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ENSEMBLE LEARNING-BASED AUTOMATIC DETECTION OF LANDSLIDE AREAS FROM AERIAL PHOTOGRAPHS

Jonpaul Nnamdi Opara[1], Ryo Moriwaki[2] and *Pang-jo Chun[3]

[1,2] Graduate School of Science and Engineering, Ehime University, Japan; [2,3] School of Engineering, The University of Tokyo, Japan

*Corresponding Author, Received: 18 May 2023, Revised: 01 Aug. 2024, Accepted: 05 Aug. 2024

ABSTRACT: Landslides pose a significant threat to human life and property worldwide. Japan, with its vulnerability to these natural disasters, records a high incidence of landslides. The Geospatial Information Authority of Japan employs experts to visually examine aerial photographs before and after landslide events, a costly and time-consuming approach that can limit accuracy. This study aims to aid in mitigating the damage caused by landslides through accurate and efficient mapping and prediction. An Ensemble U-Net model integrating three U-Nets has been proposed to predict landslide areas from aerial photographs. Comparative analysis with a single U-Net model revealed that the Ensemble model significantly outperformed the single model in all accuracy measures, including precision, recall, and F1-score. The ensemble model's average intersection over union (IoU) value of 0.80 also indicated a stronger agreement between the predicted outcome and ground truth than the single U-Net model. Visual analysis of prediction results further demonstrated the superiority of the ensemble model in aligning closely with the ground truth, thereby reducing misidentification and missed detections. The proposed Ensemble U-Net model's potential to enhance the accuracy and efficiency of landslide mapping seems promising.

Keywords: Landslide, U-Net, Ensemble learning, Bagging, Bootstrap aggregating

1. INTRODUCTION

Landslides are significant natural hazards caused by various factors, including heavy rainfall, earthquakes, and human activities. In Japan, landslides have increased by 50% over the past decade, with approximately 1,500 landslides reported in 2020. Extreme floods in Kyushu, southwestern Japan, have caused significant loss of life due to landslides, with over 114 deaths reported in 2018 and at least 50 deaths in 2019. In addition to heavy rainfall, earthquakes have been known to trigger landslides. For instance, just one day after Typhoon Jebi hit Hokkaido, Japan, a 6.7-magnitude earthquake caused over 5,600 landslides [1]. The earthquake killed 41 people, and the resulting landslides killed 36 people. In July, debris floods and landslides in western Japan killed 87 people in Hiroshima [2].

While this study focuses on Japan, landslides are a global phenomenon that has resulted in significant loss of life and damage worldwide. For instance, 24 residents of Quito, Ecuador, died due to landslides, floods, and mudflows caused by severe rains. Heavy rains and landslides in Durban, South Africa, killed at least 443 people and displaced over 40,000 in April 2022. Human-caused climate change, socioeconomic vulnerability, and inadequate disaster management worsened these disasters. In 2009, Typhoon Morakot in Taiwan killed 450 people and caused significant downstream damage. The 2013 Uttarakhand landslides destroyed 14 bridges and 1,500 villages, killing almost 4,000 people [3].

Landslide disaster planning requires precise and timely monitoring of landslide-prone regions. Landslide maps aid in damage assessment, planning, and government loss mitigation. Due to the physical risks and challenges of accessing these areas, Japan's Geospatial Information Authority creates maps from aerial photos for damage assessment and recovery [4]. The manual mapping process is sometimes limited and incorrect, highlighting the need for automation.

Researchers today use machine learning methods like image detection and computer vision to monitor engineering and asset management processes. The authors' infrastructure and asset management research group previously used machine learning, including deep learning, to identify concrete cracks [5-10]. Different studies detect damage in asphalt and steel structures [11-15], detect buried pipes from Ground Penetrating Radar (GPR) images [16], and explain the bridge damage with vision and language techniques [17-20]. These previous efforts yielded significant findings. Using machine and deep learning, many landslide detection models have been developed. These methods are accurate and resource-efficient. Kubo et al. [4], created a mask R-CNN model that employed deep learning-based semantic segmentation to automatically predict landslide areas from aerial pictures of post-disaster landslide zones in Japan. Kubo's method earned a 0.65 F-Score, making it suitable for machine learning. The method partially matched the ground truth.

Predictive accuracy is essential for successful landslide mapping. However, due to inherent inconsistency, machine learning classifiers in landslide investigations are often questioned.

Furthermore, the performance of these models may vary from one study area to another [21]. Kimura [22] echoed similar concerns and highlighted the challenges associated with the data preparation process for landslide maps. Kimura suggested multiple methods for detecting landslides and evaluated the performance of several Deep Neural Network (DNN)-based methods using labelled and unlabeled data. This was due to the challenge of annotating data during an emergency. Recent research has explored hybrid models for landslide prediction to address their complex nature and reduce traditional extraction method inaccuracies. For instance, Bui et al. introduced a soft computing approach by combining fuzzy-K-NN and DE for spatial prediction of rainfall-induced shallow landslides [23]. Similarly, Pham et al. evaluated the performance of multiple neural networks and ensemble frameworks, including AdaBoost, Bagging, Multi-Boost, Rotation Forest, and Random Subspace [24]. Pham et al. developed three hybrid models for landslide mapping in the Guangchang area using J48T and various ensemble techniques [25]. Additionally, a new model called L-UNet, which combines the U-Net model with a multi-scale feature-fusion (MFF) module to improve the model's ability to extract multi-scale landslide information was proposed [26]. L-UNet beat the baseline U-Net model in accuracy, recall, MIoU, and F1 values by 4.15%, 2.65%, 4.82%, and 3.37%, respectively. These studies show that hybrid models can enhance landslide prediction and disaster management.

The primary objective of this study is to enhance the accuracy and efficiency of landslide mapping in Japan through the development of an Ensemble U-Net model. By integrating multiple U-Nets, this model aims to provide more precise predictions of landslide areas from aerial photographs. Combining multiple learning algorithms to obtain better predictive performance than what could be obtained from any of the constituent learning algorithms alone is called Ensemble Learning, illustrated in Fig.2 [27]. Ensemble Learning brings us back to the primary objective of machine learning models, which is to improve prediction accuracy while avoiding overfitting. Overfitting is a concept defining when a model precisely matches its training data; Overfitting in machine learning models can elicit concern, and Ensemble learning can enhance accuracy by mitigating the issue of overfitting.

This research seeks to minimize the physical risks and challenges of accessing landslide-prone regions and reduce the damage caused by such natural disasters. Ultimately, the proposed model aims to contribute to disaster risk management and planning by offering a reliable tool for landslide prediction and mapping.

Fig.1 This study's landslide-prone locations in Japan

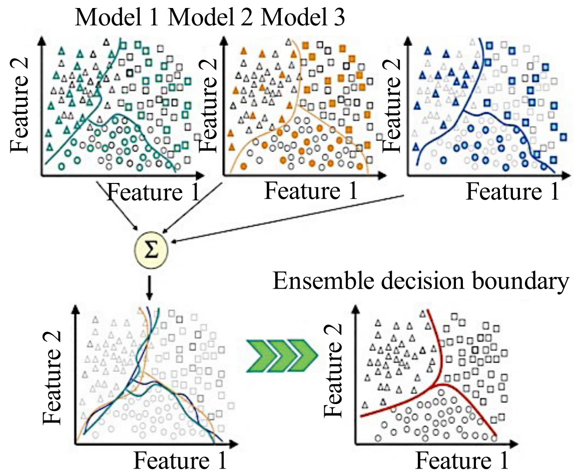


Fig.2 Illustration of ensemble learning.

2. RESEARCH SIGNIFICANCE

This research aims to enhance the accuracy and efficiency of landslide mapping in Japan, minimizing the physical risks and challenges of accessing these areas and reducing the damage caused by these disasters. It addresses a critical challenge in disaster risk management and planning by leveraging machine learning and image segmentation models, such as the U-Net model and its ensembles. This research can contribute to the global community and infrastructure safety in Japan and other landslide-prone regions.

3. RESEARCH METHOD

3.1 Classifier

3.1.1 U-net model

The U-Net model is the primary model in this research. Initially proposed in 2015, the U-Net architecture was originally designed for biomedical image segmentation. However, it is now commonly used in image segmentation across various sectors. It performs well even with little training data.

The architecture of the U-Net model incorporates a symmetric expanding path, which facilitates accurate localization in conjunction with a contracting path that captures contextual information [28]. The architecture of U-Net is characterized by a U-shaped encoder-decoder structure, as depicted in Fig. 3. The encoder path consists of blocks, including two 3x3 convolutional layers, followed by a 2x2 max-pooling layer. The convolutional layers are composed of moving windows with dimensions of 3x3 that traverse the image and perform a dot product calculation, as denoted by Eq. (1) [29]:

$$O^l = \sigma(O^{l-1} * W^l + b^l) \quad (1)$$

O^{l-1} is the output of the (l-1) layer, W^l is the weights, and b^l is the bias. σ indicates the non-linear activation function.

The U-Net model uses semantic segmentation, which involves classifying pixels in an image into predefined categories. This enables a deeper understanding of the image by assigning distinct labels to each pixel [30]. The distinctive architectural design of U-Net enables efficient image segmentation, making it a highly appropriate option for the present research.

3.2 Models

3.2.1 Ensemble learning

Ensemble learning combines the salient properties of two or more machine learning models to reach a consensus in predictions, making it a transformative approach in the AI field [26]. Ensemble learning validates the notion of the "wisdom of crowds," which posits that the decision-making ability of a larger group of individuals is typically superior to that of a solitary expert. Ensembling techniques reduce variance in prediction errors, increasing the robustness of the final model compared to stand-alone models. The current study aims to enhance landslide prediction precision via image segmentation and incorporates a bagging ensemble technique using a trio of U-Net models.

3.2.2 Bagging

Bagging, or "bootstrap aggregating," is an ensemble method pioneered by Leo Breiman in the early 1990s. The approach utilized in this methodology involves using a substitution technique to create arbitrary subgroups, commonly referred to as "bootstrap samples," from the provided dataset. As a result, a single data point can be present in multiple subsets [31]. Fig.4 demonstrates the network's use of bootstrap samples and their combined predictions. To reduce the variance in the model, bagging can be used.

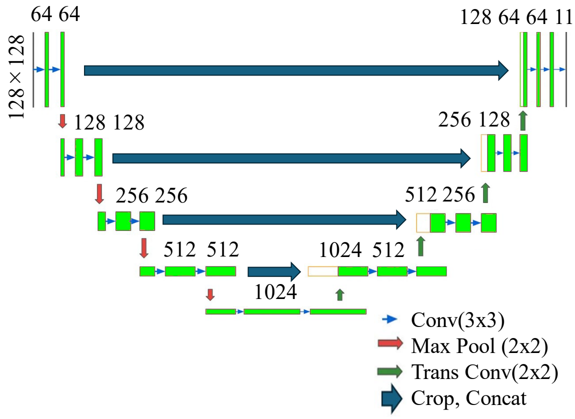


Fig.3 Illustration of the U-Net architecture

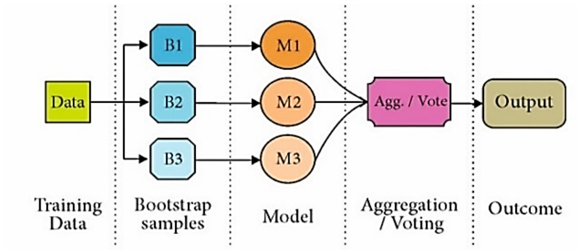


Fig.4 Illustration of bootstrap aggregating [28]

The equation for the weighted average is as follows:

$$y = w_1y_1 + w_2y_2 + \ldots + w_ny_n \quad (2)$$

where y is the predicted output, $y_1, y_2, \ldots, y_n$ are the outputs of the individual models, and $w_1, w_2, \ldots, w_n$ are the weights assigned to each model based on its performance on the validation set.

3.3 Date Preparation and Model Training

3.3.1 Data preparation

Fig. 5 summarizes the flow of this research, while Table 1 lists aerial photographs from Japanese locations with landslide histories, as shown in Fig. 1. The VGG Image Annotator (VIA) was utilized to mark landslide-prone locations with red masks. Classes 0 and 1 were assigned to the backgrounds and landslide areas, respectively. The annotated photos were converted into grayscale images, with white representing the landslide and black representing the backdrop (Fig. 6). Grayscale simplifies algorithms, computing, and image processing [32].

3.3.2 Model training and validation

Two models were constructed to examine whether ensemble models could enhance landslide prediction accuracy from aerial photographs. The Ensemble U-Net model, using bagging, integrated three U-Nets, while the Singular U-Net operated independently.

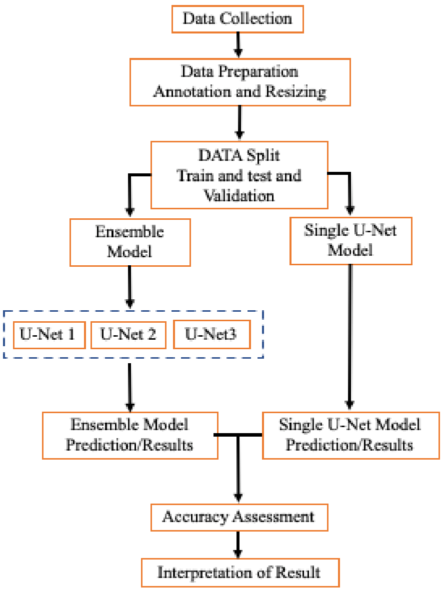


Fig.5 Research flowchart

Table 1 Displays the locations/year/number of images collected

Location/Occurrence	Year	Images
Kumamoto Earthquake	2016	125
Typhoon No. 10	2016	36
Northern Kyushu,	2017	145
Oita Prefecture	2018	10
Hokkaido Earthquake	2018	286
Western Japan	2018	502
East Japan	2019	40
Yamagata Prefecture	2019	35
Heavy rainfall	2019	23
Total		1,202

Note: The table shows the locations/year/number of images collected in Japan.

Both models ingested identical datasets, with the ensemble model integrating three U-Nets in a 4:3:3 ratio, as seen in Tables 2 and 3. The models utilized had a 256 x 256 input size, three image channels, a kernel size of 3, and adopted the he_normal kernel initializer. A rectified linear unit (ReLU) activation function was employed, followed by softmax activation and a 0.2 dropout ratio. Adam was used as the optimizer, and the loss function was sparse categorical cross-entropy.

All models were trained for 50 epochs, and the batch size was set to 16, which is the maximum allowable for running the program. Total parameters were 8,630,530 for Single U-Net and 2,589,159 for U-Net 1 and 2, and 3,452,212 for U-Net 3, with all parameters trainable. Fig.7 illustrates the ensemble model construction methodology.

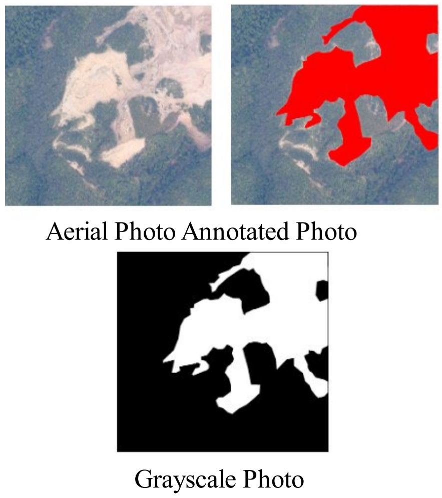


Fig.6 Image annotation and processing display

Table 2 Single U-Net model image distribution

Distribution	Num. of Images
Training	985
Validation	180
Test	60
Total	1198

Note: The table shows the image distribution of a single U-Net model.

Table 3 Ensemble U-Net model image distribution

Distribution	Training	Validation	Test
U-Net 1	299	60	20
U-Net 2	299	60	20
U-Net 3	400	60	20
Total	998	180	60

Note: The table shows the image distribution of an ensembled U-Net model.

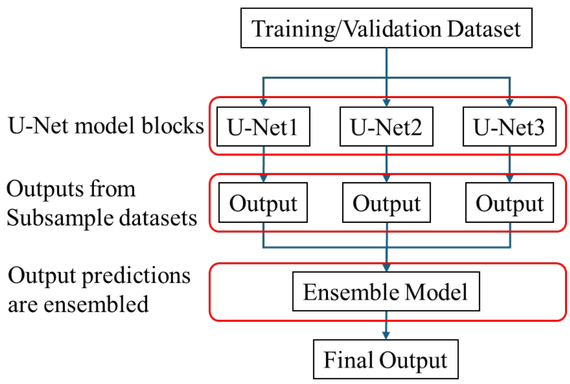


Fig.7 Illustration of ensemble U-Net process

4. RESULTS AND DISCUSSIONS

4.1 Equations

Precision, recall, F1-score, and Average IoU were pixel-wise performance indicators for landslide area identification. Precision measures category recognition accuracy, recall measures category pixel accuracy, and the F1 score is the harmonic mean of precision and recall. Avg. IoU measures accuracy by demonstrating the overlap between expected and ground truth. The equations below define these indices.

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

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

$$F1\ score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (5)$$

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union} \quad (6)$$

TP refers to correctly identified pixels, FP to misidentified pixels, and FN to undetected pixels, as shown in Fig.8.

Table 4 elucidates that the Ensemble U-Net model surpasses the Single U-Net model in all accuracy measures. The variations in Precision for both models are visually represented in Fig.9, underscoring the superior performance of the Ensemble U-Net model.

4.2 Analyzing Test Images

The prediction results of both the Single U-Net and Ensemble U-Nets, as depicted in Figs. 10-13, were scrutinized. It was discerned through analysis that the optimal precision level for both models was achieved at the 30-epoch threshold, which was subsequently adopted for the study.

4.3 Discussion

The study results demonstrate that the Ensemble U-Net model outperformed the Single U-Net model in all metrics, exhibiting a high precision of 0.97, recall of 0.88, and F1-score of 0.82, compared to the respective scores of 0.79, 0.69, and 0.58 for the Single U-Net model. Furthermore, the Ensemble U-Net model's average intersection over union (IoU) value of 0.80 indicated a stronger agreement between the predicted and ground truth boundaries than the Single U-Net model.

Upon examination, it becomes apparent that the Single U-Net model can predict landslide regions, although it exhibits some deficiencies. As seen in Fig. 11, it correctly discerned a landslide region but inaccurately labeled an additional area as such,

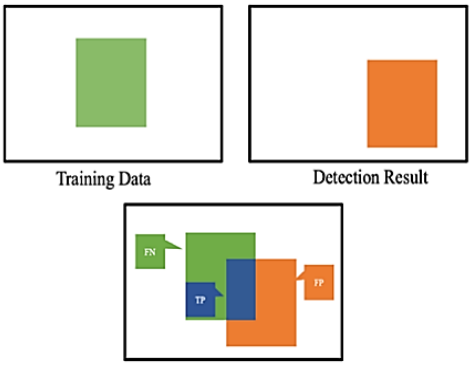


Fig.8 Definition of TP, TN, FP, FN

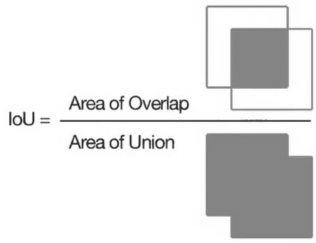


Fig.9 Definition of average intersection of union

Table 4 The models' best performance metrics values

Metrics	Single U-Net	Ensemble U-Net
Precision	0.79	0.97
Recall	0.69	0.88
F1-Score	0.58	0.82
Avg. IoU	0.55	0.80

Note: The table shows the best performance metrics of the single and ensemble U-Net models.

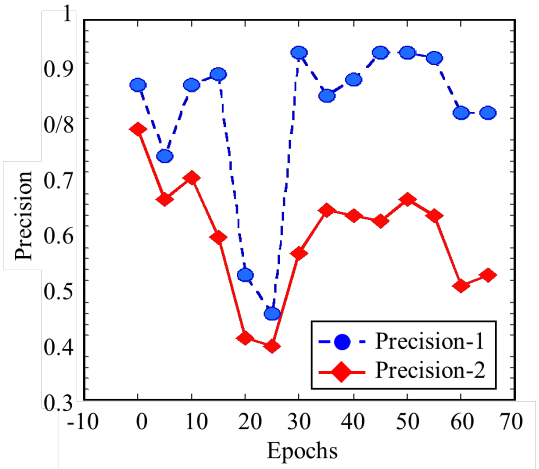
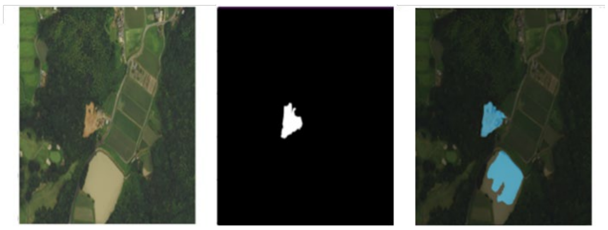


Fig.10 Changes in precision

deviating from the ground truth. Similarly, in Fig. 12, the model detected the landslide region but did not fully encompass the entire area. In contrast, the Ensemble model's predictions in Fig. 13 demonstrated a closer alignment with the ground truth.

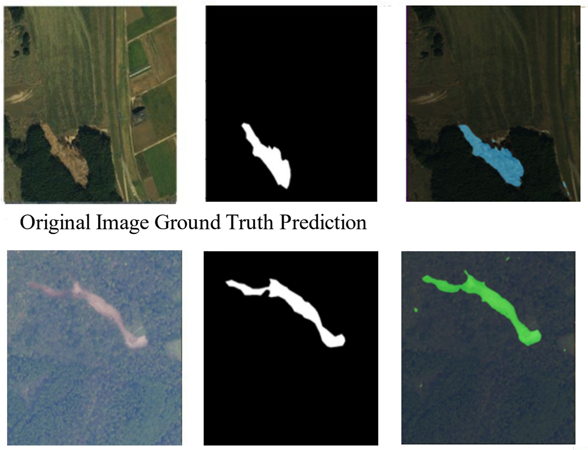


Original Image Ground Truth Prediction

Fig.11 Single U-Net prediction 'A'

Original Image Ground Truth Prediction

Fig.12 Single U-Net prediction 'B'



Original Image Ground Truth Prediction

Original Image Ground Truth Prediction

Fig.13 Ensemble U-Net detection

These findings confirm the underlying hypothesis of this research, which posits that using multiple models could enhance the accuracy of landslide prediction from aerial images.

5. CONCLUSION

This study proposed an ensemble U-Net framework to automate the mapping and prediction of landslide regions through aerial photography. This approach aimed to enhance the precision and efficacy of landslide mapping with a focus on Japan. The ensemble U-Net model outperformed the single U-Net model in accuracy, recall, F1-score, and average IoU by utilizing the technique of model bagging, which involves combining multiple models. The enhanced predictive capabilities of the ensemble U-Net model have the potential to improve the process of landslide mapping by complementing human assessment, leading to improved forecast accuracy and efficiency. When landslides are detected, considering the mechanical properties of the soil is crucial, as changes in soil properties and slope geometry significantly impact bearing capacity and settlement behavior [33].

Although the quantity of the dataset limits this research, it is a positive step and can be improved further. To enhance the predictive capability of the model, it is recommended that researchers explore alternative ensemble methodologies or incorporate topographical and meteorological data. The efficacy and generalizability of the model can be assessed by evaluating it in other landslide-prone regions worldwide.

While this study successfully utilized aerial photography for the detection of landslides, future research aiming for three-dimensional detection would be highly beneficial. The authors have previously implemented 3D processing techniques in bridge damage detection, as discussed in references [34, 35], which could be adapted for landslide analysis. Additionally, in reference [36, 37], the authors developed a method for constructing a surrogate model of the ground to assess the risk of re-collapse. Combining this method with the current study's approach could potentially enable the automatic evaluation of risks associated with detected landslide areas. Ongoing research is focusing on integrating these methodologies to further enhance landslide detection and risk assessment.

6. ACKNOWLEDGMENTS

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