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Ground Coverage Classification in UAV Image Using a Convolutional Neural Network Feature Map

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Abstract

Background: To understand land transformation at the local level, there is a need to develop new strategies appropriate for land management policies and practices. In various geographical research, ground coverage plays an important role particularly in planning, physical geography explorations, environmental analysis, and sustainable planning.
Objective: The research aimed to analyze land cover using vegetation density data collected through remote sensing. Specifically, the data assisted in land processing and land cover classification based on vegetation density.
Methods: Before classification, image was preprocessed using Convolutional Neural Network (CNN) architecture's ResNet 50 and DenseNet 121 feature extraction methods. Furthermore, several algorithm were used, namely Decision Tree, Naïve Bayes, K-Nearest Neighbor, Random Forest, Support Vector Machine (SVM), and eXtreme Gradient Boosting (XGBoost).
Results: Classification comparison between methods showed that using CNN method obtained better results than machine learning. By using CNN architecture for feature extraction, SVM method, which adopted ResNet-50 for feature extraction, achieved an impressive accuracy of 85%. Similarly using SVM method with DenseNet121 feature extraction led to a performance of 81%.
Conclusion: Based on results comparing CNN and machine learning, ResNet 50 architecture performed the best, achieving a result of 92%. Meanwhile, SVM performed better than other machine learning method, achieving an 84% accuracy rate with ResNet-50 feature extraction. XGBoost came next, with an 82% accuracy rate using the same ResNet-50 feature extraction. Finally, SVM and XGBoost produced the best results for feature extraction using DenseNet-121, with an accuracy rate of 81%.

Keywords: Classification, CNN Architecture, Feature Extraction, Ground Coverage, Vegetation Density.

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I. INTRODUCTION

Indonesia is home to 149,056 km² of peatlands, distributed across three islands: Kalimantan, Sumatra, and Papua. [1]. Previous research has shown that these peatlands are the second most abundant in the world [2]. Typically, peatlands offer numerous essential services to nearby communities, including maintaining air and water quality and supporting fish populations. However, the intentional or accidental human activities often cause fire outbreaks, disrupting many operations in the country and neighboring countries [3], [4]. Peatlands conditions are strongly influenced by drought characteristics, particularly during El-Nino [5], [6]. The reductions in peatlands are also caused by factors such as Drought Index, Evapotranspiration, and Interception Loss. Analysis of this area requires ground coverage data based on vegetation density [7]. Conceptually, the term "vegetation" refers to all plants covering ground in a given area. To determine drought level, the drought index is obtained using Keetch-Byram Dryness Index (KBDI) method. Moreover, density of vegetation cover on KBDI peat is classified into three categories namely, bare, medium, and high [8]. Vegetation analysis is a method for exploring the arrangement and composition of vegetation in terms of its structure. Remote sensing technology can be used to access data related to vegetation density effectively.

Remote sensing uses two types of data, namely satellite and Unmanned Aerial Vehicle (UAV). Specifically, remote sensing with satellite data operates at high altitudes and is easily affected by external factors such as weather and clouds. Satellites have limitations such as low spectral and temporal resolution, relatively long review times, difficulties in data extraction and image interpretation, and climatic conditions affecting image capture. These

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limitations, along with high costs, lack of flexibility, and operational complexity, make satellite remote sensing impractical and not recommended [9]. On the other hand, UAV produce high-resolution image and are widely used in agricultural research, successfully bridging the gap between ground data and larger-scale observations but require more preprocessing. UAV drone offer great potential for developing remote sensing technology such as area classification by creating spatial data from aerial image. However, optimal results can be achieved using a UAV or drone for classification based on the object and the appropriate processing method. Convolutional Neural Network (CNN) in deep learning methods revolutionizes image classification by learning basic shapes in the first layer and deeper layers into learned image features, leading to more accurate classification [10].

CNN profound learning strategy produced the most significant results in image recognition among developing deep learning methods [11]. CNN has been extensively used, improving classification and enabling the use of its feature in the current algorithms. Furthermore, this procedure has been especially applied to tasks related to remote sensing image analysis, such as segmentation, object-based image analysis, recording image, grouping scenes, objects detection, and ordering ground inclusion and land use classification. CNN can automatically learn image feature representations and outperform many feature extraction methods [12]. Additionally, previous explorers have used CNN method for feature extraction. For example, Simon and Uma [13] used deep learning-based feature extraction for texture classification, using Support Vector Machine (SVM) as the classification method. The explorers used architecture such as DenseNet 201, ResNet 50, ResNet 101, Inception v3, and AlexNet. The accuracy results obtained after using CNN feature are significantly improved, achieving a 95% accuracy rate [13]. Suganya Athisayamani et al [14] conducted research on ResNet 152 feature extraction and optimal feature dimension reduction for MRI brain tumor classification. The research found that using CNN architecture for image processing, especially for feature extraction, achieved an accuracy of 98.85% [14]. Several other explorations have also applied CNN method for feature extraction in processing image data before classification. However, there is a lack of application of CNN architecture in processing vegetation density image data, as identifying and characterizing plants requires space and time [16]. The research proposes a method for Ground Coverage Classification based on vegetation density. The exploration uses CNN feature extraction to analyze image data more efficiently, accurately, and flexibly [15]. When CNN is used as feature extractor, an additional classification method is needed. The exploration uses machine learning methods to classify UAV image.

The application of machine learning algorithms to remote sensing image for ground coverage classification has been widely used in previous research [16]. Recent advancements in land use and ground coverage classification methodology have shown significant progress, particularly with the implementation of machine learning methods [17]. Furthermore, these machine learning models are leading analytical tools used to monitor, map, and measure land and ground coverage changes over time. Based on literature explorations, widely used methods for ground coverage classification based on vegetation density include Decision Tree, Naïve Bayes, K-Nearest Neighbor (KNN), Random Forest, SVM, and eXtreme Gradient Boosting (XGBoost) [16], [17], [18]. This research will apply machine learning classification methods to achieve its objectives. The use of these methods has acquired significant interest among explorers, especially with satellite image data [19]. However, machine learning methods have generally been limited to satellite data and have not been widely applied to UAV data [20].

The research aims to combine architectural principles with machine learning methods. In this context, CNN is used for feature extraction, which is further combined with machine learning methods for classification. Previous exploration primarily focused on comparing results between methods without combining different methods. However, the current research combined different architectures for land cover classification to achieve better results. CNN should be considered the best component extractor because it offers several advantages over other strategies. For instance, it can capture better and stronger elements from a large amount of image data and significantly improve precision more quickly [12]. Furthermore, CNN learns image feature representations automatically and outperforms many feature extraction methods [13]. This research uses ResNet-50 and DenseNet-121 architecture for feature extraction. ResNet 50 has a simple design strategy with a single identity shortcut, while DenseNet 121 has higher capacity by combining feature multiple layer, which helps in training deep network more effectively. Additionally, DenseNet 121 uses feature more efficiently with fewer parameters [21]. Consequently, this research examines feature extraction using architecture and classification using machine learning. The analysis determines results based on precision, precision, recall, and F1 score.

II. LITERATURE REVIEW

Research on Ground Coverage Classification based on vegetation density has been conducted by several previous explorers. Consequently, the explorers have processed complex image data before classification, signifying that achieving good accuracy depends on both the method and the quality of image data processing. Several members recommend using deep learning methods to process complex image data effectively.

Camile Sothe et al. processed UAV dataset using CNN method and feature extraction in 2020 [22]. This research examines classification of 14 different tree species in Southern Brazil's subtropical forests. The performance of CNN method is compared to other traditional machine learning methods, specifically SVM and Random Forest (RF), using the original training data. Furthermore, the process of extending and adjusting the sample set (data expansion) for tree species classification is associated with CNN method. Execution of SVM and RF classifiers combines data expansion and spatial elements extracted by CNN. The outcomes show that CNN classifier outperforms traditional SVM and RF classifiers, achieving a total accuracy (TA) of 84.37% and a Kappa coefficient of 0.82. Despite the initial poor accuracy with original spectral groups (TA 62.67% and 59.24%), SVM and RF classifiers showed significant improvement in TA by 14% to 21% when combined with data expansion and spatial feature extracted by CNN [22].

Tanmay Kumar Behera and colleagues presented a dense module-influenced deep learning model in 2022 [20]. This model, known as UDD tackles the vanishing gradient problem commonly observed in mechanisms and improves the feedforward properties of networks. The proposed end-to-end CNN architecture accurately extracts global feature to segment vegetation classes from aerial image through symmetric downscaling and upscaling passes. Furthermore, two UAV image datasets were used to evaluate the proposed architecture which includes the NITRDrone dataset and the UDD. Compared to the current methods, this method achieved intersection over union (IoU) values of 74% on UDD dataset and 84% on NITRDrone dataset [20].

Guilia Cecilia et al. used UAV image classification to monitor ground coverage in 2023. The research examined and compared prediction models built with CNN, VGG16, DenseNet 121, and ResNet 50 using multitemporal and single-date Sentinel-2 satellite data. Specifically, VGG16 model achieved a TA of 71% when applied to single-dated and multi-temporal image, showing improved performance [23]. Following this result, Darwin Alexis Arrechea-Castillo et al. conducted research in 2023 using UAV to classify ground coverage by applying CNN architecture, specifically LeNet to sentinel-2 image. Analysis of the validation data showed that the proposed CNN achieved a kappa coefficient and TA of 0.962 and 96.51%, respectively [24].

Several previous explorations have applied CNN feature extraction to datasets beyond UAV data. For example, Suganya Athisayamani et al. (2023) used Residual Deep Convolutional Neural Network (ResNet-152) to extract feature and minimize ideal feature dimensions for tumor classification. Feature classification procedure was then completed using the softmax classifier and ResNet-152. It should be acknowledge that this method was applied to the Figshare dataset using Python. Various criteria, including sensitivity, specificity, and accuracy, were used to evaluate the total effectiveness of the proposed cancer classification system. Consequently, the proposed method outperformed others, achieving a final evaluation accuracy of 98.85%. However, Enhanced Chimpanzee Optimization Algorithm (EChOA) was used to select feature by reducing the dimensions of the retrieved feature [14].

Research has also conducted ground coverage classification trials using CNN method in data processing or classification fields. However, very few have compared deep learning and machine learning methods or combined the two for ground coverage classification based on vegetation density. To classify ground coverage based on vegetation density, this research used CNN for both data processing and classification. Classification results were then compared with those obtained using machine learning methods.

III. METHODS

A. Research Flow

The flowchart in Fig. 1 showed the steps of the research process and the methodologies used in this research. The process started with capturing image from a standard camera or UAV. This image was then passed through preprocessing, which included tasks such as resizing and augmentation to facilitate easier handling during the training. After preprocessing, the data was divided into training and examining sets with 80:20 ratio. Following this division, feature extraction was performed using CNN architecture, specifically ResNet 50 and DenseNet 121. The extracted feature was subsequently used for classification through various machine learning methods, including Decision Tree, Naive Bayer, KNN, Random Forest, SVM, and XGBoost. After classification, the results for each class were obtained.

B. Dataset

The dataset was collected in Liang Anggang Protected Forest, South Kalimantan using DJI Mavic Pro drone, and a total of 10,000 vegetation image was obtained. Classification classes in this research were divided into 3 categories namely, bare, medium, and high, with each class comprising 1000 image. In addition, this classification was based on the state of the Liang Anggang Protected Forest, which had an abundance of plants suitable for data collection on ground coverage characteristics and vegetation density types. Certain areas of Liang Anggang protected forest were inaccessible to drone due to proximity to Syamsudin Noor airport, which was in a restricted fly zone limiting drone flight to a maximum altitude of 60 meters. Consequently, the capture area was limited to a maximum of 60 meters in height, with drone operating at an altitude of 20 meters to ensure adequate area coverage. The dataset was accessible through Mendeley at this link: https://data.mendeley.com/datasets/tb26zy2jst/1.

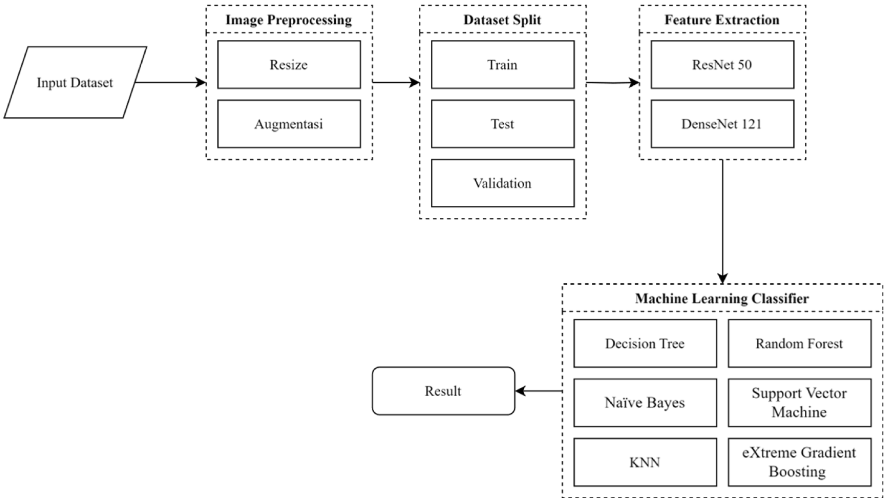
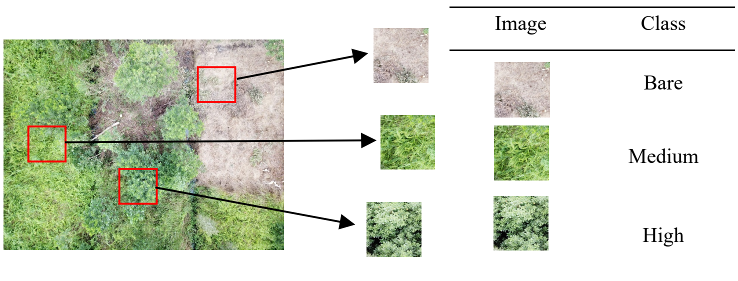


Fig. 1 Research flow

The dataset consisted of three classes, each containing 1000 image of vegetation density categorized as high, medium, and bare. Image data acquired by the drone had a high resolution of 4000 x 3000 pixels. To make the classification process easier, image was cropped, which reduced the space and memory required during classification. For training, image was resized to 256 x 256 pixels to improve learning efficiency, and the next step included labeling. Moreover, pre-processing was crucial because the obtained dataset was used to design the distribution of training and examined data at this stage. [25], [26]. Image cropping and labeling process was shown in Fig. 2.



(a) (b)

Fig. 2 Dataset processing (a) image cropping; (b) labelling process

C. Feature Extraction from CNN Architecture

Before conducting the classification process, features were extracted to improve prediction accuracy, increase confidence in calibration, and make interpretation easier. [27]. Various research developed different methods for feature extraction, each based on distinct principles, but none was perfect. Additionally, numerous explorations showed the effectiveness of deep learning in feature extraction [12]. An example of deep learning used to extract visual features was CNN [28], which was used alongside Transfer Learning for both feature extraction and classification purposes [29].

CNN feature was extracted from the resulting feature map and the first convolution layer. In the context of this research, cross-entropy was computed as a loss hyperparameter. The exploration predicted feature map from the first convolution layer, which provided discriminative feature to expedite the classification process. In addition, a remnant network known as ResNet 50 was good at capturing distinctive feature. Moreover, DenseNet 121 was used because the algorithm could analyze millions of image from ImageNet database [13]. The model also resized input image to 224x224 pixels and used relatively few parameters, improving interconnections throughout the network. This research used ResNet 50 and DenseNet 121 feature extraction from CNN architecture.

1) ResNet-50 Architecture

ResNet, which was a complex CNN based on residual blocks, tackled the problem of gradient degradation in extremely deep networks [12]. ResNet introduced residual blocks by combining shortcut connections between layers, which improved accuracy without increasing network depth and prevented corruption as the process became more complex. Furthermore, ResNet had over eleven million parameters and 152 layers. The model used a 3x3 convolution filter, batch normalization, residual blocking, global average pooling, and classification layer (SoftMax). For this research, ResNet 50 was used to propose multiple variations with different numbers of layers. An overview of the ResNet-50 architecture was shown in Fig. 3 [30].

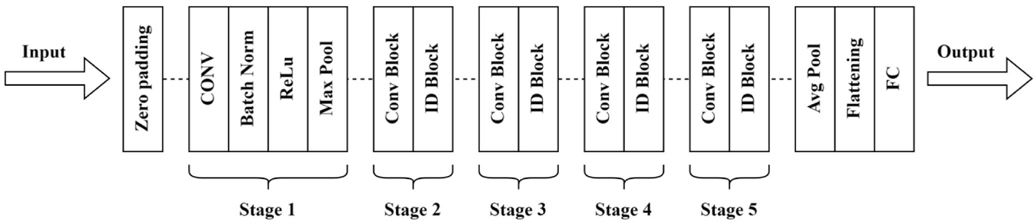


Fig. 3 ResNet-50 architecture [30]

2) DenseNet-121 Architecture

DenseNet 121 architecture connected all layers gradually compared to the conventional CNN architecture [26]. This architecture provided various methods for handling image data, using dense blocks with multiple layers. Each layer in DenseNet 121 had feature map connected from the first layer until a new layer was created. Additionally, architecture introduced benefits such as feature reuse and reduction in bursting or gradient loss. Changes were made to DenseNet 121 structure to enable feature extraction, including downsampling feature map to facilitate combining. A solid block concept was proposed to facilitate downsampling, with transitional layer containing convolution and batch normalization operation in between the solid blocks. Furthermore, DenseNet 121 also took advantage of shortcut connections, comprising transition layer connecting dense group of blocks [12]. As feature map from the previous layer were transferred to the next layer, the network became denser and thinner. Architecture included classification layer, a convolution and pooling layer, a transition layer, and multiple dense blocks arranged in series. An overview of DenseNet-121 architecture was shown in Fig. 4 [31].

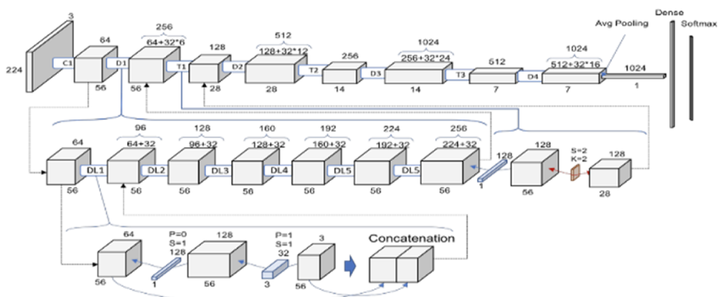


Fig. 4 DenseNet-121 architecture [31]

D. Classification Methods Classification Methods

The research proposed decision trees and machine learning methods for classification. This classification included Nave Bayes, KNN, Random Forest, SVM, and XGBoost.

1) Decision Tree

A decision tree was a graph showing a sequence of actions and different outcomes by using the branching method. [12]. Decision trees were effective for both numerical and categorical variables because assumptions were not made about data distribution or the structure of classification. Large data sets were efficiently and accurately classified using decision trees [12].

2) Naïve Bayes

Bayes's classification methods relied on Bayes' theorem, which calculated the probability of an event based on prior knowledge of associated conditions. When all of the class probabilities for the aimed feature were calculated, the naïve Bayes classifier identified the class with the highest probability. Additionally, naïve Bayes assumed that each class value for each feature followed a Gaussian distribution [12].

3) KNN

KNN excelled as a favored method for guided classification in multivariate scenarios, known for its simplicity and efficacy [12]. The method operated as a non-parametric algorithm, leveraging training data to construct a model that retained the classifier's memory [10]. Using KNN, unlabeled data was sorted into categories based on the nearest and most analogous labeled data points. The parameter K integral to KNN dictated the number of nearest neighbors to consider. Typically, K value ranging from 3 to 10 was selected to mitigate overfitting and underfitting [12]. By comparing all training image and transferring labels from K most similar prior training examples, the method assigned classification to each examined image [12].

4) Random Forest

Random Forest identified an ensemble by combining several hierarchical tree structure predictors. The Random Forest was based on the idea that when a single decision tree makes a mistake and is unable to correlate, a collection of tree models can outperform it. [32]. This ensemble classifier known as Random Forest comprised numerous random decision trees. Each decision tree produced individual classification output, and the values were combined to generate final classification outcome [32].

5) Support Vector Machine (SVM)

SVMs were used in both kernel-based and non-linear classification, where input data was implicitly mapped into high-dimensional feature spaces. [32]. To classify data, SVM typically built a hyperplane or straight line that divided space into two homogeneous zones. The kernel's role was to determine high-dimensional space to which data should be mapped. Following the context, data points had to be linearly separable. By using the delta margin feature, SVM ensured that the learning model assigned higher score to the correct class than the incorrect one. As a result, the model produced more accurate results [10].

6) eXtreme Gradient Boosting (XGBoost)

XGBoost used a Gradient Boosting Machine (GBM), which combined gradient descent and boosting method [33]. Boosting, as an ensemble learning algorithm, adjusted the weight of the training data distribution for each iteration. Furthermore, the method increased the weight of misclassified error samples and decreased the weight of correctly classified samples in each method iteration, effectively modifying the training data distribution [33].

$$L(\emptyset) \sum_i 1(\hat{y_i}, y_i) + \sum_k \Omega(f_k) \tag{1}$$

$$where\ \Omega(f) = \gamma T + \frac{1}{2}\alpha||w||^2 \tag{2}$$

As a descending tree-based algorithm, GBM found split points that were not trivialized large data sets. Consequently, Chen and Guestrin in 2016 developed a new distributed quantile sketching algorithm that handled weighted data with provable theoretical guarantees of GBM derivatives, leading to a new scalable and efficient algorithm called XGBoost [32].

E. Model Evaluation

The accuracy of the training from each experiment was examined using the training dataset in the final stage. Subsequently, confusion matrix was used to calculate the accuracy of the available data. To evaluate the effectiveness of accurate classification using 3000 datasets, training and examining data was divided into 80:20 ratio for analysis. The four terms in Table 1 showed the result of classification process when a confusion matrix was used to measure performance.

TABLE 1
CLASSIFICATION CONFUSION MATRIX

Multiclass Confusion Matrix		Predicted		
		Bare	Medium	High
Actual	Bare	TP	FP	FN
	Medium	FP	TN	TN
	High	FP	TN	TN

*TP=true positive; FP=false positive; TN=true negative; FN=false negative

The terms true positive, true negative, false positive, and false negative were used to calculate accuracy, precision, recall, and F1 score. The predictive power of a model was a measure of how well it predicted the future [26]. Based on the confusion matrix results, The formulation provided in the equation was used to determine classification model prediction's accuracy, sensitivity, and specificity.

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

$$recall = \frac{TP}{TP+FN} \quad (4)$$

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \quad (5)$$

$$F1\ Score = 2\ x\ \frac{Recall\ x\ Precission}{Recall+Precission} \quad (6)$$

When the false positive and false negative rates were the same, accuracy worked optimally. Precision and recall were considered when there was a significant difference between false positive and false negative rates. Additionally, this research found accuracy, precision, recall, and f1 score values.

IV. Results

A. Preprocessing

The acquired image data were 4.92MB resolution of 4000x3000. However, because image from the drone were too large, it was cropped and resized to create learning data. Image data was manually cropped to a size of 256x256 pixels using Photoshop, reducing the file size to 159KB. The cropped image was later categorized into 3 classes, namely bare, medium, and high. Additionally, each pre-trained model was trained with 100 epochs, using the same parameters. Fig. 5 showed the result of image data cropping process. After cropping, the three class categories were labeled. There were 1000 data in each class labeling to facilitate future use of the method with ease of operation.

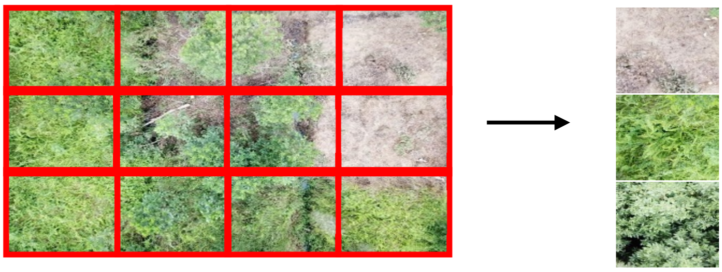
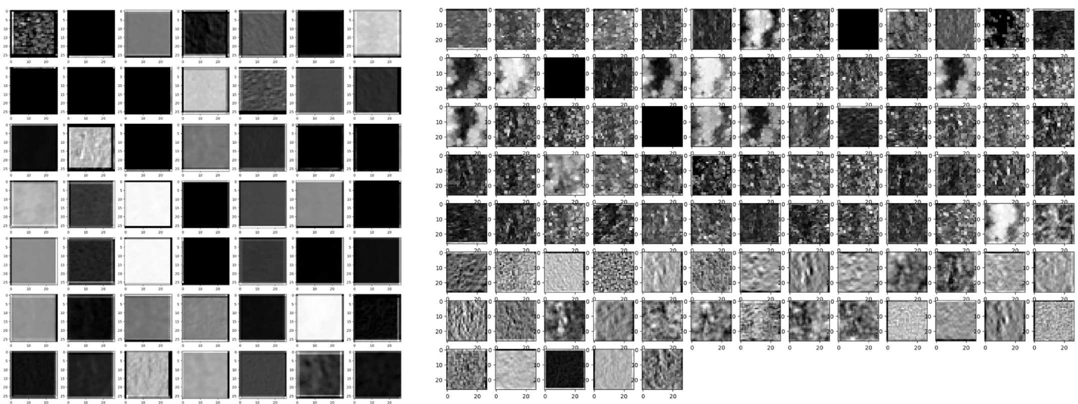


Fig. 5 Image cropping

B. Model Performance Evaluation



(a) (b)

Fig. 6 Feature extraction results from (a) ResNet 50 and (b) DenseNet 121

The research included trials on land cover classification based on vegetation density using UAV datasets and Google Colabs Pro (online) tools, primarily using Tensorflow and Keras libraries in Python. This research evaluated the accuracy of feature extraction using CNN architecture and classification through machine learning methods. The results of feature extraction from CNN method, presented as a heatmap were shown in Fig. 6.

Fig. 6 showed feature extraction using ResNet 50 and DenseNet 121. The left image showed feature extraction from ResNet 50 at layer conv 2 block 1, while the right image showed extraction from DenseNet 121 at the same layer. The difference between the two was evident when DenseNet 121 produced more textured feature extraction results compared to ResNet 50.

V. DISCUSSION

The results obtained in this research compared the performance of different CNN architecture in feature extraction. ResNet-50 combined with SVM produced an accuracy of 84%, precision of 91%, recall of 77%, and f1 score of 84%. Following the context, the performance was a better result compared to other models. The second-best result was achieved by DenseNet 121 with SVM and XGBoost, which yielded an accuracy of 81% and the ShuffleNet V2 achieved an accuracy of 80% [34]. Meanwhile, other explorations using the same case and similar dataset reported the following results. ResNet 18 with an accuracy of 81.90%, MobileNet V2 with 82.30%, Xception with 83.40%, InceptionResNet v2 with results of 84.10%, and VGG16 with results of 83.33% [35], [36]. The following results of the research were shown in Table 2.

TABLE 2
CLASSIFICATION COMPARISON RESULTS

Model	Accuracy	Precision	Recall	F1 Score	Time
Resnet-50 + Decision Tree	58%	71%	53%	58%	4mnt 28s
ResNet-50 + Naïve Bayes	61%	84%	62%	62%	2mnt 6s
ResNet-50 + KNN	70%	90%	70%	70%	5mnt 6s
ResNet-50 + RF	77%	92%	66%	77%	5mnt 32s
ResNet-50 + SVM	**84%**	**91%**	**77%**	**84%**	**8mnt 58s**
ResNet-50 + XGBoost	82%	93%	71%	81%	1h 32mnt
DenseNet-121 + Decision Tree	65%	76%	58%	65%	2mnt 55s
DenseNet-121 + Naïve Bayes	68%	83%	66%	68%	2mnt 3s
DenseNet-121 + KNN	77%	93%	65%	77%	4mnt 5s
DenseNet-121 + RF	78%	91%	68%	78%	4mnt 32s
DenseNet-121 + SVM	**81%**	**85%**	**74%**	**81%**	**5mnt 19s**
DenseNet-121 + XGBoost	**81%**	**90%**	**72%**	**81%**	**59mnt 36s**
Back Propagation Neural Network [8]	85.67%	-	-	-	-
ResNet18 [35]	81.90%	-	-	-	-
MobileNet V2 [35]	82.30%	-	-	-	-
Xception [35]	83.40%	-	-	-	-
InceptionResNetV2 [35]	84.10%	-	-	-	-
VGG16 [36]	83.33%	-	-	-	-

Table 2 showed the results for CNN and the combination of it with machine learning methods. CNN architecture was used for extraction methods while machine learning was applied for classification. By combining ResNet-50 with SVM, the explorers achieved an accuracy of 84%, precision of 91%, recall of 77%, and f1 score was 84%. Following this context, the performance outperformed other models. The second-best result, 81%, was achieved by using DenseNet 121 with SVM and XGBoost. Regarding the processing time, XGBoost method required significantly more time for classification. Graphical representation comparing all models in classifying vegetation density was shown in Fig. 7.

Classification process using CNN combined with machine learning methods still faced several obstacles, particularly in encountering misclassifications. These inaccuracies resulted from the challenge of precisely classifying image. According to the explorer's analysis, the issue arose from the characteristics of the land cover dataset. The dataset consisted of predominantly green-colored and textured areas, with variations primarily seen in the foliage. However, upon initial observation, distinguishing between the medium and high classes of land cover proved difficult due to similar color and texture. Misclassification often occurred in these two classes because image was almost similar and significantly different from the bare class. A similar dataset and the frequent occurrence of errors in classification were shown in Table 3.

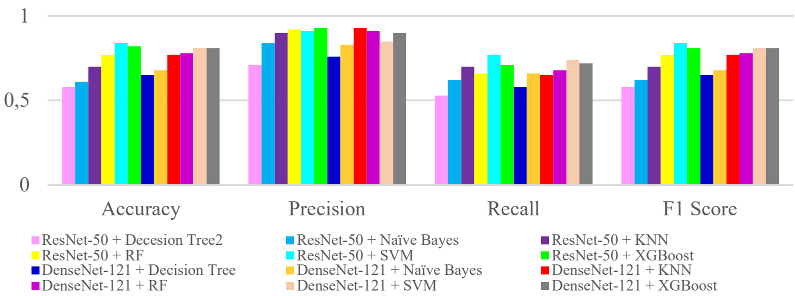


Fig. 7 Classification results

TABLE 3
RESULTS MISS CLASSIFICATION

Class	
Medium	High
	
	

VI. CONCLUSIONS

In conclusion, the research discussed the advantages of using feature extraction from CNN architecture. Given this scenario, CNN was combined with several machine learning methods to evaluate accuracy. Additionally, the research compared the classification performance of CNN architecture, namely ResNet-50 and DenseNet-121. To improve the classification accuracy, machine learning methods were used with the architecture for feature extraction. The machine learning methods proposed included Decision Tree, Naïve Bayes, KNN, Random Forest, SVM, and XGBoost. Based on the analysis, the comparison between machine learning methods showed that SVM was superior to others. This superiority was evidenced by 84% accuracy through feature extraction using ResNet-50. The second-best performance was observed with XGBoost, achieving 82% accuracy using ResNet 50 feature extraction. Finally, for feature extraction with DenseNet-121, the best results were also obtained with SVM and XGBoost, producing an accuracy of 81%.

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All authors have read and agreed to the published version of the manuscript.

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Data Availability: The data used is open to the public and can be found on Mendeley. The dataset is available at the following address: https://data.mendeley.com/datasets/tb26zy2jst/1.

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