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Effective Land Damage Classification using Deep Neural Network Method

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Abstract
Tsunami disasters can cause substantial damage to land and residential areas, making rapid and accurate damage classification important for disaster assessment. This study applied a Deep Neural Network (DNN) method to classify tsunami-related land damage into three categories: Severe, Light, and Moderate. The dataset consisted of disaster impact records from 34 provinces in Indonesia during 2013–2018. The input variables included the number of deaths, injured people, affected people, and houses with severe, moderate, light, and submerged conditions. We divided the data into training and testing datasets and evaluated the model using accuracy, precision, recall, and F1-score. The proposed DNN achieved an overall accuracy of 83.33% on 18 testing samples. The Moderate category produced the best performance, with precision, recall, and F1-score of 1.00. The Severe category achieved a recall of 1.00 and an F1-score of 0.73, while the Light category obtained a precision of 1.00, recall of 0.62, and F1-score of 0.77. The confusion matrix showed that the model correctly classified all Severe and Moderate samples but misclassified three Light samples as Severe. These findings demonstrate that the DNN can effectively classify tsunami-related land damage, although additional and more diverse data are required to improve the distinction between Light and Severe damage categories.

Keywords:
DNN, Land Damage, Classification, Tsunami, Machine Learning

1. Introduction

Natural hazards and environmental changes can cause extensive damage to land, infrastructure, ecosystems, and human activities. Earthquakes, landslides, floods, wildfires, and coastal processes produce different damage patterns across geographic areas. This variation makes land damage assessment difficult when researchers rely only on field surveys or manual interpretation. Manual assessment also requires considerable time and resources, especially when the affected area is large or difficult to access. Ansari *et al.* demonstrate this challenge in tunnelling projects located in earthquake- and landslide-prone regions. Their study develops a multi-hazard damage prediction model using an Artificial Neural Network (ANN) to address damage associated with different hazard conditions [1]. This issue shows the need for computational methods that can classify damage patterns more efficiently and consistently. A deep neural network provides a potential solution because it can learn complex relationships from data and support automated classification of damage conditions.

The classification of land damage also requires models that can distinguish different physical conditions from complex environmental data. Conventional approaches often

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depend on manually selected characteristics and predefined rules. These approaches may become less effective when damage patterns vary in shape, scale, location, and environmental context. Nhu *et al.* compare Logistic Model Tree, Logistic Regression, Naïve Bayes Tree, ANN, and Support Vector Machine for shallow landslide susceptibility mapping. They use 20 conditioning factors and show that different machine learning models produce different predictive capabilities. The Logistic Model Tree achieves the highest AUC of 0.932, while ANN and SVM achieve lower values of 0.860 and 0.834, respectively [3]. This finding highlights an important issue in land damage classification. The model must learn from multiple environmental characteristics without depending on a single factor. It also indicates that selecting an appropriate neural network architecture and input representation remains important for obtaining reliable classification results.

Image-based analysis offers another important direction for land damage classification. Satellite and high-resolution imagery can provide spatial information over large areas without requiring continuous field observation. Peshkin *et al.* apply a convolutional neural network to satellite images collected before and after the 2004 Indian Ocean Tsunami in Indonesia. Their model classifies eight land-cover classes and uses changes in land cover to examine the consequences of the disaster over time [14]. The study demonstrates that neural networks can extract meaningful spatial information from post-disaster imagery. However, land-cover classification does not directly represent the severity or type of physical damage. This distinction creates an important research issue. A model designed specifically for land damage should identify damage-related visual patterns rather than only classify general land-cover categories. Such a model can provide more direct information for damage assessment and post-disaster decision making.

The classification problem becomes more complex when researchers analyze damage across different types of natural hazards. Forest and land fires, for example, can produce different levels of physical and ecological damage. Hidayat *et al.* apply a CNN with the MobileNetV2 architecture to classify forest and land fire severity using field photographs from four villages in Jambi Province. Their model achieves an accuracy of 77.7% with the evaluated image configurations [5]. The result confirms that CNN-based methods can recognize severity patterns from visual information. However, the study also identifies the need for additional field images to improve model training [5]. Limited training data can reduce the ability of a deep neural network to learn diverse damage patterns. This issue becomes more important when a land damage classification model must operate across different locations, environmental conditions, and damage levels. Therefore, sufficient and representative image data remain essential for developing a robust classification model.

The use of multiple data sources can further improve the representation of land conditions. Yang *et al.* develop a deep convolutional neural network using multi-source remote sensing data for alpine land-cover classification in the Yarlung Zangbo River Basin. Their model achieves an overall accuracy of 86.24% and a kappa value of 0.8156, outperforming traditional classification algorithms [6]. Their findings demonstrate the advantage of deep learning when the model receives diverse spatial information. However, multi-source data also increase the complexity of preprocessing, feature representation, and model development. Vasudevaiah *et al.* address a similar issue in landslide prediction by combining multispectral satellite bands with environmental and topographical information. Their CNN accuracy increases from 67.97% with three bands to 79.47% with 16 bands [12]. These findings indicate that richer feature representations can improve prediction performance. At the same time, they raise the issue of determining which features provide useful information for land damage classification without introducing unnecessary complexity.

Another issue concerns the classification of damage to specific land infrastructure. Road damage provides a clear example because cracks, potholes, surface deterioration, and other defects can vary considerably in appearance. Padila *et al.* apply CNN-based

YOLOv5 to classify asphalt road damage using Google Street View imagery. Their model obtains an F1-Score of 73.5% and a mean Average Precision of 75% [8]. The results show that deep learning can automatically identify infrastructure damage from images. However, the moderate F1-Score also indicates that image-based damage classification remains challenging. Variations in image quality, damage appearance, background conditions, and class characteristics can affect model performance. A general land damage classification framework therefore needs to handle heterogeneous visual patterns rather than focus only on one type of infrastructure. This issue supports the use of deeper neural network approaches that can automatically learn hierarchical visual features from complex images.

The spatial and temporal characteristics of natural hazards also create challenges for damage classification. Damage does not occur in isolation. It can develop or change according to rainfall, terrain, vegetation, fire progression, flooding, or other environmental conditions. Aydın and Raja demonstrate the importance of temporal information in flood prediction by using rainfall observations from multiple weather stations and consecutive rainfall inputs to predict flow conditions [4]. Similarly, Lee and Lee use satellite fire detections together with environmental context layers to forecast wildfire spread. Their three-dimensional CNN processes spatial and temporal information and achieves high Dice coefficients for many test clusters [19]. These studies indicate that deep neural networks can process complex spatial and temporal patterns. However, many existing studies focus on predicting individual hazards rather than classifying the resulting land damage across multiple damage conditions. This creates a gap for a classification framework that focuses directly on the observed damage state of land and integrates spatial information into the learning process.

The existing studies demonstrate the strong potential of neural networks for hazard prediction, land-cover mapping, infrastructure damage detection, and environmental monitoring. However, the literature still shows a separation between hazard prediction and direct land damage classification. Some studies predict landslide or flood susceptibility [3], [4], [11], [12], while others classify land cover, burned areas, or infrastructure damage [5], [6], [8], [14], [16]. Multi-hazard damage prediction has also been explored using ANN, but the focus remains on tunnelling projects and engineering damage rather than general land damage classification [1]. Therefore, this study focuses on developing a DNN method for classifying land damage from relevant input data. We aim to utilize the capability of deep learning to automatically learn complex patterns and distinguish different damage conditions. This approach addresses the need for a more automated, consistent, and scalable method for land damage assessment and provides a foundation for supporting disaster response, environmental monitoring, and land management.

2. Related Works

Ansari *et al.* developed a Multi-Hazard Damage Prediction (MhDP) model for tunnelling projects located in earthquake- and landslide-prone regions. They applied an Artificial Neural Network (ANN) to address damage prediction under multiple hazard conditions. The study showed the potential of neural networks to represent complex relationships between hazard-related factors and infrastructure damage. Its main strength was the multi-hazard perspective. The model considered earthquake and landslide conditions rather than treating each hazard independently. This approach was relevant to land damage assessment because natural hazards often produce overlapping physical impacts. However, the study focused on tunnelling projects and engineering structures. It did not directly classify general land damage from visual or remote sensing data. The research therefore provided a useful foundation for applying neural networks to damage prediction, but it left a gap in image-based classification of broader land damage categories. [1]

Nhu *et al.* compared five machine learning algorithms for shallow landslide susceptibility mapping in Bijar City, Iran. They evaluated Logistic Model Tree, Logistic Regression, Naïve

Bayes Tree, ANN, and Support Vector Machine using 20 conditioning factors and 111 shallow landslide locations. The researchers assessed the models using sensitivity, specificity, accuracy, MAE, RMSE, and AUC. All models produced useful results, while Logistic Model Tree achieved the strongest performance with an AUC of 0.932. ANN achieved an AUC of 0.860, while SVM obtained 0.834. The strength of this study was its systematic comparison of several machine learning approaches. It also demonstrated the importance of environmental conditioning factors in land hazard analysis. However, the study focused on landslide susceptibility rather than direct classification of existing land damage. It also relied on structured environmental factors instead of image-based damage features. These limitations indicated the need for a model that could learn visual damage characteristics directly from land imagery. [3]

Hidayat *et al.* investigated the classification of forest and land fire severity using a Convolutional Neural Network with the MobileNetV2 architecture. They used field photographs collected from four villages in Jambi Province. The model achieved an accuracy of 77.7% with the evaluated image configurations and produced a minimum loss of 0.618. The study showed that CNN-based models could learn visual characteristics associated with different levels of fire severity. This result was important for land damage classification because visual information can represent physical changes that are difficult to describe using conventional numerical variables. The main strength of the study was its direct use of photographs for severity classification. However, the researchers also identified the need for additional field photographs to improve model training. The relatively limited dataset could restrict the model's ability to generalize to other locations and environmental conditions. This limitation showed that data diversity remained an important issue in deep neural network-based damage classification. [5]

Yang *et al.* developed a deep convolutional neural network for alpine land-cover classification using multi-source remote sensing data in the Yarlung Zangbo River Basin. They implemented the model through Google Earth Engine and established a classification system containing 14 alpine land-cover types. The model achieved an overall accuracy of 86.24% and a kappa value of 0.8156. The results exceeded those of traditional classification algorithms. The study demonstrated the strength of deep convolutional networks in extracting spatial patterns from remote sensing data. It also showed that multi-source data could support large-scale land classification. However, the study classified land-cover types rather than damage conditions. The distinction is important because land cover and land damage represent different analytical objectives. A land-cover model may identify forests, agriculture, barren areas, or built-up areas without determining whether those areas experienced damage. Therefore, the study supported the use of deep neural networks and remote sensing data but also highlighted the need for a more damage-oriented classification framework. [6]

Padila *et al.* applied a CNN-based approach with YOLOv5 to classify asphalt road damage from Google Street View images. They focused on several damage types, including fine cracks, alligator cracks, potholes, and asphalt grain release. The research followed several stages, including data selection, preprocessing, transformation, data mining, and evaluation using a confusion matrix. The model achieved an F1-Score of 73.5% and an mAP of 75%. The study showed that deep learning could automatically identify infrastructure damage from high-resolution images. Its main strength was the direct application of image-based deep learning to a practical damage classification problem. The results also demonstrated the usefulness of object detection for identifying localized damage. However, the study focused specifically on asphalt roads. It did not address broader land damage caused by multiple environmental or natural hazard conditions. The moderate F1-Score also suggested that visual variation among damage classes remained a challenge. These limitations created an opportunity to extend deep learning from infrastructure-specific damage toward more general land damage classification. [8]

Vasudevaiah *et al.* investigated landslide prediction using multispectral satellite imagery and a multi-band CNN. They combined satellite image bands with environmental and topographical information, including rainfall, temperature, soil moisture, elevation, slope, aspect, and curvature. The researchers tested models using 3, 5, 10, and 16 satellite bands. The prediction accuracy increased from 67.97% with three bands to 79.47% with 16 bands. These results demonstrated that richer feature representations improved model performance. The study provided strong evidence for combining remote sensing information with environmental variables in deep learning-based land analysis. However, increasing the number of features also increased the complexity of the input data. The research focused on predicting landslide and non-landslide locations rather than classifying different degrees or categories of land damage. It therefore provided an important methodological basis for the proposed study, particularly in feature integration, but did not directly solve the problem of general land damage classification. [12]

Peshkin *et al.* applied a modified DeepLabV3+ CNN to high-resolution QuickBird satellite imagery of Aceh, Indonesia, before and after the 2004 Indian Ocean Tsunami. They trained the network to perform pixel-level segmentation for eight classes, including water, rubble, foundations, buildings, roads, agriculture, beaches, and clouds. The approach allowed the researchers to measure destruction and reconstruction across multiple time points. Its major strength was the use of high-resolution satellite imagery and pixel-level segmentation to capture spatial changes after a major disaster. The study also demonstrated that image-derived land-cover changes were associated with population health, demographic changes, and economic conditions. However, the model primarily classified land-cover and landscape objects rather than directly assigning a general land-damage class. Its categories were also designed around the specific characteristics of the Aceh tsunami. Consequently, the approach provided a strong foundation for spatial damage analysis but still required adaptation for a general land damage classification problem across different damage types and environments. [14]

Kim *et al.* developed a deep learning approach for burned-area mapping using post-fire PlanetScope imagery. They tested the method in three cases from the Republic of Korea and Greece and evaluated its transferability to another site. Their U-Net model achieved F1-Scores between 0.964 and 0.965 and IoU values between 0.938 and 0.942 for burned-area mapping. The study demonstrated the strong capability of deep learning to extract damaged areas from high-resolution satellite imagery. Its use of transferability assessment was also valuable because damage classification models need to perform across different geographic conditions. However, the study focused only on burned areas. The model therefore addressed one specific type of land damage rather than multiple damage categories. The study also noted that differences in vegetation structure and seasonality could reduce transferability. This limitation showed that a general land damage classifier must account for variation in environmental and geographic conditions. [16]

Overall, the reviewed studies showed that neural networks and deep learning methods had strong potential for hazard prediction, land-cover analysis, and damage classification. ANN models had supported multi-hazard damage prediction and landslide susceptibility analysis [1], [3]. CNN and related architectures had achieved useful results in fire severity classification, remote sensing classification, road damage detection, landslide prediction, tsunami impact mapping, and burned-area mapping [5], [6], [8], [12], [14], [16]. However, most previous studies addressed a specific hazard, a particular type of infrastructure, or a specific land-cover condition. Few studies directly classified land damage as a general problem across different environmental and physical conditions. The existing studies also showed recurring challenges in data diversity, feature representation, spatial variation, and model generalization. These gaps supported the development of the proposed DNN method for Classification of Land Damage. The proposed approach focused on learning damage-related patterns directly from the available data and classifying land conditions into relevant damage categories. This direction extended previous work from hazard-specific prediction toward a more direct and scalable land damage classification framework.

3. Proposed Method

The In this study, we proposed a DNN to classify land damage caused by tsunami-related disasters into three categories: Severe, Light, and Moderate. The proposed method processed disaster-impact attributes obtained from the dataset and transformed them into numerical input vectors. Let the input vector be represented as $X = [x_1, x_2, \ldots, x_n]$, where each x_i denotes a disaster-impact attribute. We normalized the numerical features using min-max normalization:

$$x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x_i represents the original feature value, while x_{min} and x_{max} denote the minimum and maximum values of the corresponding feature. This transformation placed the input values within the range $[0,1]$ and helped the DNN process features with different numerical scales.

This paper employed a fully connected DNN consisting of an input layer, hidden layers, and an output layer with three neurons corresponding to the three damage classes. Each hidden layer applied the ReLU activation function:

$$ReLU(z) = \max(0, z) \tag{2}$$

The output layer used the Softmax function to generate the probability of each damage class:

$$P(y = k \mid X) = \frac{e^{z_k}}{\sum_{j=1}^{3} e^{z_j}} \tag{3}$$

where z_k represents the output value for class k. The model selected the class with the highest probability as the final prediction:

$$\hat{y} = \mathrm{argmax}_k P(y = k \mid X) \tag{4}$$

During training, we minimized the categorical cross-entropy loss:

$$L = -\sum_{k=1}^{3} y_k \log(\hat{y}_k) \tag{5}$$

where y_k represents the actual class label and $\hat{y}_k$ represents the predicted probability for class k. We trained the network using the training dataset and evaluated its generalization using the testing dataset. Finally, this study measured classification performance using accuracy, precision, recall, and F1-score. The F1-score for each class was calculated as:

$$F1 = 2\frac{Precision \times Recall}{Precision + Recall} \tag{6}$$

This formulation allowed the proposed DNN to learn nonlinear relationships among tsunami-impact attributes and classify the resulting land damage conditions.

4. Experimental Setup

The study used tsunami-prone area data published by the National Disaster Management Agency (BNPB) of Indonesia. The dataset covered disaster records from 2013 to 2018 across 34 provinces in Indonesia. Each record included the province name, number of deaths, injured people, affected people, and houses classified as severely damaged, moderately damaged, lightly damaged, or submerged. These variables captured the human and physical impacts of tsunami-related disasters. The data preprocessing stage checked the numerical attributes for missing values and converted them into a consistent numerical format. The researchers also encoded the province name as a numerical attribute to make it suitable as an input for the DNN.

We divided the dataset into training and testing subsets using an 80:20 ratio. The training subset contained 163 records, while the testing subset contained 41 records. The DNN used the training data to learn patterns between tsunami impact variables and land damage conditions. The researchers kept the testing data separate during the training process to measure the model's performance on unseen observations. They evaluated the classification results using accuracy, precision, recall, and F1-score.

Table 1. Dataset Distribution for Training and Testing

Dataset	Number of Records	Percentage	Purpose
Training Dataset	163	80%	Model training and learning
Testing Dataset	41	20%	Evaluation on unseen data
Total	204	100%	34 provinces × 6 years

5. Result and Analysis

The proposed model achieved an overall accuracy of 0.83 on 18 testing samples. The classification results showed that the model performed best on the Sedang category, with precision, recall, and F1-score reaching 1.00. The Ber at category also obtained a recall of 1.00, which means that the model correctly identified all four Ber at samples. However, its precision reached only 0.57 because several samples from the Ringan category were incorrectly classified as Ber at. The Ringan category produced a precision of 1.00 but a recall of 0.62, indicating that the model correctly identified only five of its eight samples.

The confusion matrix further showed that the model correctly classified all four Ber at samples and all six Sedang samples. For the Ringan category, the model correctly classified five samples and misclassified three samples as Ber at. The macro-average produced a precision of 0.86, recall of 0.88, and F1-score of 0.83, while the weighted average reached 0.90 precision, 0.83 recall, and 0.84 F1-score. These results indicate that the model provided strong classification performance overall, particularly for the Sedang and Ber at categories, but still experienced difficulty distinguishing some Ringan samples from Ber at samples.

Table 2. Classification Results of the Proposed Model

Damage Category	Precision	Recall	F1-Score	Support	Accuracy
Severe	0.57	1.00	0.73	4	1.00
Light	1.00	0.62	0.77	8	0.62
Moderate	1.00	1.00	1.00	6	1.00
Macro Average	0.86	0.88	0.83	18	—
Weighted Average	0.90	0.83	0.84	18	—
Overall Accuracy	—	—	0.83	18	0.83

Table 3. Confusion Matrix of the Proposed Model

Actual \ Predicted	Severe	Light	Moderate
Severe	4	0	0
Light	3	5	0
Moderate	0	0	6
Total	7	5	6

The model correctly classified 15 of 18 testing samples, achieving an overall accuracy of 83.33%. The main classification error occurred between the Severe and Light categories, where three Light samples were classified as Severe.

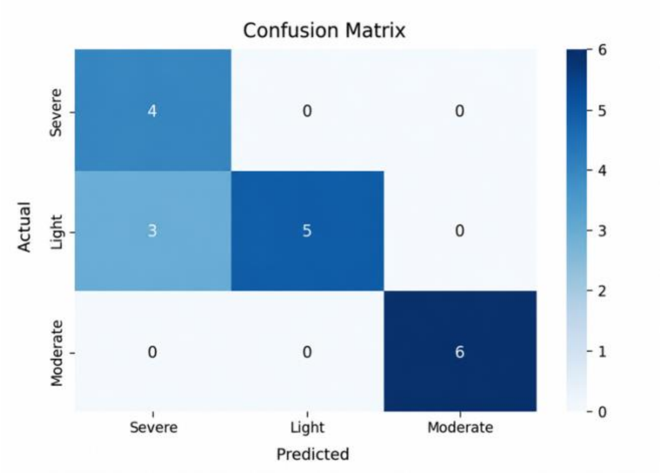

Fig. 1 Confusion Matrix

Fig. 1 shows that the model correctly classified all 4 Severe samples and all 6 Moderate samples. For the Light category, the model correctly identified 5 of 8 samples, while it incorrectly classified 3 samples as Severe. The model did not confuse any Moderate samples with the other categories. These results indicate that the proposed model distinguished the Moderate category most consistently, while the main classification difficulty occurred between the Severe and Light categories.

5. Conclusion

This paper applied a DNN to classify land damage into three categories: Severe, Light, and Moderate. We utilized tsunami-related disaster data from 2013 to 2018 as the input for the classification process. The proposed approach achieved an overall accuracy of 83.33% on 18 testing samples. This result indicates that the DNN successfully learned the relationship between disaster-impact variables and land damage categories.

The classification results showed different performance across the three categories. The model classified all Severe and Moderate samples correctly. The Moderate category achieved the strongest performance, with precision, recall, and F1-score of 1.00. The Severe category obtained a recall of 1.00 and an F1-score of 0.73. Meanwhile, the Light category achieved a precision of 1.00, recall of 0.62, and F1-score of 0.77. The confusion matrix showed that the model misclassified three Light samples as Severe. Therefore, the main challenge in this study involved distinguishing between Light and Severe damage conditions.

This study demonstrates that the DNN can provide an effective approach for land damage classification using tsunami-related disaster data. We obtained a macro-average precision of 0.86, recall of 0.88, and F1-score of 0.83, while the weighted-average precision, recall, and F1-score reached 0.90, 0.83, and 0.84, respectively. These findings confirm the potential of the proposed method for automated land damage assessment. However, the limited testing samples and misclassification between the Light and Severe categories indicate the need for a larger and more diverse dataset. Future work can apply additional data, feature optimization, and improved DNN architectures to enhance classification reliability.

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