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Utilization of Deep Learning for Mapping Land Use Change Base on Geographic Information System: A Case Study of Liquefaction

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Abstract: This study aims to extract buildings and roads and determine the extent of changes before and after the liquefaction disaster. The research method used is automatic extraction. The data used are Google Earth images for 2017 and 2018. The data analysis technique uses the Deep Learning Geography Information System. The results showed that the extraction results of the built-up area were 23.61 ha and the undeveloped area was 147.53 ha. The total length of the road before the liquefaction disaster occurred was 35.50 km. The extraction result after the liquefaction disaster was that the area built up was 1.20 ha, while the buildings lost due to the disaster were 22.41 ha. The total road length prior to the liquefaction disaster was 35.50 km, only 11.20 km of roads were lost, 24.30 km. Deep Learning in Geographic Information Systems (GIS) is proliferating and has many advantages in all aspects of life, including technology, geography, health, education, social life, and disasters.

Keywords: Deep learning; Geographic information system; Land use change; Liquefaction

Introduction

The use of automatic land cover extraction on images using machine learning techniques has grown significantly over the last few decades. Fast, efficient, and high-accuracy data extraction are the three advantages of this method (Iskandar & Hanafi, 2022; Rodriguez-Galiano et al., 2012; Tsai et al., 2018). One of these advances is artificial neural networks (ANNs) towards deeper neural network architectures with enhanced learning capabilities which are summarized as deep learning (Bengio & LeCun, 2007; Goodfellow et al., 2016).

Artificial Intelligence (AI) and Deep Learning are always associated with Machine Learning, and many companies in Indonesia often use AI technology. The application of this technology can complete tasks more successfully because Artificial Intelligence can complete tasks by assuming a human mindset. A machine learning technique called deep learning is designed to continuously adapt at a certain level where the desired level of abstraction can be changed (Putra, 2019).

The deep learning method is a key component of artificial intelligence because it can improve the AI learning process, including for processing images and understanding natural language (Meileni et al., 2022; Putra, 2019). The data owned contains deep learning technology. Decisions taken will be better if the data collected is more diverse. Convolutional Neural Networks (CNN), which process input data in the form of images, are one of the common deep learning techniques (Nurhikmat, 2018; Hong & Kim, 2018). Convolution layers, which are unique to this approach, are used. In this layer, images created from input images create patterns from various other image areas to make them easier to categorize. The convolution layer functions so that image learning results can be implemented more effectively by providing output in the form of patterns (Meileni et al., 2022).

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Extracting traces of buildings and infrastructure automatically from high-resolution imagery is very important for urban planning applications, especially for disaster management planning (Gupta et al., 2021). Identification of buildings and infrastructure is essential for monitoring urban settlements and updating administrative databases (Li et al., 2019). In several studies, reliable and accurate building extraction methods have been developed which have received great attention (Ivanovsky et al., 2019) such as parametric and non-parametric classifiers, shadow-based methods, edge-based methods, and object-based methods (Cheng & Han, 2016; Matin & Pradhan, 2021; Ziaei et al., 2014).

Remote sensing provides valuable information for scientists and authorities regarding this matter. In recent years, deep learning technology has been widely used in remote sensing applications. It has the potential to overcome the problems of traditional classification algorithms. Among various deep learning technologies, Convolutional Neural Network (CNN) is primarily used for Computer Vision (CV) tasks. Since 2014, CNN-based semantic segmentation algorithms (Long et al., 2015) have been applied to many pixel-based remote sensing image analysis tasks, such as road extraction (Gao et al., 2019), building extraction (Li et al., 2018), classification of urban land use (Cao et al., 2018), vehicle detection (Audebert et al., 2017; Gupta et al., 2021), and identification of building damage CNN is mostly used for image classification, structural and land use change detection.

Many studies aim to identify buildings and other infrastructure automatically from satellite imagery under normal conditions (before) and after a disaster occurs. Several studies have been proposed that aim to use deep learning techniques for automatic identification of buildings in emergency situations. Remote sensing (Gupta et al., 2021; Joyce et al., 2009) and artificial intelligence (Sun et al., 2020) are useful supports for effective decision making in disaster management planning. Deep Learning can be used to analyze countless data and extract reliable.

Deep learning has proven to be a powerful tool for mapping land use changes based on Geographic Information System (GIS) data for several reasons: land use changes are often characterized by intricate and complex spatial patterns. Deep learning models, particularly convolutional neural networks (CNN), are well suited to capturing these patterns; capable of automatically extracting land cover features, elevation data, population statistics, and more can analyze temporal data sets, such as time series satellite imagery, to identify and predict changes; can handle large and complex data sets, making it suitable for analyzing extensive GIS databases and satellite image time series; can be seamlessly integrated into GIS systems making it easier for GIS professionals to use and utilize this technique, and shows strong performance in many computer vision tasks (accurate).

However, it's important to note that while deep learning offers many advantages for mapping land use change, it also comes with some challenges, such as the need for large labeled datasets, computational resources, and potential overfitting. Moreover, the interpretability of deep learning models can be a concern in applications like land use change mapping, where decision-makers may require transparent and interpretable results. Balancing the strengths and limitations of deep learning with the specific needs of a land use change mapping project is essential for its successful implementation.

The rapid development of Geographic Information System (GIS) technology offers high useful value (Purwanto et al., 2022) integrated with deep learning research aimed at extracting buildings and roads before and after a liquefaction disaster, knowing the extent of change before the disaster and after liquefaction disaster.

Method

Study Area

The research area is in the Petobo sub-district, South Palu District, Palu City. Astronomically the Petobo Sub-District affected by liquefaction is at $119^0$54′0″-$119^0$55′0″ E and $0^0$56′0″-$0^0$57′00″ S. Administratively, the southern part of Petobo sub-district is bordered by Sigi Regency, in the north it is bordered by South Palu sub-district, to the east it is bordered by Natabaru village, Sigi Binnomoru sub-district, Sigi district and to the west is Birobuli village, south of South Palu sub-district. The study area can be seen in Figure 1.

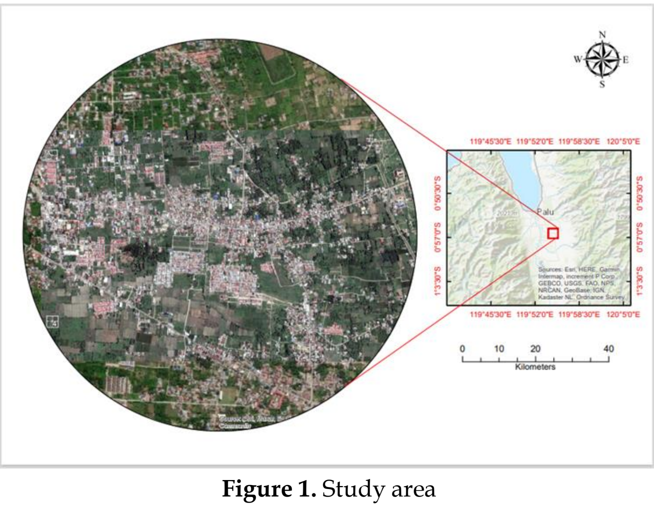

Figure 1. Study area

Data and Tools

The data used in this study include Google arth images for 2017 and 2018. Research data can be seen in Figures 2 and 3. The tool used is QGIS 3.26, with the addition of the Map Flow plugin. The Map Flow plugin is a tool used by QGIS for Deep Learning analysis. Mapflow provides an Artificial Intelligence (AI) model for automatic feature extraction from satellite imagery. Mapflow can extract buildings (optionally, with elevation), farm fields, forests (optionally, with elevation), roads, construction sites.

Figure 2. Image of 2017 before liquefaction

Figure 3. Image of 2018 After liquefaction

Method

In post-disaster detection, data is analyzed to take policy steps from events or conditions in the escalation of a particular event. This aims to minimize further crises from unpredictable disasters. Post-disaster identification or detection, detection, and possible risks refer to the mitigation and preparedness phases of disaster management (Linardos et al., 2022; Sankaranarayanan et al., 2020; Yuan & Moayedi, 2020). The use of Machine Learning (Deep Learning) can provide solutions that can be utilized by stakeholders.

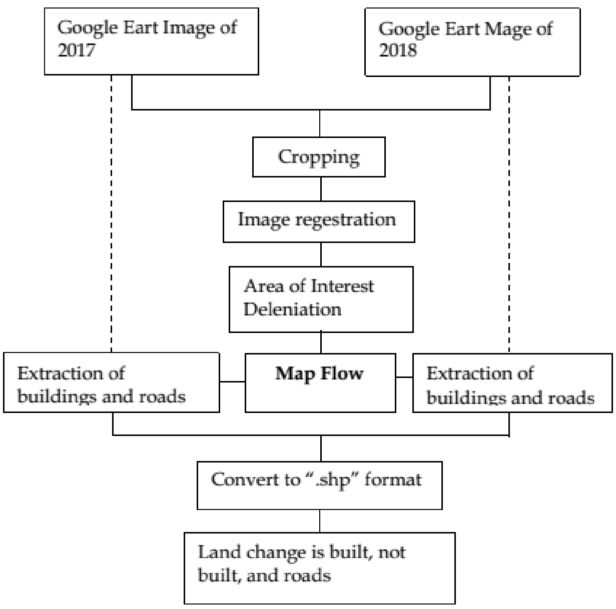

Figure 4. Deep learning extraction method

The method used in this study is to extract buildings and roads automatically using deep learning. The process of extracting buildings and roads is carried out by the following process: Google Earth image cropping was carried out using serial years, namely 2017 and 2018 before liquefaction occurred and after liquefaction; image register is done to get image coordinates to match the coordinates on earth; creating an Area of Interest (AOI) for a disaster area; extraction of buildings and roads prior to liquefaction; extraction of buildings and roads after liquefaction; converting to ".shp" type, to facilitate the detection and analysis of changes in land use (buildings) and roads; calculating the area of land use change after liquefaction.

Result and Discussion

Based on the interpretation and identification of the image of the Petobo sub-district and the results of the creation of the Area of Interest (AOI), the area that experienced the liquefaction disaster was 171.14 ha. Prior to the liquefaction disaster, this land use was divided into two parts, namely the built up area or area of 23.61 ha and the undeveloped area of 147.53 ha. The total length of the road before the liquefaction disaster occurred was 35.50 kilometers. The results of the extraction and detection of buildings and roads using deep learning, prior to the occurrence of a liquefaction disaster can be seen in Figure 5.

Extracting traces of buildings and infrastructure automatically from high-resolution imagery is very important for urban planning applications, especially for disaster management planning (Gupta et al., 2021). Deep Learning can identification of buildings and infrastructure is essential for monitoring urban settlements and updating administrative databases (Li et al., 2019). In several studies, reliable and accurate building extraction methods have been developed which have received great attention (Ivanovsky et al., 2019) such as parametric and non-parametric classifiers, shadow-based methods, edge-based methods, and object-based methods (Cheng & Han, 2016; Matin & Pradhan, 2021; Ziaei et al., 2014).

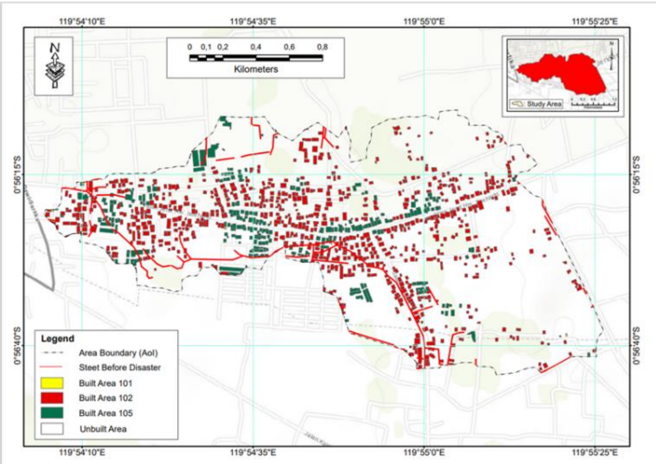

Figure 5. Extraction results using deep learning before the disaster

Land use, in this case, the built-up area and transportation (roads) have an interactive relationship, that is, both are determinants of movement and activity. Deep learning in Geographic Information Systems can be used to manage spatial data and detect changes in land as well as to extract them (Meileni et al., 2022; Syarifuddin et al., 2016).

The result of the extraction of buildings and roads after the liquefaction disaster occurred, the area of the built-up area or buildings still standing was 1.20 ha, while the buildings lost due to the disaster were 22.41 ha. The total road length prior to the liquefaction disaster was 35.50 kilometers to 11.20 kilometers. Deep Learning developed for disaster management, in particular, focus has been given to studies in the areas of disaster and hazard prediction, risk and vulnerability assessment, disaster detection, early warning systems, disaster monitoring, damage assessment and post-disaster response as well as case studies (Linardos et al., 2022).

Based on the results of post-disaster deep learning extraction, changes can be quickly and easily detected. This allows representations with high, and simple, levels of abstraction, each level transforming the representation to become more abstract, to eventually study invariant features and very complex functions (LeCun et al., 2015). The results of the extraction and detection of buildings and roads after liquefaction using deep learning can be seen in Figure 6. In brief, changes in the area of land use before and after the liquefaction disaster can be seen in Table 1.

Table 1. Changes in Area of Land Use before and After Liquefaction

Land Use	Before Liquefaction (ha)	After Liquefaction (ha)	Lost/Increase (ha)
Built Area	23.61	1.20	(-) 22.41
No Built Area	147.53	169.94	(+) 22.41
Road	35.50	11.20	(-) 24.30

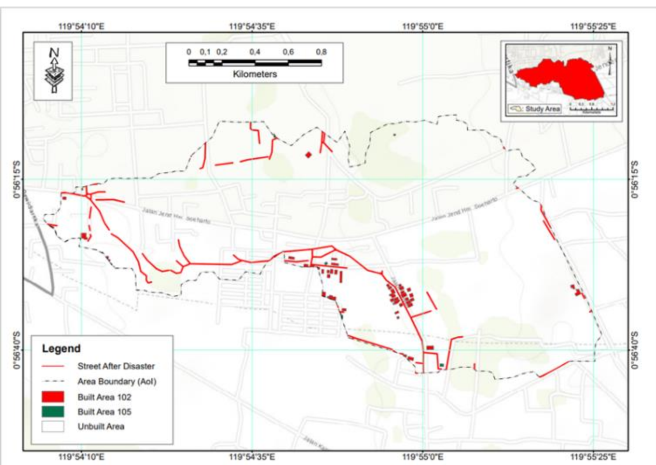

Figure 6. Extraction results using deep learning after the disaster

Based on the Table 1, it is known that after the liquefaction disaster the built-up area decreased by 22.41 ha (95%) from the initial built-up area. This reduction occurred because buildings collapsed, were damaged and swallowed by mud into the earth. The damaged road due to liquefaction is 24.30 km (68.45%) of the original road length. Deep learning is able to provide fast and accurate information as an alternative method in publications related to specific uses such as building extraction or detection. Deep learning in GIS technology uses artificial neural networks which are commonly called Artificial Intelligence (AI) where AI has the intelligence to think like humans (Deng & Yu, 2014).

The liquefaction natural disaster had a significant impact on the area in Petobo and its surroundings. Loss of life and services to the community and limited access to information causes the flow of communication and information to be disrupted. Therefore deep learning using a Geographic Information System with satellite imagery data accelerates automatic risk assessment and can improve the overall regional disaster management system (Francini et al., 2022).

Conclusion

The results showed that the extraction results of the built-up area were 23.61 ha and the undeveloped area was 147.53 ha. The total length of the road before the liquefaction disaster occurred was 35.50 km. The result of extraction after the liquefaction disaster was that the area built up was 1.20 ha, while the buildings that were lost due to the disaster were 22.41 ha. The total road length prior to the liquefaction disaster was 35.50 km, only 11.20 km of roads were lost, 24.30 km. Deep Learning in Geographic Information Systems (GIS) is growing rapidly and has many advantages. in all aspects of life, including technology, geography, health, education, social life, and disasters.

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Author Contributions
Ajun Purwanto conceptualized the research idea, designed of methodology, management and coordination responsibility, analyzed data, conducted a research and investigation process; Paiman conducted literature review and provided critical feedback on the manuscript.

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Conflict of interest
The authors declare that there is no conflict of interest regarding the publication of this paper.

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