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Patch based Classification using ResNet for Land Cover changes detection of Batu City

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Abstract—**The purpose of this study is to analyze the variations in land cover in Batu City, East Java Province, Indonesia, utilizing a patch-based classification strategy and deep learning. This study provides a preliminary estimation of land cover change in Batu City. The research also highlights the possibility of using deep learning techniques to analyze land use and land cover (LULC) variations in other urban areas with greater precision and efficiency. The EuroSAT dataset is used to train a classification model for patch labeling using the ResNet-50 architecture. Comparing the land cover of Batu City in 2001 and 2022 allows us to detect LULC changes, with almost 50% of the patch changing. The results indicate that 'Housing' and 'Road' become the most changed categories, while the vegetation areas decrease in number. The results demonstrate that the ResNet-50 architecture is capable of classifying patches and detecting LULC changes with an accuracy of 88% and an execution time of approximately 126.53 seconds.**

Index Terms—**Batu City; land cover and land use changes; patch-based classification; ResNet-50.**

I. Introduction

LAND cover changes has become a major concern in the study of natural resource management and the environment, especially in the context of urban areas. Batu City, which is an administrative city located in East Java Province, Indonesia, has experienced rapid growth in the last few decades, resulting in massive changes in land cover. Several studies have been conducted to analyze changes in land cover in Batu City. However, most of these studies are carried out using conventional methods such as visual interpretation [1] or spatial analysis techniques only [2], which can produce relatively low accuracy and take quite a long time.

There are various factors that could potentially drive changes in Land Use Land Cover (LULC) changes. These factors may include the fast-paced growth of urbanization, which could result in urban sprawl, peri-urban migration, and the conversion of agricultural land to paved areas. Other potential drivers of LULC changes could be industrial areas, transportation networks, educational and cultural facilities, agricultural activities, and tourism. However, it is important to note that the actual changes in LULC changes are often the result of a combination of these different types of development [3].

Typically, researchers analyze changes in LULC by comparing two or more maps created at different times. Both traditional maps and satellite images can be used to explore the causes and effects of LULC changes on society and the environment. Various studies have utilized Landsat imagery to investigate LULC changes to simulate the flood inundation from Brantas River in Batu, Malang [4]. Also the study by Wati et al. [5] that used the Sentinel image to detect the LULC changes in Pasuruan and Probolinggo. Researchers have also examined how LULC changes relate to the biodiversity in Batu. For instance, this study by Albab et al. [6] that analyzed the diversity, composition, and community structure of odonata in the highland and lowland ecosystems and the type of lotic and lentic waters based on the land use analysis.

Beselly et al. [7] analyze the the spatiotemporal variability of LULC changes to highlights the importance of quantitative assessment for sustainable watershed management in the Upper Brantas Basin and its effects on river discharge variation. The study reveals that changes in LULC, particularly cultivated and managed vegetation and urban/built-up area, significantly contribute to river discharge. Specifically, in the upper Brantas Basin, almost half of the increased river discharge was explained by the increase of urban/built-up and the decrease in cultivated and managed vegetation area [8].

However, there is no research that specifically analyzes changes in land cover in Batu City using a patch-based classification approach with deep learning. Therefore, this study aims to fill this research void and contribute to a better understanding of land cover change in Batu City with higher accuracy and a shorter time. In this context, the use of a patch-based classification approach with deep neural network architecture, can be an effective and efficient alternative in analyzing changes in land cover in Batu City. Several studies have been conducted using a deep learning approach, such as research by Wang et al. [9] that used

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a deep learning approach to perform LULC change detection on High-Resolution Remote Sensing. Fahmi and Sari [10] have also conducted an initial analysis regarding the effective deep neural network architecture for patch-based land cover classification.

II. Methods

In this study, a deep neural network architecture was used to classify patch-based land cover and find changes in LULC in the Batu City area between 2001 and 2022. ResNet-50 is an architecture used to train a classification model used for patch labeling. The EuroSAT dataset is used in the model training process. This ResNet architecture has proven to be more effective in classifying patches when compared to VGG and LeNet [10].

The steps in this study shown in Fig. 1. The deep learning models were used to do a patch-based land-cover classification and detect LULC changes. ResNet-50 is the model that was used to train the model using the EuroSAT dataset. After the model has been generated, the Batu images from 2001 and 2022 are compared to see the land use changes.

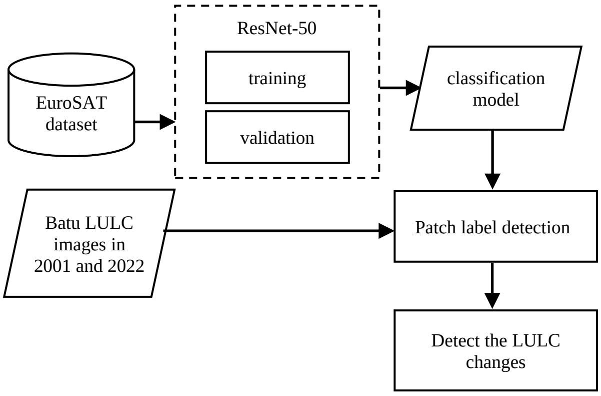


Fig. 1. LULC change detection flow

A. Dataset

The EuroSAT dataset was used in order to get the train information. Farm, Forest, Grass, Herbaceous, Housing, Industry, Permanent Crop, River, Road, and Water are the 10 classes that make up the dataset. The example patch image as in Fig. 2, with a total number of patch images of 21,600 images. The land cover in the Batu City area in the year 2001 and the land cover in the year 2022 are the two images that are being compared as in Fig. 3. The Sentinel-2 instrument was used to take pictures from space that were used to make the land cover image of Batu City.

The coordinates of the area of Batu City that were used are -7.86 to -7.88 S and 112.52 to 112.55 E, with the scale of 1:20000. On each image, a patch with dimensions of 64 by 64 is extracted, and from that patch, a land cover class classification is carried out using the ResNet model that has been trained. This detection is based on the information contained in the patch.

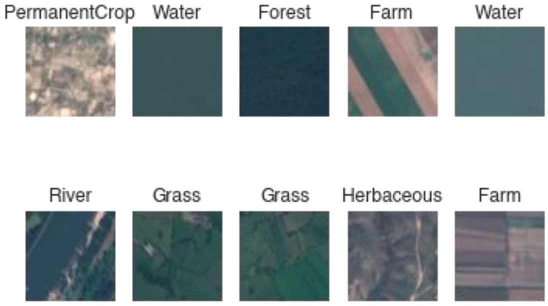
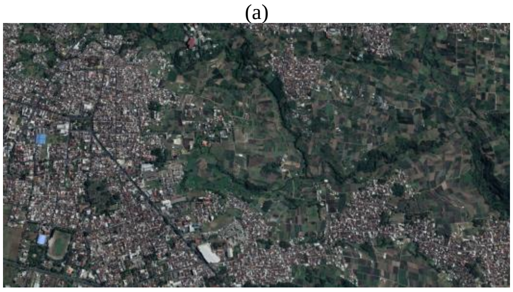


Fig. 2. Area EuroSAT image patch example

(a)



(b)

Fig. 3. Area of Batu, Malang from satellite image in a) 2001 and b) 2022

B. ResNet

ResNet, short for residual network, is a deep learning architecture that was introduced by Kaiming He et al. [11]. ResNet is a type of convolutional neural network (CNN) that is specifically designed to tackle the problem of vanishing gradients in very deep networks. The ResNet architecture consists of several convolutional layers with a residual connection. In a regular convolutional neural network, the input flows through a series of convolutional layers and is then transformed into a prediction. In ResNet, a shortcut connection is added to skip over some of the convolutional layers. This shortcut connection allows the output from an earlier layer to be directly added to the output of a later layer, creating a residual block. The residual block consists of two or more convolutional layers with a shortcut connection.

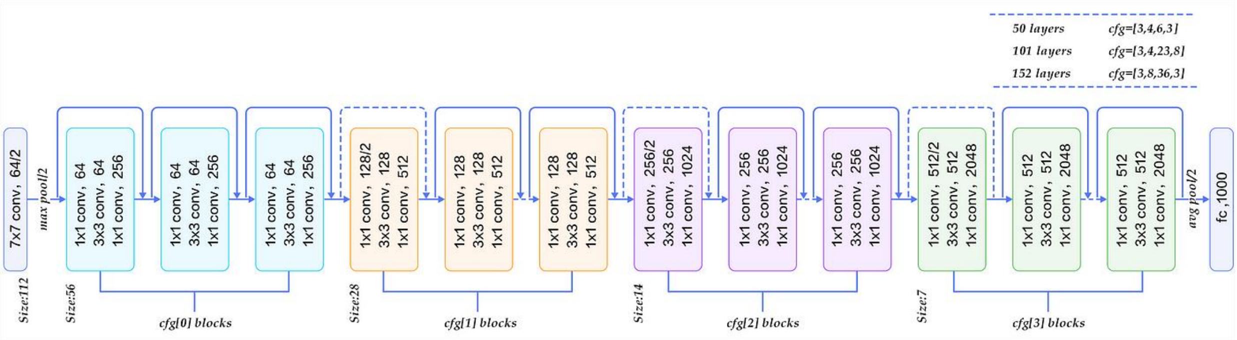


Fig. 4. ResNet-50 architecture [12]

The use of residual connections allows for the creation of very deep neural networks. By incorporating shortcut connections, ResNet is able to mitigate the vanishing gradient problem, which is often encountered in very deep neural networks. The vanishing gradient problem occurs when the gradients become too small to update the weights of earlier layers during backpropagation.

ResNet has several versions, with the most common being ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152, which differ in the number of layers. ResNet-50, for example, consists of 50 layers with bottleneck blocks like in Fig. 4, which reduce the computational cost of the network. The structure of ResNet has been shown to be effective in various computer vision tasks, such as object detection, image classification, and semantic segmentation.

ResNet models have achieved state-of-the-art performance in various computer vision tasks such as image classification, object detection, and semantic segmentation. The original ResNet model had 152 layers and won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2015, which is one of the most prestigious competitions in computer vision. ResNet is a widely used and influential architecture in the deep learning community, and it has inspired many subsequent models with similar skip connections or shortcut connections.

Several parameters have default values assigned to them when they are first initialized. Because increasing either the batch size or the learning rate beyond 32 will not produce correct results [13], [14], we have chosen to employ a batch size of 32 and a learning rate of 0.01. There is no perfect number of epochs; nonetheless, having an excessive number of epochs may cause the model to be overfit [15]. Consequently, there were only ten epochs utilized in this experiment. The optimizing algorithm that was utilized was known as Adam, and it is a stochastic gradient-based optimizer [16].

III. Results and Discussion

A. Training ResNet Model

This step covers the training model of the deep learning approach for classifying land cover using Sentinel-2 remote sensing images and EuroSAT data. The multispectral imager (MSI) aboard the satellite

Table 1. Training Evaluation of ResNet-50 for each Epoch

Epoch	Training accuracy	Validation accuracy	Time (s)
1	0.80347	0.875463	409.129
2	0.92118	0.855093	418.6425
3	0.95237	0.865046	442.9229
4	0.96626	0.867361	429.7086
5	0.97101	0.874537	407.2497
6	0.97737	0.879861	421.9054
7	0.98264	0.870602	451.1538
8	0.97766	0.876389	403.2057
9	0.98247	0.879861	391.6654
10	0.98808	0.881019	418.5003
Average	0.95225	0.872523	419.4083

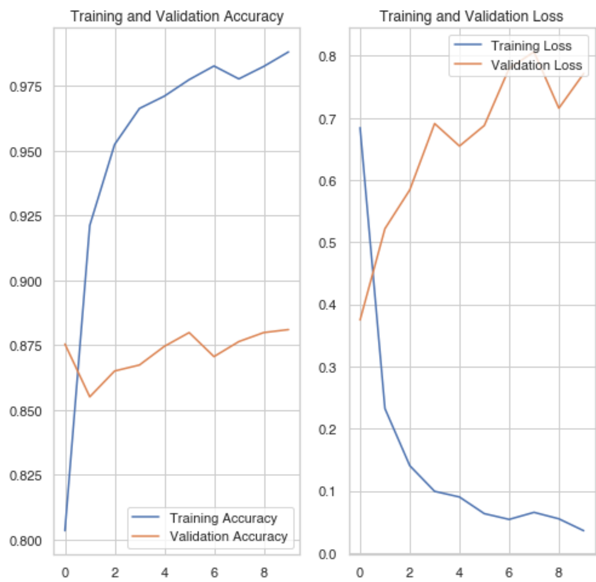


Fig. 5. Training evaluation of ResNet-50 using EuroSAT dataset

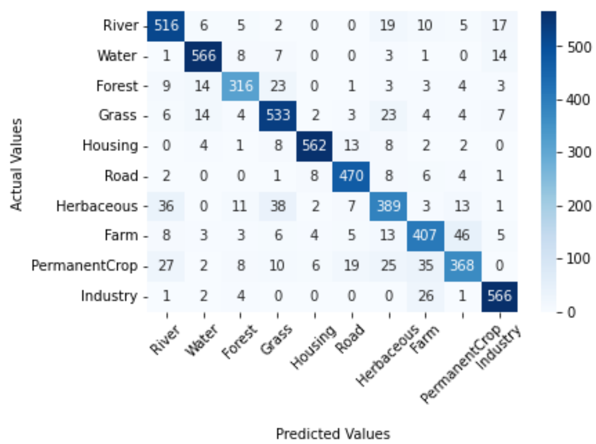


Fig. 6. Confusion matrix of EuroSAT data classification

captured the entire earth's surface in thirteen spectral bands [17]. The dataset included ten categories. This dataset is divided into two sections: 80% for training and 20% for validation. Training data are used to develop a classification model, and validation data are then used to validate the model's accuracy.

The evaluation of the training result model from ResNet-50 is very good, with a value reaching 98%, and when validation is carried out, the validation accuracy value is 88%. A detailed evaluation of the model for each epoch and its training time is shown in Table 1. Accuracy and loss of training and validation are shown in Fig. 5. The confusion matrix from the model validation results is shown in Fig. 6.

B. *Patch-based Classification of Batu Area*

Next, the patch-based remote sensing image of Batu City will be classified using the ResNet-50 model. First, a classification was performed on the 2001 image of Batu City, followed by a patch classification on the 2022 image of the same area. The dimension of the patch is 64 by 64 pixels, with the total of 464 patches in one image. The classification results of the two images at various timestamps are then compared to determine whether the class label of each patch has changed. Changes in land cover of Batu City in 2022 are shown in Fig. 7, with a different patch from 2001 marked with a red box. The percentage of LULC changes that occur based on the patch label is 50.2%. The total time needed to perform LULC change detection is 126.53 seconds.

Fig. 8 displays a comparison of land cover class categories from 2001 and 2022. Housing patches are the most prevalent in the Batu City region. In 2001, there were 218 patches in the 'Housing' category; by 2022, there are expected to be 229 patches. The 'Road' category has also grown, from 36 patches in 2001 to 119 patches in 2022, an increase of 115. Similarly, the

Land Cover in 2022

Land Cover in 2001	Farm	Forest	Grass	Herbaceous	Housing	Industry	PermanentCrop	River	Road	Water	**Total**
Farm	0	0	0	0	0	0	0	0	1	1	**2**
Forest	0	2	3	0	4	0	4	0	3	1	**17**
Grass	1	1	23	0	24	0	9	0	38	3	**99**
Herbaceous	0	0	0	2	16	0	1	0	2	0	**21**
Housing	0	1	6	2	165	3	12	3	23	3	**218**
Industry	0	1	2	0	3	0	0	0	2	0	**8**
PermanentCrop	0	0	6	0	9	1	11	2	19	0	**48**
River	0	0	3	0	3	0	1	0	2	0	**9**
Road	0	0	3	0	4	0	2	0	26	1	**36**
Water	0	0	0	0	1	0	0	0	3	2	**6**
Total	**1**	**5**	**46**	**4**	**229**	**4**	**40**	**5**	**119**	**11**	

Fig. 8. Batu Land Cover Changes

number of 'Water' regions has nearly doubled from six in 2001 to eleven in 2022. Other categories were also seeing a decrease in numbers.

C. Discussion

The results of the LULC change detection in Batu City in 2001 and 2022, as presented in the paragraph, offer valuable insights into the transformation of this region's land cover. The patch-based remote sensing image classification approach contributes to the detection of LULC changes in general with a relatively quick. Performing LULC change detection required 126.53 seconds, which is a reasonable amount of time.

The results indicate that LULC varied by 50.2% based on the patch label. This significant change indicates the transformation of the region's landscape. The result indicates an increase in urbanization and infrastructure development in Batu City. From the results obtained it can also be seen that the vegetation area is decreasing in number. These changes indicate that Batu is undergoing urbanization, resulting in a transformation of the natural landscape.

These findings are consistent with previous research that has highlighted the impacts of urbanization on land cover change in Batu City and also in East Java [18], [19]. The study's results also highlight the decreasing vegetation area in Batu City, which is another common phenomenon associated with urbanization [20]. The loss of vegetation has significant implications for the region's biodiversity, water resources, and air quality, and it underscores the importance of sustainable urban planning and development.

The findings of this research can be utilized to comprehend the spatial and temporal changes in Batu City's land cover. The data presented in this study can be used for preliminary estimation to develop more effective strategies for managing and conserving the region's natural resources, and for promoting sustainable development that considers the need to balance economic growth with environmental protection. This study contributes to the growing body of literature on LULC change detection and its implications for sustainable development and emphasizes the need for further investigation in this area. For more precise detection, a different method, such as pixel-based classification, is required.

IV. Conclusion

Deep learning with a ResNet-50 architecture revealed to be an effective and efficient alternative for analyzing changes in LULC in Batu City when used for patch labeling. This research contributes to a more precise and expedient comprehension of LULC changes in Batu City.

Urbanization, the conversion of agricultural land to paved areas, industrial areas, transportation networks, and tourism are potential drivers of LULC changes in Batu City, according to the study's conclusion. The findings of this study can serve as a guide for policymakers and stakeholders in Batu City to develop more effective land use and management strategies. In addition, the deep learning approach with ResNet-50 is a viable alternative for future research on LULC changes in other regions.

In future studies, it is necessary to analyze changes in LULC not only based on patches. Because, if you use a patch-based classification, detailed and accurate area information cannot be obtained. This patch is only used to estimate the initial amount of land change that occurs in an area.

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