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Research Article

Landslide Detection Using Transformers-Based Deep Learning Models

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Abstract **–** Landslides are caused by earthquakes and rainstorms, especially in densely populated areas. There are different types of landslides depending on the type of material such as soil, rock, rubble, and the type of movement such as falling, sliding, and overturning. In order to automatically detect landslides with artificial intelligence, a dataset was first created from open source images on the internet. There are two different classes in the dataset itself, land and landslide. Data augmentation was done in order to have an equal number of images containing classes in the datasets obtained in different amounts. Thus, a total of 400 image datasets were created, 200 from each class. In addition, normalized and resized operations were performed in data preprocessing. Then the dataset is randomly divided into 80% training and 20% validation and testing. Transformers-based deep learning models were used to perform Landslide detection. These models are Swin transformer, Vision Transformer (ViT) and Bidirectional Encoder representation from Image Transformers (BEiT). For detection processes, the results obtained using a total of three models, namely ViT, BEiT, and Swin Transformer, were compared. When the obtained results were analyzed, it was observed that both f1 score and accuracy were over 90%. Thus, in the future, this and similar classification studies can automatically detect landslides with artificial intelligence.

Keywords – Artificial Intelligence; Deep Learning; Image Classification; Landslide; Transformers.

I. INTRODUCTION

Landslides are explained as the downward movement of rocks, organic materials or soil under the influence of gravity. When landslides are examined in detail, it is observed that they are classified according to their material or movement types. In terms of movement types, there are various types such as falls in the form of topple and rockfall, spreads in the form of lateral, slides in the form of rotational and translational, flows in the form of debris and earthflow. In terms of material types, there are rock, soil or debris types. When the reasons for the formation of landslides are examined, it is understood that they occur for two main reasons: human activities or natural occurrences. Human activities include changing or disrupting drainage systems, removing vegetation, destabilizing slopes, improper excavation on slopes in stable areas and lawn watering. Natural occurrences include flooding of slopes, riverbank overtopping, seismic activities such as floods, earthquakes and ground shaking, volcanic activities that can cause rockslides and tsunamis [1].

Within the scope of the study, a dataset of open source images was collected regarding land and landslide images and landslide detection operations were performed with various deep learning based models. The literature contributions of the study are listed below.

- Instead of an existing dataset in the literature, a dataset containing landslides from open source images was collected specifically for the study.
- Various data augmentation methods were used to eliminate imbalances in the landslide dataset.
- For landslide detection, classification operations were performed using multiple transformer-based deep learning models in a two-class structure.
- All important evaluation metrics related to landslide detection, especially accuracy and f1-score, were obtained.

II. RELATED WORKS

An analysis of landslide detection studies in the literature reveals that many different studies have been conducted on artificial intelligence. As a result of the landslide recognition operations performed by Yang et al using datasets consisting of images from three different co-seismic landslide regions, namely Jiuzhaigou Earthquake, Palu Earthquake and Iburi Earthquake, the f1-score value of 68.75% was obtained with the proposed ResU-SENet model [2]. In the landslide detection operations performed by Şener and Ergen using an open source dataset called Landslide4Sense, the accuracy value found with the new deep learning model called LandslideSegNet, which includes the Efficient Hybrid Attentional Atrous Convolution Module, is 97.60% [3]. In the landslide identification study conducted by Sreelakshmi and Chandra using the open source Bijie landslide dataset using high-resolution remote sensing images belonging to the TripleSat Satellite system, 94% accuracy was found with the visual saliency-based approach proposed based on U-net [4]. In the study conducted by Ren and Isobe using landslide images from Hokkaido, Niigata Prefecture, Iwate and Miyagi Prefectures in Japan, AUC (Area Under the Receiver Operating Characteristic (ROC) Curve) values of 0.95 and above were obtained with the convolutional neural networks based model [5].

Pham et al. proposed CResU-Net model based on ResU-Net using Landslide4Sense dataset and consisting of two components, spatial attention and channel attention, and a 9.1% improvement in f1-score was achieved in landslide detection performed with CResU-Net model including Convolutional Block Attention Module [6]. YOLOX based global landslide detection model (GLDM) was developed by Liu et al. using remote sensing images of Tibetan Plateau including Freeze-Thaw induced debris, Rainfall Induced Debris and Landslide [7]. A new deep learning model called DeforNet based multi-source data fusion network (MSDF-Net) was developed for landslide detection operations performed by Li et al. on Sentinel-1 SAR image dataset consisting of many different classes such as landslide, groundwater and mine [8]. Within the scope of segmentation studies related to landslide prediction performed by Kaushal et al on Landslide4Sense database, 87% f1-score value was obtained by using a hybrid U-net based pyramid model [9]. Detection operations were performed with six different deep learning based segmentation models using unmanned aerial vehicle (UAV) images including landslide and sinkhole by Kariminejad et al [10]. ENVINet5 Multi-Feature model was developed for co-seismic landslide detection using PlanetScope database including images from Mainling, China and Hokkaido, Japan [11].

Ghorbanzadeh et al. used machine learning models such as random forest, support vector machines as well as deep learning-based approaches such as convolutional neural networks for landslide detection operations on images obtained from the RapidEye satellite [12]. In the study conducted by Gao et al. using Google 3D Scene and orthophoto-view image dataset belonging to multiple counties in Shaanxi Province in China, f1-score was obtained with 81.4% in a hybrid deep learning model with weighted boxes fusion [13]. The highest f1-score result obtained by Ganerød et al. using an ensemble structure model including various segmentation methods such as U-net, DeepLab is 69% in image datasets related to Sentinel-1 and Sentinel-2 [14]. Dang et al. first performed the operations on the dataset containing Sentinel-2 images and then performed landslide detection operations using various deep learning models with three different U-net architectures [15]. Landslide detection operations were performed using an auto-encoder model based on SwAV and including a U-net framework customized with ResNet18, proposed by Ghorbanzadeh et al. [16]. Cheng et al. examined three different datasets in the literature regarding landslide remote sensing datasets, namely the Chinese Academy of Sciences (CAS) Landslide Dataset, Bijie Landslide Dataset and High-Resolution Global Landslide Detector Database, and various deep learning-based models such as ResNet, U-net, and YOLO were investigated in depth for landslide detection [17]. After data preprocessing operations such as resampling and standardization were performed on the dataset taken from two different regions by Chen et al., landslide detection operations were performed with the deep learning model called BisDeNet, proposed based on DenseNet [18]. Studies on the use of remote sensing technologies, artificial intelligence, machine learning and deep learning algorithms in landslide susceptibility mapping, detection, prediction, monitoring and management processes in the literature have been systematically addressed by Akosah et al. [19]. Detection of slow-moving landslides using Interferometric Synthetic Aperture Radar (InSAR) products has been addressed by Chen et al.; for this purpose, the Multi-Scale Swin Transformer InSAR Products Detection Network (MSIDNet), a deep learning model based on Swin Transformer, was trained with deformation phase gradient, InSAR deformation rate and Generalized Random C-Index (GRCI) data, and higher accuracy and generalization success were achieved compared to existing models [20]. The Generalized Efficient Layer Aggregation Network (GELAN) model, developed with Efficient Channel Attention (ECA) and Convolutional Block Attention Module (CBAM) mechanisms for landslide detection from satellite images, achieved a high f1-score accuracy of 81.5% and was discussed by Chandra et al. as an effective approach for disaster response and early warning systems [21].

An examination of landslide detection studies in the literature shows that various models based on machine learning and deep learning are used using many different datasets. In this study, landslide detection operations were performed using transformer-based deep learning models on a two-class dataset that also includes landslide images.

III. MATERIALS AND METHOD

Within the scope of the study, in order to perform landslide detection operations, a dataset specific to the study was collected by searching the Google Images site with the keywords land and landslide, and using Creative Commons licensed (open access) images [22]. The dataset consists of two different classes, land and landslide. Since the collected dataset was initially unbalanced in terms of quantity, data augmentation operations were performed on the images by rotating them to certain directions at certain angles. In addition, resized and normalized operations were also performed before the detection operations. Thus, there are a total of 400 image data, 200 for land images and 200 for landslide images, so that the amount of data is balanced in each dataset. The dataset distribution was carried out randomly as 20% validation/testing and 80% training. As a result, there were 320 images in total, 160 for each of the land and landslide image classes for the deep learning model training process, and 80 images, 40 for validation and testing processes. Sample images for the dataset consisting of land and landslide images are given in Figure-1, and information about the distribution of the amount of data is given in Figure-2.

a) Land images

b) Landslide images

Fig. 1 Sample of land and landslide images [22]

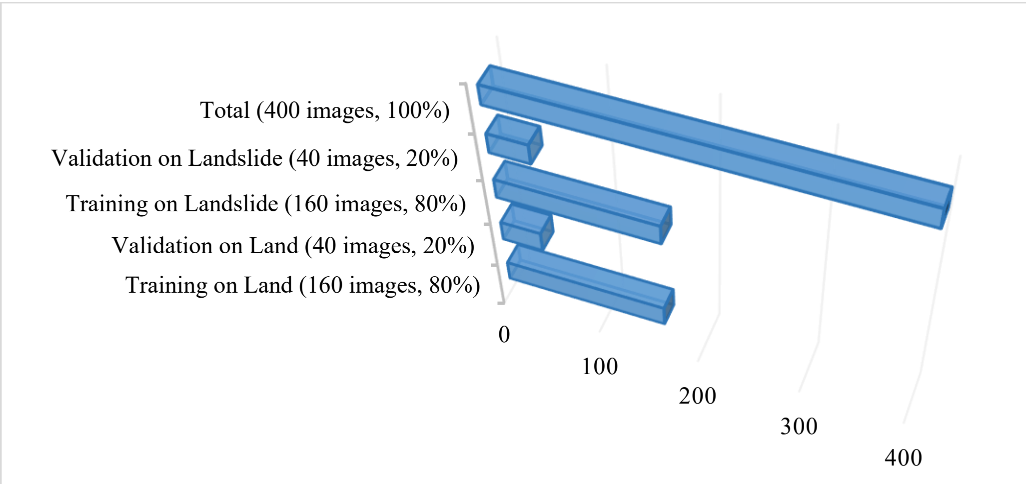

Fig. 2 Dataset distribution

Following the data augmentation and data preprocessing steps on the Landslide dataset, the distribution of which is shown in Figure-2, landslide detection operations were performed with three different deep learning models, namely Swin Transformer [23], Vision Transformer [24] and Bidirectional Encoder representation from Image Transformers [25]. In the application phase, the versions shared from the Hugging Face platform were used for all three deep learning models [26]. The flowchart for the landslide detection operations performed within the scope of the study is given in Figure-3 below.

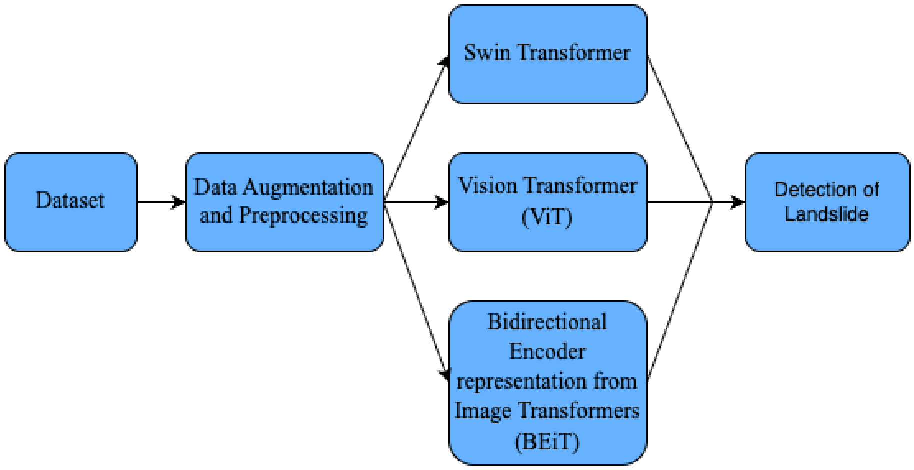

Fig. 3 Flowchart of landslide detection with deep learning models

IV. RESULTS

With the classification operations performed for Landslide detection operations, important metrics such as loss, accuracy, precision, recall, AUC and f1-score were obtained. Detailed results for all deep learning models used in the classification, including ViT, BEiT, Swin transformer, are given in Table-1 below.

Table 1. Landslide detection results

Models	Loss	Accuracy	Precision	Recall	AUC	F1-score
Swin	0.047	0.988	1.000	0.975	0.997	0.987
ViT	0.092	0.938	0.907	0.975	0.996	0.940
BEiT	0.146	0.963	0.951	0.975	0.985	0.963

A detailed examination of Table-1 shows that the highest f1-score value of 98.7% is obtained in the Swin transformer model. When examining in terms of other metrics, while the recall values are equal in all three transformer models, when all metrics are analyzed in general, it is seen that the best performance is again in the Swin transformer model. In order to observe the results better, some detection results of all models are given in Figure-4 below.

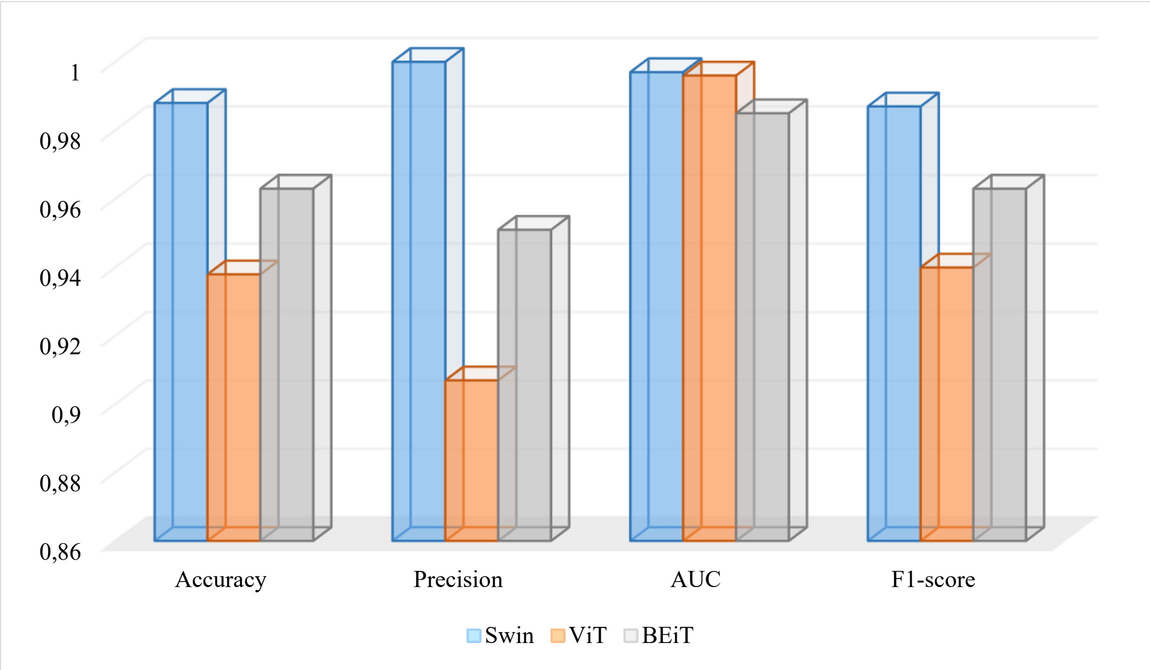

Fig. 4 Comparison of landslide detection results

According to the results given in Figure-4, it is seen that the highest results in accuracy, precision, AUC and f1-score metrics are obtained in the Swin transformer model. When the ViT model is compared with the other models, it is seen that although it has the lowest result in accuracy, precision and f1-score, it is closest to the highest result in terms of AUC. Similarly, the BEiT model has the lowest AUC score, but it is the second best in terms of accuracy, precision and f1-score.

V. CONCLUSIONS

In the study, classification operations were performed on a dataset consisting of two different classes, land and landside, in order to perform landslide detection operations. For this purpose, three different transformer-based models were preferred in this study, and all six different metrics that are important were obtained for all models. The dataset was not used raw, and by passing through data augmentation and data preprocessing steps, the quality of both the study and the dataset was increased. In the study where the highest performance was obtained with Swin transformer, classification operations can be performed with different landslide datasets in future studies. In addition, deep learning-based object detection and segmentation studies can be performed by labeling the relevant regions in the datasets. In landslide detection studies where machine learning can also be used, it is observed that deep learning-based hybrid approaches have the potential to make a great contribution to further improving the results in the future, considering both this study and the literature.

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