USD**	**520 USD**
Bank Processing Fee depending on Author's Country Bank	**X USD**	**If applicable**
Extra pages after 20 pages	**20 USD per page (Y)**	**Total = 520 USD+X+Y**

For Fee Transfer through Cash Deposit/Internet Banking:

Account Name: IJETAE
Account Type: Current
Account Number: 045605500436
Bank Name: ICICI Bank Limited
Branch Name: (0456) Nani Daman Branch
Branch Code: 0456
Branch Address: ICICI Bank Ltd., Vapi Kunta Road, Opp. Police Colony, Daman (UT), Pincode: 396210.
RTGS/NEFT IFSC Code: ICIC0000456
SWIFT Code: ICICINBBCTS
Note: Please inform with scanned copy of Sealed Bank Deposit Slip (for cash depositor)/Transaction ID (for Internet Banking) on editor@ijetae.com, ijetae@gmail.com.

Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model

Novitasari Novitasari[1], Yuslena Sari[2], Yudi Firmanul Arifin[3], Mohammad Reza Faisal[4],

Andreyan Rizky Baskara[5], Rian Ridhani[6]

[1]*Department of Civil Engineering, Universitas Lambung Mangkurat, Banjarbaru, Indonesia*
[2, 5,6]*Department of Information Technology, Universitas Lambung Mangkurat, Jl. Brig. Hasan Basri, Banjarmasin, Indonesia*
[3]*Faculty of Forestry, Universitas Lambung Mangkurat, Banjarbaru, Indonesia*
[4]*Department of Computer Science, Universitas Lambung Mangkurat, Banjarbaru, Indonesia*

Abstract— **Land cover is the appearance of the earth's surface covered by biological and non-biological diversity. Land cover as a parameter for assessing the susceptibility of land to fire during drought. Types of land cover based on the ministry of environment and forestry and S.N.I. In the Liang Anggang protected forest area are primary swamp forest, secondary swamp forest, open swamp, wet bush, pure dry agriculture, mixed dry agriculture, open water, transmigration areas, plantation forest, and vacant land. The type of land cover in the Liang Anggang protected forest area can be classified into 3 types, namely bare, softly, and heavily. Land cover classification can be done from two types of data, namely satellite data and unmanned aerial vehicle (UAV). This research will use UAV data for better image detail. The model used is YOLOv5. The results of this study obtained mAP@.5 74.8%, mAP@.95 31.3%, precision 81.7%, recall 66.4% for bare class. mAP@.5 81.1%, mAP@.95 45.7%, precision 80.1%, recall 78.6% for "softly" class. mAP@.5 40.1%, mAP@.95 21.9%, precision 49.5%, recall 36.9% for "heavily" class. mAP@.25 72.8%, mAP@.5 65.6%, mAP@.75 53.6%, mAP@.95 33%, precision 70.4%, recall 60.7%, and accuracy 60% for all class. With the improvements made on YOLOv5, it can be used to design a peatland fire early warning system.**
Keywords—**Classification, Land Cover, YOLOv5, UAV**

I. INTRODUCTION

Land cover is the appearance of the earth's surface covered by biological and non-biological diversity. Land cover can provide important information for modelling and understanding natural phenomena that occur on the earth's surface. Land cover data can also be used to study climate change and understand the relationship between human activities and global change [1]. Land cover was a parameter used in the Keetch-Byram Drought Index (KBDI) to measure land vulnerability to fire [2]–[4]. One type of land cover in South Kalimantan is peat land. One of the peatland areas in South Kalimantan is the Liang Anggang protected forest, Banjarbaru block 1 area which has an area of 494 hectares and is filled with land such as agriculture, plantations, roads, settlements, and shrubs. Apart from the fact that the location is peatland, the location in block 1 fulfils the characteristics and suitability of the needs in collecting data for the classification of peatland cover. So as the selection of this research location is in accordance with the data requirements.

Destructive changes in land use including on peatlands are the main cause of loss of biodiversity, damage to ecosystems and drastic climate change. Monitoring land cover change is useful for designing and managing better regulations to prevent or remedy losses arising from land cover change activities. Monitoring land cover changes can help in predicting and avoiding natural disasters or other hazardous events [1], [5], [6]. Monitoring and analysis of land cover can be carried out by classifying land cover, according to the

Ministry of Environment and Forestry and the National Standardization Agency, especially the Indonesian National Standard, land cover is classified into 23 classes, consisting of 6 forest classes, 16 non-forest classes, and 1 rehabilitation forest class [7]. The types of land cover based on the ministry of environment and forestry and the Indonesian National Standard (S.N.I) found in the Liang Anggang protected forest area are primary swamp forest, secondary swamp forest, open swamp, wet shrub, pure dry agriculture, mixed dry agriculture, open water, transmigration areas, plantation forests, and bare ground. The types of land cover in the Liang Anggang protected forest area can be classified into 3 types, namely bare (surface that has no vegetation at all), Softly (surface covered with medium and high vegetation), and Heavily (surface covered with moderate vegetation). The data collection technique is carried out using the Unmanned

Aeiral Vehicle (UAV) which can take pictures from a lower altitude so that the spatial resolution obtained is 1cm, more detailed than the satellite (30cm). And also, the UAV can take pictures in cloudy weather conditions because the UAV's height is lower than the clouds [8]–[11].

The technique that is highly favoured for classification is Machine Learning. Machine Learning is continually evolving and producing new fields such as Deep Learning. Deep Learning is popular in image analysis and intelligent image processing [12]–[15]. One of the popular models used in Deep Learning is You Only Look Once (YOLO).

The YOLO model is well-known for its use in object detection [16]. Several studies have used YOLOv5 for research purposes, such as Jun-Hwa Kim et al., who conducted a study on maritime object classification and optimized the Singapore Maritime Dataset (SMD) [17]. Nidhi et al. conducted a study on seed classification and quality using YOLOv5 and K-Means [18]. Linfeng et al. detected traffic signs using SSD300, Faster RCNN, YOLOv3, YOLOv4, and YOLOv5 to compare the accuracy of these models [19]. Daniel Padilla Carrasco et al. detected small vehicles in parking lots using YOLOv5 to manage parking spaces efficiently and achieve the goal of a smart city [20]. Tian-Hao Wu et al. used YOLOv5 to detect vehicles and their distances in real-time in a virtual environment to optimize autonomous vehicle technology [21]. Lastly, How Yong Chen et al. used YOLOv5 to detect defects in glove production [22].

II. LITERATURE REVIEW

A. Land Cover

Land cover was one of the parameters in the KBDI peat, which is a drought index used to measure the vulnerability of land to fires [2]. Accurate land cover information is one of the determining factors in improving the performance of early warning system peatland fire. One type of land cover found in South Kalimantan is peatland. Peatland is a water-saturated land composed of organic material (>12%) that occurs due to the accumulation of decomposing plant remains and tissues with a thickness of more than 50 cm. The accumulation is caused by the slow rate of decomposition compared to the rate of organic material accumulation inundated by water over a long period of time [1], [5], [6].

B. Peatland

Peatland is a water-saturated land composed of organic material (>12%). Peatland is formed by the accumulation of plant residues and decomposed plant tissues with a thickness of more than 50 cm. The accumulation is due to the slow rate of decomposition compared to the rate of organic material accumulation that is inundated with water for a long period of time [1]. Peat is classified as marginal land and is vulnerable to disturbances, so any increase in the productivity of peatland must be accompanied by efforts to prevent ecosystem damage. Peatland damage is caused by tree felling and forest conversion, fires, and reclamation. Peat can be considered a renewable resource only on a geological time scale. Peat growth estimates vary between 0.5 to 1 mm per year, and the subsidence rate of drained peatland is between 1.5 to 3 cm per year. Because the subsidence rate is 15-30 times that of the growth rate, peatland cannot be categorized as a renewable resource.

Several types of land cover based on the ministry of environment and forestry and S.N.I. located in the Liang Anggang area include:

1. Primary swamp forest: Forests growing in wet habitats include mangroves, sago, and peatlands.
2. Secondary swamp forest: Forests growing in wet habitats include mangroves, sago, and peat, often with human interventions such as logging and agriculture.
3. Open swamp: Open swamp with little vegetation.
4. Wet shrub: Wet area filled with shrubs.
5. Mixed dry agriculture: Areas used for agricultural activities and still have wild plants such as shrubs and trees scattered in the agricultural area.
6. Open water: Open water areas such as rivers and lakes.
7. Transmigration areas: The area surrounding the forest that is related to human activities such as houses, parks, and huts.
8. Pure dry agriculture: Areas used for agricultural activities.
9. Plantation forest: An area that has been planted with vegetation as part of forest rehabilitation efforts.
10. Bare ground: An area of empty land without vegetation.

Pictures of land cover types in the Liang Anggang protected forest can be seen in Table 1.

TABLE I
TYPES OF LAND COVER IN THE LIANG ANGGANG PROTECTED FOREST

Land Image	Land Type	Land Image	Land Type
	Primary Swamp Forest		*Wet Shrub*
	Secondary Swamp Forest		*Mixed Dry Agriculture*
	Open Swamp		*Open Water*
	Plantation Forest		*Transmigration Area*
	Pure Dry Agriculture		*Bare Ground*

C. Image Classification

Image classification is the process of arranging or grouping pixels into several classes based on object categories or certain criteria. Each pixel in each class is assumed to have homogenous characteristics. The goal of classification is to extract spectral patterns found within the image [23]–[25].

III. RESEARCH METHODOLOGY

A. Problem Identification

The first stage of this research is to identify the problem. Problem identification is carried out qualitatively by focusing on in-depth observation to discover a problem. The problem identified is the importance of classifying land cover using a reliable model to produce accurate land cover types with good accuracy results. The solution to this problem is to use the best object detection model for land cover classification and then observe the accuracy results of using the model. Good accuracy results in using the model can be a recommendation for the next researchers in land cover classification and object detection in general. And land cover classification information can be a further action by researchers or agencies related to land cover.

B. Image Acquisition

Image acquisition is carried out to collect the necessary data and to determine the digital image recording model to be used [26]. Land images were taken using a DJI Mavic Pro drone in November - December 2021 and July - August 2022. The drone is automatically controlled using the DroneDeploy application. The drone follows a predetermined path on DroneDeploy but can still be manually controlled with a remote. Image capture is done in clear or slightly cloudy weather conditions. The drone is set to fly at a height of 20 meters from the surface. Image capture is done between 8 am and 12 pm.

Because the Liang Anggang protected forest is located near the Syamsudin Noor airport, some areas cannot be captured with a drone because they are in a restricted fly zone with a maximum height of 60 meters in yellow areas and not allowed to fly at all in blue areas. Therefore, the area to be captured is located within a maximum of 60 meters with a drone capture height of 20 meters so that the drone can still capture images with sufficient coverage. The restricted fly zone in the Liang Anggang protected forest can be seen in Figure 1.

Figure 1**.** Restricted Fly Zone Around Liang Anggang Protection Forest

IV. RESULT

A. Image Capture Process

The first stage of taking images with a drone is determining the area to be photographed. Area capture settings are made in the Google Earth Pro application to determine the area to be captured. After the area marking has been completed, the results will be exported into a file with the .KML format. Then the file will be imported into the DroneDeploy application. From the DroneDeploy application, drones can be set to take pictures automatically according to the area that has been marked.

UAV image data obtained from the results of drone capture conducted in July - August 2022 collected 7437 images with an area of 22.6 hectares. The total image data collected after being combined with data taken in November - December 2021 collected 17,674 images with an area of 40.6 hectares. Areas that have been taken using drones are marked in orange which can be seen in Figure 2.

Figure 2**.** Territory That Has Been Taken by Drones

1. *Labelling*

   Labelling process is carried out to label objects in the image that will be detected. The label will assist the trained model to identify the objects to be detected.

   After all images have been preprocessed, the dataset construction is carried out to divide the dataset according to its usage in each stage. The dataset is divided into three folders, namely train, val, and test.

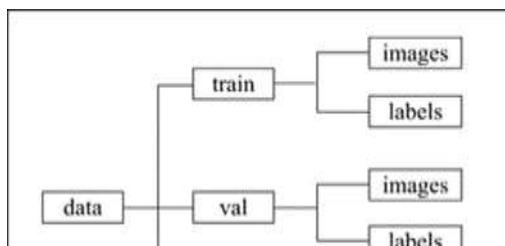   The complete structure of the dataset can be seen in Figure 3.

Figure 3**.** Complete Structure of Dataset

B. Training Model

Training is conducted using the Google Colab platform. The training stage in the YOLOv5 model is divided into 3 stages, namely the training, validation, and testing stages.

1. Training

   At the training model stage, the first step is to run the code to download the YOLOv5 file into the Google Colab project. After the download process is complete, the project will display the YOLOv5 folder. Then the next step is to connect the project with the dataset that has been stored on Google Drive and determine the location of the dataset from the coco128.yaml file.

   Model training is carried out by conducting training several times with different batch and epoch values to find out the optimal setting values to get the best precision, recall, and mAP values. The training results from the YOLOv5 training model for land classification for all classes obtained values of mAP@.25 0.728, mAP@.5 0.656, mAP@.75 0.536, mAP@.95 0.33, precision 0.704, recall 0.607. Complete values of training results for 100 epochs and 5 batches can be seen in table 2.

   TABLE III
   TRAINING RESULT VALUE

Class	Precission	Recall	mAP@.25	mAP@.5	mAP@.75	mAP@.95
All	0.704	0.607	0.728	0.656	0.536	0.33
Bare	0.817	0.664	0.688	0.748	0.418	0.313
Softly	0.801	0.786	0.841	0.811	0.661	0.457
Heavily	0.495	0.369	0.656	0.41	0.528	0.219

Class	Precission	Recall	mAP@.25	mAP@.5	mAP@.75	mAP@.95
All	0.696	0.614	0.728	0.661	0.536	0.326
Bare	0.798	0.676	0.688	0.75	0.418	0.309
Softly	0.798	0.79	0.841	0.815	0.661	0.455
Heavily	0.492	0.376	0.656	0.418	0.528	0.213

2. Validation

After the training process is complete, the validation stage is carried out. The validation results of the YOLOv5 model for land classification for all classes obtained values of mAP@.25 0.728, mAP@.5 0.661, mAP@.25 0.536, mAP@.95 0.326, precision 0.696, recall 0.614. the complete value of the validation calculation can be seen in Table 3.

3. Testing

The last stage is testing the model that has been trained in detecting objects. The mAP@.5 value of 0.65 indicates that the model can detect Softly land cover types quite well. However, it struggles to detect bare and heavily land cover types, as well as photos with more than one land cover type. Some test results can be seen in Figure 4.

Figure 4. Testing Result Image Examples

TABLE IIIII
VALIDATION VALUE

V. ANALYSIS

A. Training and Validation Result Analysis

Based on the precision-recall curve and the values of mAP, precision, and recall result can be seen in Figure 5 and Table 4.
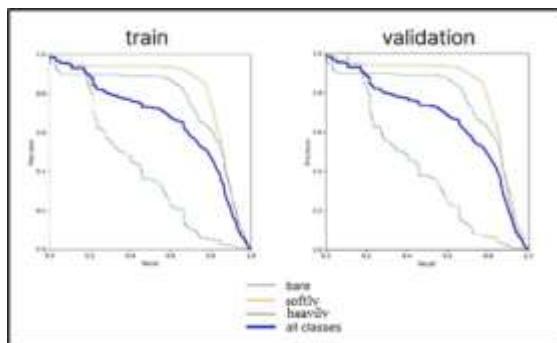

Figure 5. Precision-Recall Curve on Training and Validation

TABLE VI
COMPARISON OF MAP VALUE ON TRAINING AND VALIDATION

mAP / Stage	All	Bare	Softly	Heavily
Train	65.6%	74.8%	81.1%	41%
Validation	66.1%	75%	81.5%	41.8%
Difference	0.5%	0.2%	0.4%	0.8%

The identical and quite good precision-recall graph and mAP values are above 70% and have a difference of less than 1% for the bare and Softly land cover types indicating the model's best fitting. However, the low precision-recall graph and mAP values below 70% for the Heavily land cover type indicate an underfitting model for that land cover type. The low value of the Heavily land cover type results in a low total mAP value for all classes, which is 65%, so it can be concluded that the model is underfitting.

B. Accuracy Analysis

The accuracy calculation was done using land photos that were not used in training the model and was calculated using Microsoft Excel. The resulting image for the accuracy calculation can be seen in Figure 6.

Figure 4. Example Used in Accuracy Calculation

The accuracy calculation was done using formula (5), Microsoft Excel, and images outside the training dataset to avoid bias with the training phase. The result of the calculation yielded an accuracy value of 0.6 or 60%. Based on the very small difference in values between the train and validation phases, below 1% (0.5% for all classes, 0.2% for the bare class, 0.4% for the Softly class, and 0.8% for the Heavily class), but having an mAP value below 70%, which is 65.6%, it can be concluded that the model is underfitting to classify land cover types.

C. Model Performance Comparison

This research will also use another deep learning model, YOLOv4, to compare its performance with the currently used YOLOv5 model. The comparison results between the performance of YOLOv4 and YOLOv5 can be seen in Table 5.

TABLE V
PERFORMANCE COMPARISON OF YOLOv4 AND YOLOv5 MODEL

Model / Value	YOLOv4	YOLOv5
mAP@.5	43.45%	65.6%
mAP@.95	0.0041%	33%
Precision	66%	70.4%
Recall	31%	60.7%

From the table above it can be seen that the performance of the YOLOv4 model is lower than that of the YOLOv5 model.

VI. CONCLUSIONS

A. Accuracy Analysis

The conclusions based on the research that has been done are as follows:

1. The YOLOv5 model obtained an mAP@.5 score of 75% and 81.5% for classifying bare and Softly land covers, but obtained a low mAP@.5 score of 41.8% for classifying Heavily land cover, indicating that YOLOv5 is good at classifying bare and Softly land covers but not as good for classifying Heavily land cover.

2. The YOLOv5 model obtained a precision of 70.4%, recall of 60.7%, mAP@.25 of 72.8%, mAP@.5 of 65.6%, mAP@.75 of 53.6%, mAP@.95 of 33%, and an accuracy of 60% for all classes.

3. YOLOv5 can be recommended for designing land cover classification systems, which can be used to measure the vulnerability of peatland to fire disasters.

B. Recommendation

The recommendations given in this study are as follows:

1. Using the pro version of the Google Colab account so that the training process on Google Colab becomes more effective.

2. Using special drones for industrial use, mapping, inspection and surveys so that the process of taking land images becomes more effective.

3. Using a dataset that has Heavily image quality and a larger number, especially for Heavily land cover types, so that the classification results, especially for Heavily land cover types, are better.

4. The YOLOv5 model gets a mAP@.5 value of 65.6% which is categorized as unfavorable. Therefore, the authors suggest using a model with a better architecture so that the value of the classification results becomes higher.

References

[1] K. A. Hapsari *et al.*, "Resilience of a peatland in Central Sumatra, Indonesia to past anthropogenic disturbance: Improving conservation and restoration designs using palaeoecology," *J. Ecol.*, vol. 106, no. 6, pp. 2473–2490, 2018, doi: 10.1111/1365-2745.13000.

[2] N. Novitasari, J. Sujono, S. Harto, A. Maas, and R. Jayadi, "Drought index for peatland wildfire management in central kalimantan, indonesia during el niño phenomenon," *J. Disaster Res.*, vol. 14, no. 7, pp. 939–948, 2019, doi: 10.20965/jdr.2019.p0939.

[3] A. Garcia-Prats, D. C. Antonio, F. J. G. Tarcísio, and M. J. Antonio, "Development of a Keetch and Byram-Based drought index sensitive to forest management in Mediterranean conditions," *Agric. For. Meteorol.*, vol. 205, pp. 40–50, 2015, doi: 10.1016/j.agrformet.2015.02.009.

[4] P. Ganatsas, M. Antonis, and T. Marianthi, "Development of an adapted empirical drought index to the Mediterranean conditions for use in forestry," *Agric. For. Meteorol.*, vol. 151, no. 2, pp. 241–250, 2011, doi: 10.1016/j.agrformet.2010.10.011.

[5] A. Vali, S. Comai, and M. Matteucci, "Deep learning for land use and land cover classification based on hyperspectral and multispectral earth observation data: A review," *Remote Sens.*, vol. 12, no. 15, 2020, doi: 10.3390/RS12152495.

[6] Akhbar, I. Arianingsih, Misrah, and Naharuddin, "Application of the AR4 model image of landsat 8 on land cover classification in central sulawesi grand forest park," *Int. J. Appl. Eng. Res.*, vol. 12, no. 20, pp. 9405–9412, 2017.

[7] S. M. A. Letsoin, D. Herak, F. Rahmawan, and R. C. Purwestri, "Land cover changes from 1990 to 2019 in Papua, Indonesia: Results of the remote sensing imagery," *Sustain.*, vol. 12, no. 16, pp. 1–18, 2020, doi: 10.3390/su12166623.

[8] N. F. H. Jumaat, B. Ahmad, and H. S. Dutsenwai, "Land cover change mapping using high resolution satellites and unmanned aerial vehicle," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 169, no. 1, 2018, doi: 10.1088/1755-1315/169/1/012076.

[9] B. Prayudha *et al.*, "The application of Landsat imageries and

mangrove vegetation index for monitoring mangrove community in Segara Anakan Lagoon, Cilacap, Central Java," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 944, no. 1, 2021, doi: 10.1088/1755-1315/944/1/012039.

[10] Y. Sari, Y. F. Arifin, N. Novitasari, and M. R. Faisal, "Effect of Feature Engineering Technique for Determining Vegetation Density," *Int. J. Adv. Comput. Sci. Appl.*, vol. 13, no. 7, pp. 655–661, 2022, doi: 10.14569/IJACSA.2022.0130776.

[11] Y. Sari, Y. Arifin, Novitasari, and M. Faisal, "Implementation of Deep Learning Based Semantic Segmentation Method To Determine Vegetation Density," *Eastern-European J. Enterp. Technol.*, vol. 5, no. 2–119, pp. 42–54, 2022, doi: 10.15587/1729-4061.2022.265807.

[12] Y. Heryadi and E. Miranda, *Land cover classification based on sentinel-2 satellite imagery using convolutional neural network model: A case study in Semarang Area, Indonesia*, vol. 830, no. January. Springer International Publishing, 2020. doi: 10.1007/978-3-030-14132-5_15.

[13] Y. Sari, M. Alkaff, and M. Maulida, "Classification of Rice Leaf using Fuzzy Logic and Hue Saturation Value (HSV) to Determine Fertilizer Dosage," 2020. doi: 10.1109/ICIC50835.2020.9288585.

[14] Y. Sari, M. Alkaff, and R. A. Pramunendar, "Iris recognition based on distance similarity and PCA," *AIP Conf. Proc.*, vol. 1977, 2018, doi: 10.1063/1.5042900.

[15] M. Alkaff, H. Khatimi, W. Puspita, and Y. Sari, "Modelling and predicting wetland rice production using support vector regression," *Telkomnika (Telecommunication Comput. Electron. Control.*, vol. 17, no. 2, pp. 819–825, 2019, doi: 10.12928/TELKOMNIKA.V17I2.10145.

[16] L. Jiang, H. Liu, H. Zhu, and G. Zhang, "Improved YOLO v5 with balanced feature pyramid and attention module for traffic sign detection," *MATEC Web Conf.*, vol. 355, p. 03023, 2022, doi: 10.1051/matecconf/202235503023.

[17] J. H. Kim, N. Kim, Y. W. Park, and C. S. Won, "Object Detection and Classification Based on YOLO-V5 with Improved Maritime Dataset," *J. Mar. Sci. Eng.*, vol. 10, no. 3, 2022, doi: 10.3390/jmse10030377.

[18] N. Kundu, G. Rani, and V. S. Dhaka, "Seeds Classification and Quality Testing Using Deep Learning and YOLO v5," *ACM Int. Conf. Proceeding Ser.*, no. August, pp. 153–160, 2021, doi: 10.1145/3484824.3484913.

[19] P. Jiang, D. Ergu, F. Liu, Y. Cai, and B. Ma, "A Review of Yolo Algorithm Developments," *Procedia Comput. Sci.*, vol. 199, pp. 1066–1073, 2021, doi: 10.1016/j.procs.2022.01.135.

[20] D. P. Carrasco, H. A. Rashwan, M. A. Garcia, and D. Puig, "T-YOLO: Tiny vehicle detection based on YOLO and multi-scale convolutional neural networks," *IEEE Access*, vol. 11, no. December 2021, 2021, doi: 10.1109/ACCESS.2021.3137638.

[21] M. Krishnaveni, S. K. P. Kumar, E. A. Muthusamy, J. Kowshick, and K. G. Arunya, "Real-time Monitoring of Water Level and Storage Dynamics of Irrigation Tank Using IoT," *H2Open J*, vol. 3, no. 1, pp. 392–400, 2020, doi: 10.2166/h2oj.2020.123.

[22] Y. C. How, A. F. Ab. Nasir, K. F. Muhammad, A. P. P. Abdul Majeed, M. A. Mohd Razman, and M. A. Zakaria, "Glove Defect Detection Via YOLO V5," *Mekatronika*, vol. 3, no. 2, pp. 25–30, 2022, doi: 10.15282/mekatronika.v3i2.7342.

[23] F. A. P, H. Segah, N. S. Yusuf, and R. M. Sukarna, "Analysis Of Changes In Mangrove Cover Using Landsat Imagery In Seruyan District," vol. 2, no. 12, pp. 2717–2733, 2022.

[24] Y. Sari and P. B. Prakoso, "Detection of Moving Vehicle using Adaptive Threshold Algorithm in Varied Lighting," *2018 5th Int. Conf. Electr. Veh. Technol.*, pp. 136–141, 2018.

[25] Y. Sari, A. R. Baskara, and R. Wahyuni, "Classification of Chili Leaf Disease Using the Gray Level Co-occurrence Matrix (GLCM) and the Support Vector Machine (SVM) Methods," *2021 6th Int. Conf. Informatics Comput. ICIC 2021*, 2021, doi: 10.1109/ICIC54025.2021.9632920.

[26] A. Sharifara, M. S. M. Rahim, H. Sayyadi, and F. Navabifar, "Search space optimization and false alarm rejection face detection framework," *J. Theor. Appl. Inf. Technol.*, vol. 79, no. 3, pp. 370–379, 2015.

Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model

Novitasari Novitasari[1], Yuslena Sari[2], Yudi Firmanul Arifin[3], Mohammad Reza Faisal[4],

Andreyan Rizky Baskara[2], Rian Ridhani[2]

[1]*Department of Civil Engineering, Universitas Lambung Mangkurat, Banjarbaru, Indonesia*
[2]*Department of Information Technology, Universitas Lambung Mangkurat, Jl. Brig. Hasan Basri, Banjarmasin, Indonesia*
[3]Faculty of Forestry, Universitas Lambung Mangkurat, *Banjarbaru, Indonesia*
[4]*Department of Computer Science, Universitas Lambung Mangkurat, Banjarbaru, Indonesia*
[5]*Department of Information Technology, Universitas Lambung Mangkurat, Jl. Brig. Hasan Basri, Banjarmasin, Indonesia*
[5]*Department of Information Technology, Universitas Lambung Mangkurat, Jl. Brig. Hasan Basri, Banjarmasin, Indonesia*

[1]novitasari@ulm.ac.id
[2]yuzlena@ulm.ac.id
[3]yudifirmanul@ulm.ac.id
[4]andreyan.baskara@ulm.ac.id
[5]1710817210014@ulm.ac.id

Abstract— **Land cover is the appearance of the earth's surface covered by biological and non-biological diversity. Land cover can provide important information for modeling and understanding natural phenomena that occur on the earth's sur-face. Supervising land cover change is useful for designing and managing better actions to prevent or ameliorate loss-es resulting from land cover change activities. Types of land cover based on the ministry of environment and forestry and S.N.I. In the Liang Anggang protected forest area are primary swamp forest, secondary swamp forest, open swamp, wet bush, pure dry agriculture, mixed dry agriculture, open water, transmigration areas, plantation forest, and vacant land. The type of land cover in the Liang Anggang protected forest area can be classified into 3 types, namely bare, softly, and heavily. Land cover classification can be done from two types of data, namely satellite data and unmanned aerial vehicle (UAV). This research will use UAV data for better image detail. The model used is YOLOv5. The results of this study obtained mAP@.5 74.8%, mAP@.95 31.3%, precision 81.7%, recall 66.4% for bare class. mAP@.5 81.1%, mAP@.95 45.7%, precision 80.1%, recall 78.6% for "softly" class. mAP@.5 40.1%, mAP@.95 21.9%, precision 49.5%, recall 36.9% for "heavily" class. mAP@.25 72.8%, mAP@.5 65.6%, mAP@.75 53.6%, mAP@.95 33%, precision 70.4%, recall 60.7%, and accuracy 60% for all class.**
Keywords—**Classification, Land Cover, YOLOv5, UAV**

I. INTRODUCTION

Land cover is the appearance of the earth's surface covered by biological and non-biological diversity. Land cover can provide important information for modelling and understanding natural phenomena that occur on the earth's surface. Land cover data can also be used to study climate change and understand the relationship between human activities and global change [1]. One type of land cover in South Kalimantan is peat land. One of the peatland areas in South Kalimantan is the Liang Anggang protected forest, Banjarbaru block 1 area which has an area of 494 hectares and is filled with land such as agriculture, plantations, roads, settlements, and shrubs. Apart from the fact that the location is peatland, the location in block 1 fulfils the characteristics and suitability of the needs in collecting data for the classification of peatland cover. So as the selection of this research location is in accordance with the data requirements.

Destructive changes in land use including on peatlands are the main cause of loss of biodiversity, damage to ecosystems and drastic climate change. Monitoring land cover change is useful for designing and managing better regulations to prevent or remedy losses arising from land cover change activities. Monitoring land cover changes can help in predicting and avoiding natural disasters or other hazardous events [1]–[3]. Monitoring and analysis of land

cover can be carried out by classifying land cover, according to the

Ministry of Environment and Forestry and the National Standardization Agency, especially the Indonesian National Standard, land cover is classified into 23 classes, consisting of 6 forest classes, 16 non-forest classes, and 1 rehabilitation forest class [4]. The types of land cover based on the ministry of environment and forestry and the Indonesian National Standard (S.N.I) found in the Liang Anggang protected forest area are primary swamp forest, secondary swamp forest, open swamp, wet shrub, pure dry agriculture, mixed dry agriculture, open water, transmigration areas, plantation forests, and bare ground. The types of land cover in the Liang Anggang protected forest area can be classified into 3 types, namely bare (surface that has no vegetation at all), Softly (surface covered with medium and high vegetation), and Heavily (surface covered with moderate vegetation). The data collection technique is carried out using the Unmanned Aeiral Vehicle (UAV) which can take pictures from a lower altitude so that the spatial resolution obtained is 1cm, more detailed than the satellite (30cm). And also, the UAV can take pictures in cloudy weather conditions because the UAV's height is lower than the clouds [5]–[8].

The technique that is highly favoured for classification is Machine Learning. Machine Learning is continually evolving and producing new fields such as Deep Learning. Deep Learning is popular in image analysis and intelligent image processing [9]–[12]. One of the popular models used in Deep Learning is You Only Look Once (YOLO).

The YOLO model is well-known for its use in object detection [13]. Several studies have used YOLOv5 for research purposes, such as Jun-Hwa Kim et al., who conducted a study on maritime object classification and optimized the Singapore Maritime Dataset (SMD) [14]. Nidhi et al. conducted a study on seed classification and quality using YOLOv5 and K-Means [15]. Linfeng et al. detected traffic signs using SSD300, Faster RCNN, YOLOv3, YOLOv4, and YOLOv5 to compare the accuracy of these models [16]. Daniel Padilla Carrasco et al. detected small vehicles in parking lots using YOLOv5 to manage parking spaces efficiently and achieve the goal of a smart city [17]. Tian-Hao Wu et al. used YOLOv5 to detect vehicles and their distances in real-time in a virtual environment to optimize autonomous vehicle technology [18]. Lastly, How Yong Chen et al. used YOLOv5 to detect defects in glove production [19].

II. LITERATURE REVIEW

A. Land Cover

Land cover refers to the surface features of the Earth that are covered by biotic and abiotic elements. Land cover provides important information for modeling and understanding natural phenomena occurring on the Earth's surface. Land cover data can also be used to study climate change and understand the relationship between human activities and global changes. Accurate land cover information is one of the determining factors in improving the performance of ecosystem, hydrology, and atmospheric models. One type of land cover found in South Kalimantan is peatland. Peatland is a water-saturated land composed of organic material (>12%) that occurs due to the accumulation of decomposing plant remains and tissues with a thickness of more than 50 cm. The accumulation is caused by the slow rate of decomposition compared to the rate of organic material accumulation inundated by water over a long period of time [1]–[3].

B. Peatland

Peatland is a water-saturated land composed of organic material (>12%). Peatland is formed by the accumulation of plant residues and decomposed plant tissues with a thickness of more than 50 cm. The accumulation is due to the slow rate of decomposition compared to the rate of organic material accumulation that is inundated with water for a long period of time [1]. Peat is classified as marginal land and is vulnerable to disturbances, so any increase in the productivity of peatland must be accompanied by efforts to prevent ecosystem damage. Peatland damage is caused by tree felling and forest conversion, fires, and reclamation. Peat can be considered a renewable resource only on a geological time scale. Peat growth estimates vary between 0.5 to 1 mm per year, and the subsidence rate of drained peatland is between 1.5 to 3 cm per year. Because the subsidence rate is 15-30 times that of the growth rate, peatland cannot be categorized as a renewable resource.

Several types of land cover based on the ministry of environment and forestry and S.N.I. located in the Liang Anggang area include:

1. Primary swamp forest: Forests growing in wet habitats include mangroves, sago, and peatlands.
2. Secondary swamp forest: Forests growing in wet habitats include mangroves, sago, and peat, often with human interventions such as logging and agriculture.
3. Open swamp: Open swamp with little vegetation.
4. Wet shrub: Wet area filled with shrubs.

5. Mixed dry agriculture: Areas used for agricultural activities and still have wild plants such as shrubs and trees scattered in the agricultural area.
6. Open water: Open water areas such as rivers and lakes.
7. Transmigration areas: The area surrounding the forest that is related to human activities such as houses, parks, and huts.
8. Pure dry agriculture: Areas used for agricultural activities.
9. Plantation forest: An area that has been planted with vegetation as part of forest rehabilitation efforts.
10. Bare ground: An area of empty land without vegetation.

Pictures of land cover types in the Liang Anggang protected forest can be seen in Table 1.

TABLE I
TYPES OF LAND COVER IN THE LIANG ANGGANG PROTECTED FOREST

Land Image	Land Type	Land Image	Land Type
	Primary Swamp Forest		*Wet Shrub*
	Secondary Swamp Forest		*Mixed Dry Agriculture*
	Open Swamp		*Open Water*
	Plantation Forest		*Transmigration Area*
	Pure Dry Agriculture		*Bare Ground*

C. Image Classification

Image classification is the process of arranging or grouping pixels into several classes based on object categories or certain criteria. Each pixel in each class is assumed to have homogenous characteristics. The goal of classification is to extract spectral patterns found within the image [20]–[22].

III. RESEARCH METHODOLOGY

A. Problem Identification

The first stage of this research is to identify the problem. Problem identification is carried out qualitatively by focusing on in-depth observation to discover a problem. The problem identified is the importance of classifying land cover using a reliable model to produce accurate land cover types with good accuracy results. The solution to this problem is to use the best object detection model for land cover classification and then observe the accuracy results of using the model. Good accuracy results in using the model can be a recommendation for the next researchers in land cover classification and object detection in general. And land cover classification information can be a further action by researchers or agencies related to land cover.

B. Image Acquisition

Image acquisition is carried out to collect the necessary data and to determine the digital image recording model to be used [23]. Land images were taken using a DJI Mavic Pro drone in November - December 2021 and July - August 2022. The drone is automatically controlled using the DroneDeploy application. The drone follows a predetermined path on DroneDeploy but can still be manually controlled with a remote. Image capture is done in clear or slightly cloudy weather conditions. The drone is set to fly at a height of 20 meters from the surface. Image capture is done between 8 am and 12 pm.

Because the Liang Anggang protected forest is located near the Syamsudin Noor airport, some areas cannot be captured with a drone because they are in a restricted fly zone with a maximum height of 60 meters in yellow areas and not allowed to fly at all in blue areas. Therefore, the area to be captured is located within a maximum of 60 meters with a drone capture height of 20 meters so that the drone can still capture images with sufficient coverage. The

restricted fly zone in the Liang Anggang protected forest can be seen in Figure 1.

Figure 1. Restricted Fly Zone Around Liang Anggang Protection Forest

IV. RESULT

A. Image Capture Process

The first stage of taking images with a drone is determining the area to be photographed. Area capture settings are made in the Google Earth Pro application to determine the area to be captured. After the area marking has been completed, the results will be exported into a file with the .KML format. Then the file will be imported into the DroneDeploy application. From the DroneDeploy application, drones can be set to take pictures automatically according to the area that has been marked.

UAV image data obtained from the results of drone capture conducted in July - August 2022 collected 7437 images with an area of 22.6 hectares. The total image data collected after being combined with data taken in November - December 2021 collected 17,674 images with an area of 40.6 hectares. Areas that have been taken using drones are marked in orange which can be seen in Figure 2.

Figure 2. Territory That Has Been Taken by Drones

1. Labelling

Labelling process is carried out to label objects in the image that will be detected. The label will assist the trained model to identify the objects to be detected.

After all images have been preprocessed, the dataset construction is carried out to divide the dataset according to its usage in each stage. The dataset is divided into three folders, namely train, val, and test.

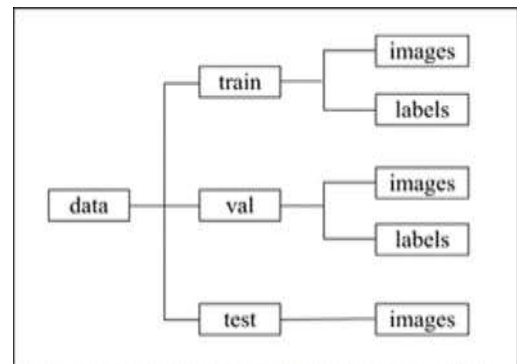The complete structure of the dataset can be seen in Figure 3.

Figure 3. Complete Structure of Dataset

B. Training Model

Training is conducted using the Google Colab platform. The training stage in the YOLOv5 model is divided into 3 stages, namely the training, validation, and testing stages.

1. Training

At the training model stage, the first step is to run the code to download the YOLOv5 file into the Google Colab project. After the download process is complete, the project will display the YOLOv5 folder. Then the next step is to connect the project with the dataset that has been stored on Google Drive and determine the location of the dataset from the coco128.yaml file.

Model training is carried out by conducting training several times with different batch and epoch values to find out the optimal setting values to get the best precision, recall, and mAP values. The training results from the YOLOv5 training model for land classification for all classes obtained values of

mAP@.25 0.728, mAP@.5 0.656, mAP@.75 0.536, mAP@.95 0.33, precision 0.704, recall 0.607. Complete values of training results for 100 epochs and 5 batches can be seen in table 2.

TABLE III
TRAINING RESULT VALUE

Class	Precission	Recall	mAP @.25	mAP @.5	mAP @.75	mAP @.95
All	0.704	0.607	0.728	0.656	0.536	0.33
Bare	0.817	0.664	0.688	0.748	0.418	0.313
Softly	0.801	0.786	0.841	0.811	0.661	0.457
Heavily	0.495	0.369	0.656	0.41	0.528	0.219

2. Validation

After the training process is complete, the validation stage is carried out. The validation results of the YOLOv5 model for land classification for all classes obtained values of mAP@.25 0.728, mAP@.5 0.661, mAP@.25 0.536, mAP@.95 0.326, precision 0.696, recall 0.614. the complete value of the validation calculation can be seen in Table 3.

TABLE IIIII
VALIDATION VALUE

Class	Precission	Recall	mAP @.25	mAP @.5	mAP @.75	mAP @.95
All	0.696	0.614	0.728	0.661	0.536	0.326
Bare	0.798	0.676	0.688	0.75	0.418	0.309
Softly	0.798	0.79	0.841	0.815	0.661	0.455
Heavily	0.492	0.376	0.656	0.418	0.528	0.213

3. Testing

The last stage is testing the model that has been trained in detecting objects. The mAP@.5 value of 0.65 indicates that the model can detect Softly land cover types quite well. However, it struggles to detect bare and heavily land cover types, as well as photos with more than one land cover type. Some test results can be seen in Figure 4.

Figure 4. Testing Result Image Examples

V. ANALYSIS

A. Training and Validation Result Analysis

Based on the precision-recall curve and the values of mAP, precision, and recall result can be seen in Figure 5 and Table 4.
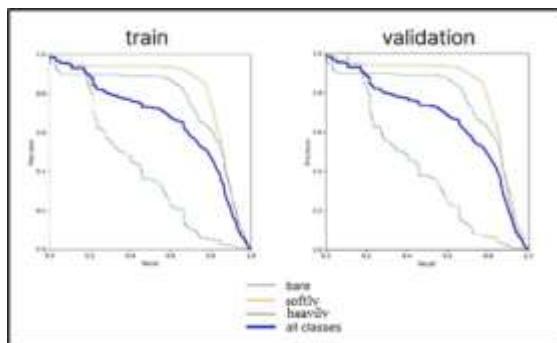

Figure 5. Precision-Recall Curve on Training and Validation

TABLE VI
COMPARISON OF MAP VALUE ON TRAINING AND VALIDATION

mAP \ Stage	All	Bare	Softly	Heavily
Train	65.6%	74.8%	81.1%	41%
Validation	66.1%	75%	81.5%	41.8%
Difference	0.5%	0.2%	0.4%	0.8%

The identical and quite good precision-recall graph and mAP values are above 70% and have a difference of less than 1% for the bare and Softly land cover types indicating the model's best fitting. However, the low precision-recall graph and mAP values below 70% for the Heavily land cover type indicate an underfitting model for that land cover type. The low value of the Heavily land cover type results in a low total mAP value for all classes, which is 65%, so it can be concluded that the model is underfitting.

B. Accuracy Analysis

The accuracy calculation was done using land photos that were not used in training the model and was calculated using Microsoft Excel. The resulting image for the accuracy calculation can be seen in Figure 6.

Figure 4. Example Used in Accuracy Calculation

The accuracy calculation was done using formula (5), Microsoft Excel, and images outside the training dataset to avoid bias with the training phase. The result of the calculation yielded an accuracy value of 0.6 or 60%. Based on the very small difference in values between the train and validation phases, below 1% (0.5% for all classes, 0.2% for the bare class, 0.4% for the Softly class, and 0.8% for the Heavily class), but having an mAP value below 70%, which is 65.6%, it can be concluded that the model is underfitting to classify land cover types.

C. Model Performance Comparison

This research will also use another deep learning model, YOLOv4, to compare its performance with the currently used YOLOv5 model. The comparison results between the performance of YOLOv4 and YOLOv5 can be seen in Table 5.

TABLE V
PERFORMANCE COMPARISON OF YOLOV4 AND YOLOV5 MODEL

Value \ Model	YOLOv4	YOLOv5
mAP@.5	43.45%	65.6%
mAP@.95	0.0041%	33%
Precision	66%	70.4%
Recall	31%	60.7%

From the table above it can be seen that the performance of the YOLOv4 model is lower than that of the YOLOv5 model.

VI. CONCLUSIONS

A. Accuracy Analysis

The conclusions based on the research that has been done are as follows:

1. The YOLOv5 model obtained an mAP@.5 score of 75% and 81.5% for classifying bare and Softly land covers, but obtained a low mAP@.5 score of 41.8% for classifying Heavily land cover, indicating that YOLOv5 is good at classifying bare and Softly land covers but not as good for classifying Heavily land cover.

2. The YOLOv5 model obtained a precision of 70.4%, recall of 60.7%, mAP@.25 of 72.8%, mAP@.5 of 65.6%, mAP@.75 of 53.6%, mAP@.95 of 33%, and an accuracy of 60% for all classes.

B. Recommendation

The recommendations given in this study are as follows:

1. Using the pro version of the Google Colab account so that the training process on Google Colab becomes more effective.

2. Using special drones for industrial use, mapping, inspection and surveys so that the process of taking land images becomes more effective.

3. Using a dataset that has Heavily image quality and a larger number, especially for Heavily land cover types, so that the classification results, especially for Heavily land cover types, are better.

4. The YOLOv5 model gets a mAP@.5 value of 65.6% which is categorized as unfavorable. Therefore, the authors suggest using a model with a better architecture so that the value of the classification results becomes higher.

References

[1] K. A. Hapsari *et al.*, "Resilience of a peatland in Central Sumatra, Indonesia to past anthropogenic disturbance: Improving conservation and restoration designs using palaeoecology," *J. Ecol.*, vol. 106, no. 6, pp. 2473–2490, 2018, doi: 10.1111/1365-2745.13000.

[2] A. Vali, S. Comai, and M. Matteucci, "Deep learning for land use and land cover classification based on hyperspectral and multispectral earth observation data: A review," *Remote Sens.*, vol. 12, no. 15, 2020, doi: 10.3390/RS12152495.

[3] Akhbar, I. Arianingsih, Misrah, and Naharuddin, "Application of the AR4 model image of landsat 8 on land cover classification in central sulawesi grand forest park," *Int. J. Appl. Eng. Res.*, vol. 12, no. 20, pp. 9405–9412, 2017.

[4] S. M. A. Letsoin, D. Herak, F. Rahmawan, and R. C. Purwestri, "Land cover changes from 1990 to 2019 in Papua, Indonesia: Results of the remote sensing imagery," *Sustain.*, vol. 12, no. 16, pp. 1–18, 2020, doi: 10.3390/su12166623.

[5] N. F. H. Jumaat, B. Ahmad, and H. S. Dutsenwai, "Land cover change mapping using high resolution satellites and unmanned aerial vehicle," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 169, no. 1, 2018, doi: 10.1088/1755-1315/169/1/012076.

[6] B. Prayudha *et al.*, "The application of Landsat imageries and mangrove vegetation index for monitoring mangrove community in Segara Anakan Lagoon, Cilacap, Central Java," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 944, no. 1, 2021, doi: 10.1088/1755-1315/944/1/012039.

[7] Y. Sari, Y. F. Arifin, N. Novitasari, and M. R. Faisal, "Effect of Feature Engineering Technique for Determining Vegetation Density," *Int. J. Adv. Comput. Sci. Appl.*, vol. 13, no. 7, pp. 655–661, 2022, doi: 10.14569/IJACSA.2022.0130776.

[8] Y. Sari, Y. Arifin, Novitasari, and M. Faisal, "Implementation of Deep Learning Based Semantic Segmentation Method to Determine Vegetation Density," *Eastern-European J. Enterp. Technol.*, vol. 5, no. 2–119, pp. 42–54, 2022, doi: 10.15587/1729-4061.2022.265807.

[9] Y. Heryadi and E. Miranda, *Land cover classification based on sentinel-2 satellite imagery using convolutional neural network model: A case study in Semarang Area, Indonesia*, vol. 830, no. January. Springer International Publishing, 2020.

[10] Y. Sari, M. Alkaff, and M. Maulida, "Classification of Rice Leaf using Fuzzy Logic and Hue Saturation Value (HSV) to Determine Fertilizer Dosage," 2020, doi: 10.1109/ICIC50835.2020.9288585.

[11] Y. Sari, M. Alkaff, and R. A. Pramunendar, "Iris recognition based

on distance similarity and PCA," *AIP Conf. Proc.*, vol. 1977, no. August 2019, 2018, doi: 10.1063/1.5042900.

[12] M. Alkaff, H. Khatimi, W. Puspita, and Y. Sari, "Modelling and predicting wetland rice production using support vector regression," *Telkomnika (Telecommunication Comput. Electron. Control.*, vol. 17, no. 2, pp. 819–825, 2019, doi: 10.12928/TELKOMNIKA.V17I2.10145.

[13] L. Jiang, H. Liu, H. Zhu, and G. Zhang, "Improved YOLO v5 with balanced feature pyramid and attention module for traffic sign detection," *MATEC Web Conf.*, vol. 355, p. 03023, 2022, doi: 10.1051/matecconf/202235503023.

[14] J. H. Kim, N. Kim, Y. W. Park, and C. S. Won, "Object Detection and Classification Based on YOLO-V5 with Improved Maritime Dataset," *J. Mar. Sci. Eng.*, vol. 10, no. 3, 2022, doi: 10.3390/jmse10030377.

[15] N. Kundu, G. Rani, and V. S. Dhaka, "Seeds Classification and Quality Testing Using Deep Learning and YOLO v5," *ACM Int. Conf. Proceeding Ser.*, no. August, pp. 153–160, 2021, doi: 10.1145/3484824.3484913.

[16] P. Jiang, D. Ergu, F. Liu, Y. Cai, and B. Ma, "A Review of Yolo Algorithm Developments," *Procedia Comput. Sci.*, vol. 199, pp. 1066–1073, 2021, doi: 10.1016/j.procs.2022.01.135.

[17] D. P. Carrasco, H. A. Rashwan, M. A. Garcia, and D. Puig, "T-YOLO: Tiny vehicle detection based on YOLO and multi-scale convolutional neural networks," *IEEE Access*, vol. 11, no. December 2021, 2021, doi: 10.1109/ACCESS.2021.3137638.

[18] M. Krishnaveni, S. K. P. Kumar, E. A. Muthusamy, J. Kowshick, and K. G. Arunya, "Real-time Monitoring of Water Level and Storage Dynamics of Irrigation Tank Using IoT," *H2Open J*, vol. 3, no. 1, pp. 392–400, 2020, doi: 10.2166/h2oj.2020.123.

[19] Y. C. How, A. F. Ab. Nasir, K. F. Muhammad, A. P. P. Abdul Majeed, M. A. Mohd Razman, and M. A. Zakaria, "Glove Defect Detection Via YOLO V5," *Mekatronika*, vol. 3, no. 2, pp. 25–30, 2022, doi: 10.15282/mekatronika.v3i2.7342.

[20] F. A. P, H. Segah, N. S. Yusuf, and R. M. Sukarna, "Analysis Of Changes In Mangrove Cover Using Landsat Imagery In Seruyan District," vol. 2, no. 12, pp. 2717–2733, 2022.

[21] Y. Sari and P. B. Prakoso, "Detection of Moving Vehicle using Adaptive Threshold Algorithm in Varied Lighting," *Proceeding - 2018 5th Int. Conf. Electr. Veh. Technol. ICEVT 2018*, no. 1, pp. 136–141, 2019, doi: 10.1109/ICEVT.2018.8628398.

[22] Y. Sari, A. R. Baskara, and R. Wahyuni, "Classification of Chili Leaf Disease Using the Gray Level Co-occurrence Matrix (GLCM) and the Support Vector Machine (SVM) Methods," *2021 6th Int. Conf. Informatics Comput. ICIC 2021*, 2021, doi: 10.1109/ICIC54025.2021.9632920.

[23] A. Sharifara, M. S. M. Rahim, H. Sayyadi, and F. Navabifar, "Search space optimization and false alarm rejection face detection framework," *J. Theor. Appl. Inf. Technol.*, vol. 79, no. 3, pp. 370–379, 2015.