ROCK MASS DISCONTINUITY DETERMINATION WITH TRANSFER LEARNING

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ABSTRACT:

Rock mass discontinuity and orientation are among the important rock mass features. They are conventionally determined with scan-line surveys by engineering geologists in field, which can be difficult or impossible depending on site accessibility. Photogrammetry and computer vision techniques can aid to automatically perform these measurements, although variations in size, shape and appearance of rock masses make the task challenging. Here we propose an automated approach for the detection of rock mass discontinuities using deep learning and photogrammetric image processing methods. Two deep convolutional neural network (DCNNs) were implemented for this purpose and applied to basalts in Kizilcahamam Guvem Geosite near Ankara, Türkiye. Red-green-blue (RGB) band images of the site were taken from an off-the-shelf camera with 1.7 mm resolution and a 3D digital surface model and orthophotos were produced by using photogrammetric software. The discontinuities were delineated manually on the orthophoto and converted to masks. The first DCNN model was based on the open-source crack dataset consisting of a total of 11,298 road and pavement images, which were used to train the Resnet-18 model (Model-1). The second model (Model-2) was based on fine-tuning of Model-1 using the study data from Kizilcahamam. After fine-tuning, Model-2 was able to achieve high performance with a Jaccard Score of 88% on the test data. The results show high potential of the methodology for transfer learning with fine-tuning of a small amount of data that can be applied to other sites and rock mass types as well.

1. INTRODUCTION

Rockfall events form almost 2% of all natural hazards occurred in Turkiye in 2020 (AFAD, 2020). They can be mainly triggered by anthropogenic factors or earthquakes, and numerous of them occurred with the recent 6 February 2023 Kahramanmaras earthquakes (Mw 7.7 and Mw 7.6). Rockfalls were among deadly and harmful secondary hazards, caused losses of hundreds of lives, and destroyed villages. The rock blocks are formed by discontinuities and, some rock failures such as planar, wedge or toppling failures are controlled by discontinuities. The parameters used in rock mass classification systems, such as Rock Mass Rating (RMR) system (Bieniawski, 1989), Q system (Barton, 2002), and Geological Strength Index (GSI) (Hoek and Brown, 1997), aim to determine the strength and deformability features including discontinuity and orientation. The discontinuity parameters are conventionally determined with scan-line surveys by engineering geologists in field, which can be difficult or impossible depending on site accessibility.

In recent years, it has been seen that photogrammetric (Singh et al., 2021) and Light Detection and Ranging (LiDAR) (Lee et al., 2022) methods have been preferred instead of traditional methods using a compass in the detection of rock discontinuities. The long computation time for dense point cloud processing exposed by LiDAR technology, and the selection of smaller worksites due to data storage problems increase the use of photogrammetry methods in the detection of discontinuities. In addition, with the technological advances in the camera equipment used in mobile phone and Unmanned Aerial Vehicle (UAV) photogrammetric methods in recent years, photogrammetric techniques can give good results with cheaper cost and shorter computation time. Ozturk et al. (2019) determined rock discontinuities in Ihlara Valley, Turkiye by using mobile phone camera instead of traditional methods.

This study proposes an automated approach for discontinuity determination using close-range photogrammetric techniques and deep convolutional neural networks (DCNNs). The main challenge remains in the detection of discontinuities that have irregular shapes and sizes, and depending on the rock mass, a wide range of radiometric variation, and diverse textural and further morphological characteristics. Although the DCNNs are known to be successful in many image segmentation tasks, labeling the learning data is a major challenge, which is also the case for rock masses. The novelty of the present study lies in reusing features learned from crack datasets (mainly involving images of roads and pavements) in a geosite area with basalts in Kizilcahamam, Ankara, Turkiye, and optimizing parts of the model for the site. Fine-tuned model achieved an F-1 score of 87% on the validation dataset yielding the highest observed performance in the literature. The study site (Figure 1) was previously evaluated by Yalcin et al. (2022) and 58% of F-1 score could be achieved with a self-trained DCNN.

2. MATERIALS AND METHODS

The overall workflow of the study is shown in Figure 1. The main steps can be listed as photogrammetric processing,

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training data preparation, and model training and prediction with the DCNN. Details about the data and the methods are explained in the following subsections.

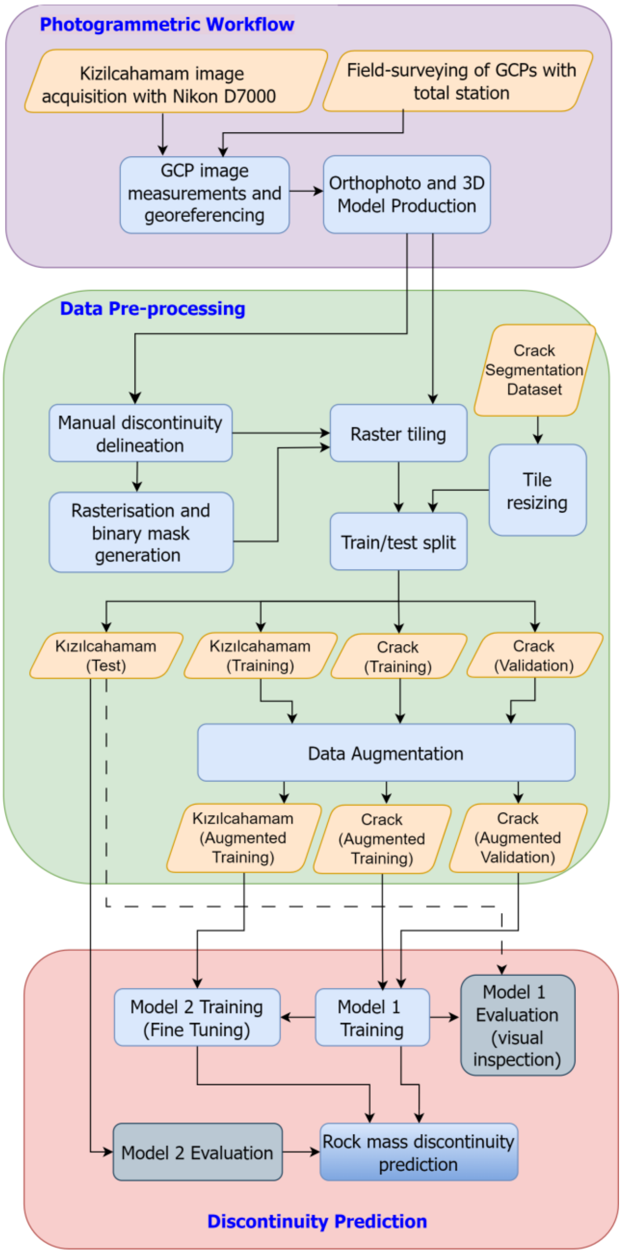


Figure 1. The workflow of the study

2.1 Study Area

The study area, Kizilcahamam/Guvem geosite, mainly consists of basalt columns. Basalts, which are volcanic rock, have smooth shapes and surfaces. The site was preferred as it is close to Ankara and has convenient accessibility (see Figure 2). The approximate dimensions of the working area are 7 meters by 17 meters. The rock blocks in the basalts vary in length, ranging from 5 centimeters to 85 centimeters. Furthermore, Figure 3 shows evidence of rockfalls at the bottom of the slope, making it hazardous for engineers and researchers to conduct traditional scan-line surveys.

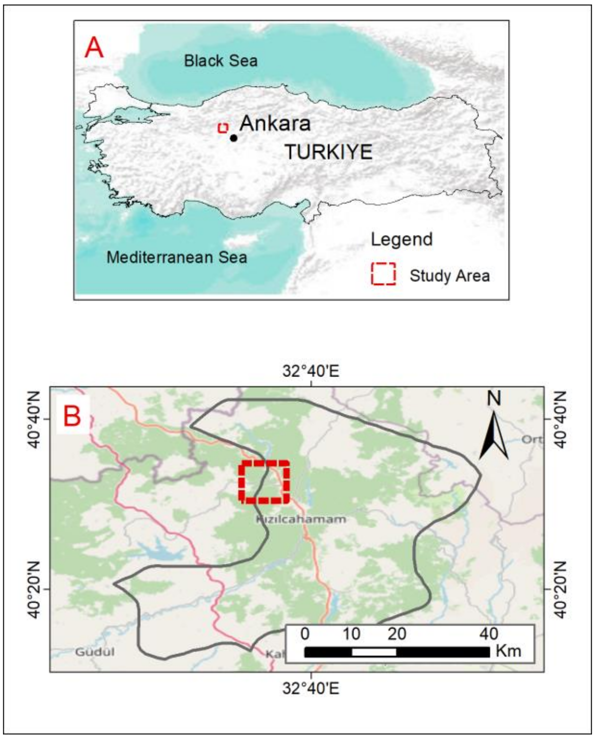


Figure 2. The location map of the study site.

2.2 Photogrammetric Processing

In the photogrammetric processing part of the study, a total of nine ground control points (GCPs) were measured with the help of a total station and a Global Navigation Satellite System (GNSS) instrument. Images of basalts were captured with a Nikon D7000 camera. Examples from 17 images taken from basalt outcrops are given in Figure 3. The camera has an effective resolution of 16.2 megapixels with a frame size of 4928 x 3264 pixels (Nikon, 2023).

Figure 3. Example photos of the study area used in photogrammetric processing.

The photogrammetric processing was carried out using Agisoft Metashape Professional Software (Agisoft LLC, 2023). The block was oriented using a total of 9 GCPs (Figure 4). The orientation accuracy was assessed using 3 of them as check points (green triangles in Figure 4). A DSM and an orthophoto of the area was produced using the same software.

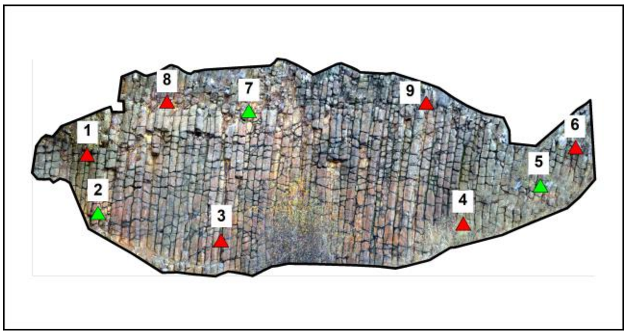


Figure 4. Location of the GCPs in the field. The red and green triangles indicate GCP and check points, respectively.

2.3 Deep Learning Model

The Kizilcahamam dataset was produced by manually delineating the discontinuities on the produced orthophoto (for further details, see Yalcin et al., 2022). The dataset was split into 259 image and mask tiles with a window size of 256 x 256. Examples from the training dataset including mask samples are given in Figure 5.

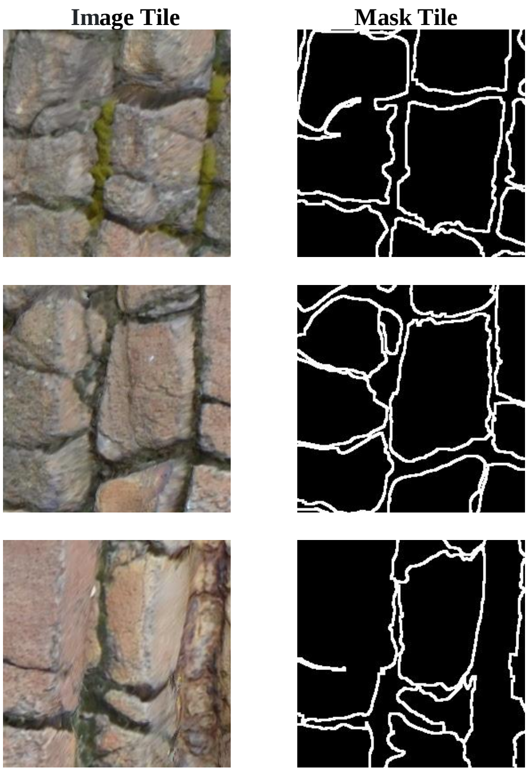
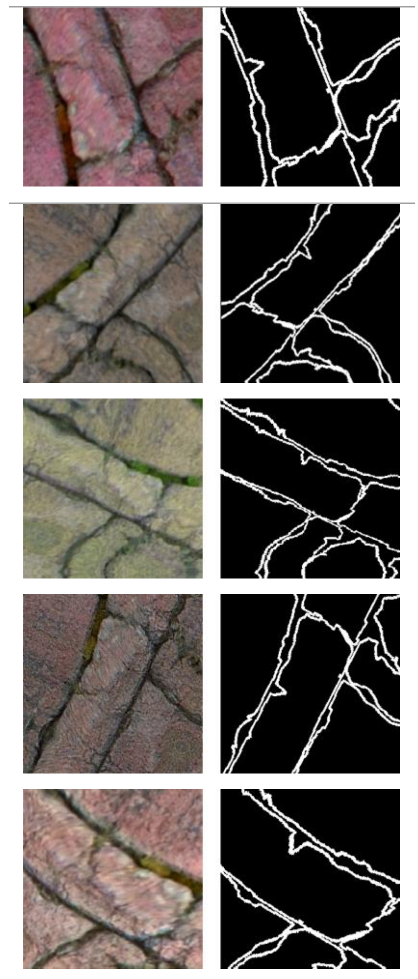


Figure 5. Examples to the images and corresponding masks in Kizilcahamam dataset.

Within the scope of the study, a base model (Model-1) was trained by using a crack dataset, which was obtained from Kaggle (Kaggle, 2023). The dataset consists of 11,298 images and corresponding masks. The amount of data was doubled using augmentation techniques. The learning set was split as 90/10 for training and validation of the base model, which is a modified version of the U-Net architecture (Ronneberger et al., 2015). Resnet-18 (He et al., 2016) was used as the encoder part of the U-Net architecture and transposed convolution layers were used in the decoder part. The base model (Model-1) was trained for 100 epochs for applying transfer learning. The Kizilcahamam dataset was split as 80/20 as training and test sets for fine-tuning of Model-1, which returned Model-2. 10% of the training part was used for validation of Model-2 after data augmentation was applied. The base model was used as transfer learning model and the fine-tuning was applied with the Kizilcahamam dataset. The hyper parameters used for Model-2 are respectively; 30 epochs, batch size 8, Adaptive Moment Estimation (Adam) optimizer, ReLU activation function and binary cross entropy-dice loss function. For the model evaluation, F-1 and Intersection over Union (IoU or Jaccard) scores were computed from the test dataset.

It is not always possible to provide sufficient amount of data for deep learning models on a specific topic. In this study, the number of image patches produced from Kizilcahamam dataset were increased from 259 to 1036 with the augmentation process. Examples to data augmentation are given in Figure 6. In the study, both pixel- and spatial-level methods such as rotation, flipping, shift scale rotate, gaussian noise, motion blur were used for augmenting the data through the Albumentations Library (Albumentations, 2023).



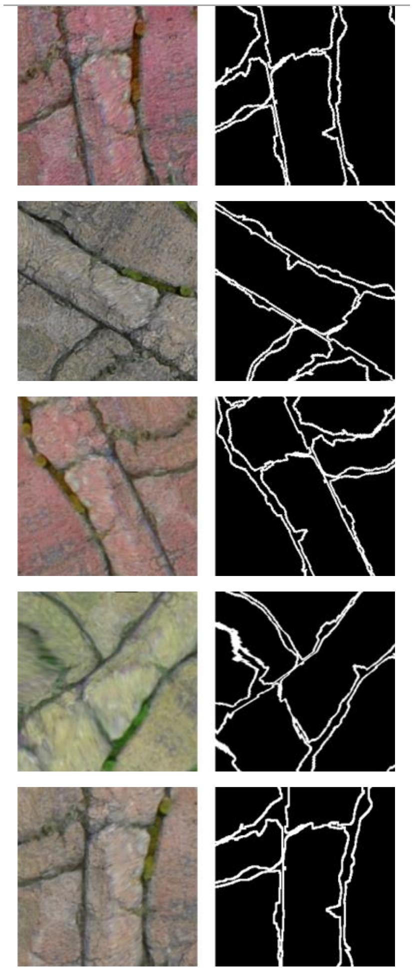


Figure 6. The left column shows the augmented image, the right column shows the corresponding mask.

3. RESULTS

The orthophoto produced in the photogrammetric part of the study is shown in Figure 7 together with the discontinuity measurements. The root mean square error (RMSE) value computed from 3 check points is 3.88 mm (Yalcin et al., 2022). Thus, the accuracy of the 3D model is sufficient for discontinuity determination, or arguably even better than the traditional scan-line surveys.

Figure 7. Manual delineating on orthophoto produced by photogrammetric process.

Here, the fine-tuned model (Model-2) achieved 88% Jaccard score on the test dataset. In Figure 8, the training and validation F-1 scores are shown with respect to the epoch number. Figure 9 shows the base model (Model-1) predictions on the Kizilcahamam dataset to provide visual impression on the quality. Figure 10 shows the predictions on test dataset after applying fine-tuning (Model-2 results). The results given in Figure 10 show that the model can reliably detect rock mass discontinuities.

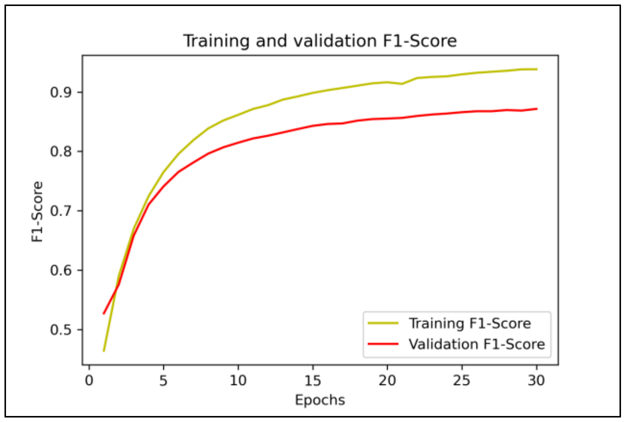


Figure 8. The accuracy of model training and validation obtained from Model-2.

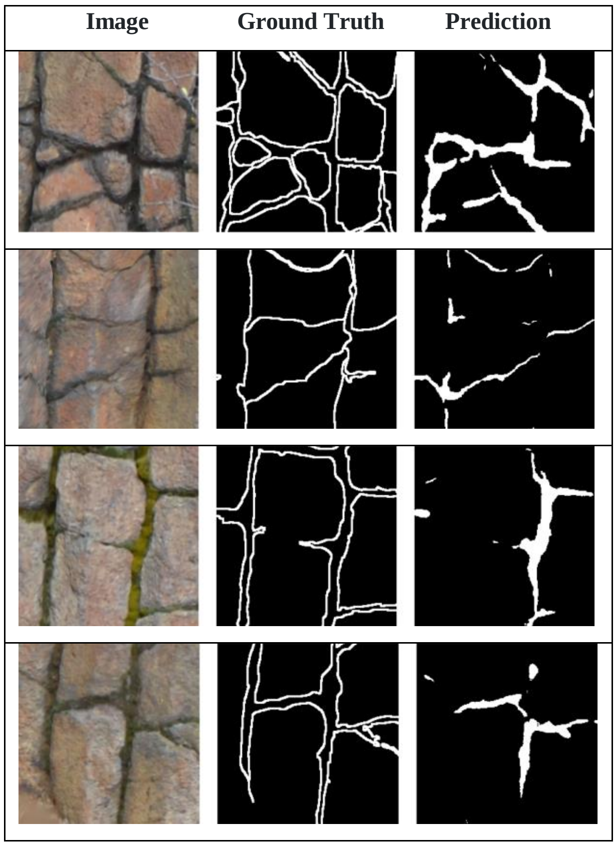


Figure 9. Kizilcahamam test dataset results obtained from the base model (Model-1, without fine-tuning).

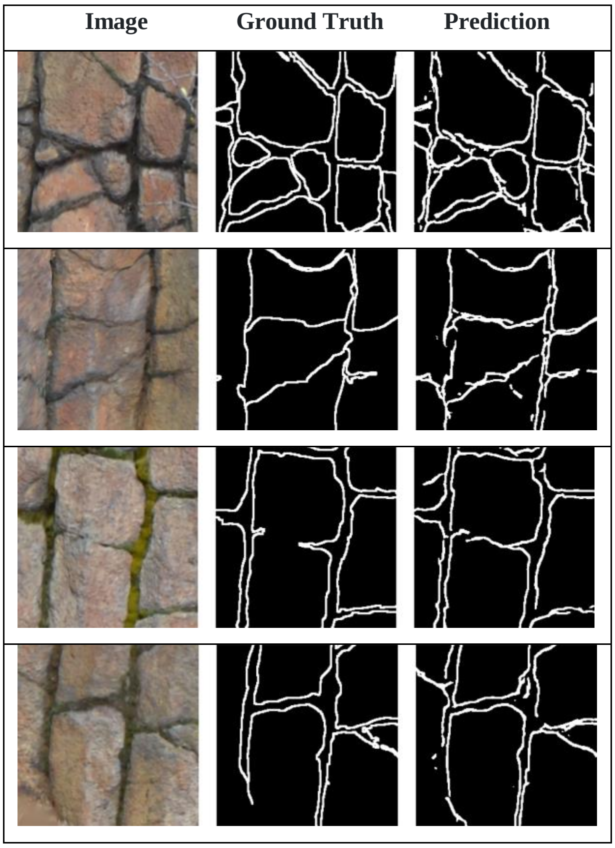


Figure 10. Kizilcahamam test dataset results obtained from the fine-tuned model (Model-2).

4. DISCUSSIONS AND CONCLUSIONS

In this study, rock mass discontinuities in Kizilcahamam Guvem geosite were detected using close range photogrammetric methods and DCNNs. The images used for 3D modeling were acquired with an off-the-shelf camera and oriented using a total of 9 GCP. The point positioning accuracy of the model is approximately 4 mm. The discontinuities were manually delineated on the orthophoto and converted to training data masks by tiling.

Two different DCNNs were trained for the study purposes. The first model was trained using a crack dataset involving roads and pavements. As the accuracy of this model was not sufficient, the images from the study site were used for fine tuning after data augmentation. The results indicated high performance of the second model, with 88% Jaccard score. The results show high potential of DCNNs for discontinuity determination also with a small amount of data thanks to transfer learning capability from the crack dataset.

The future work of the study includes investigations on different rock mass types and the determination of the rock mass boundaries in 3D. The results of the study may have a great impact on the engineering structures to be constructed on or in rock masses.

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APPENDIX

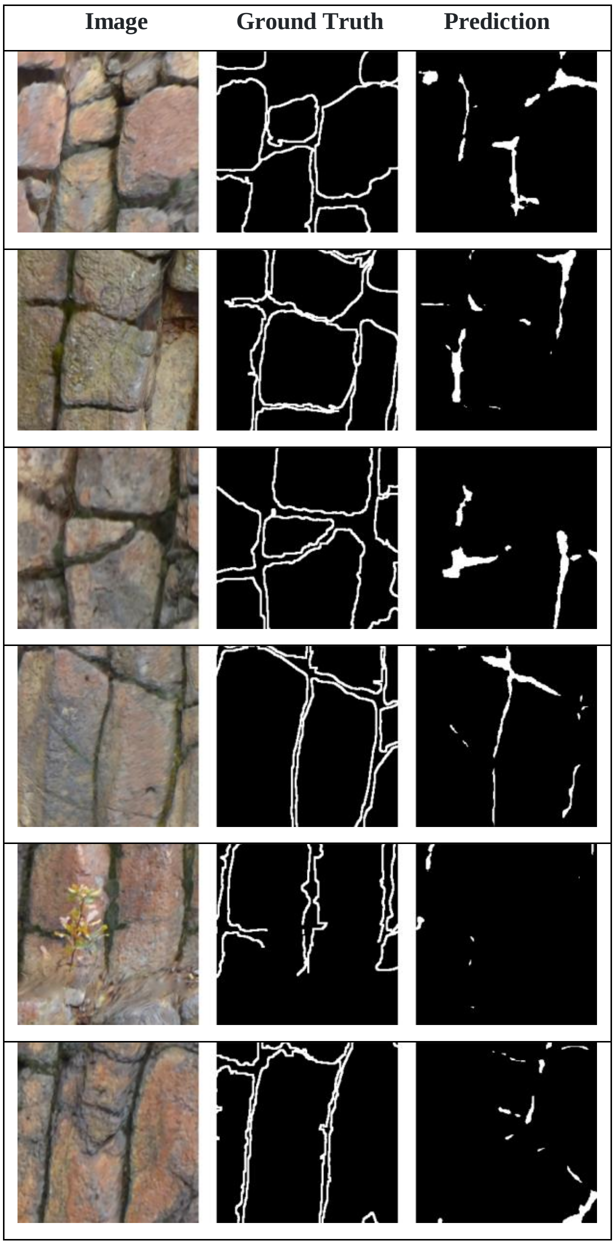

Figure A1. Further Kizilcahamam test dataset results obtained from the base model (Model-1, without fine-tuning).

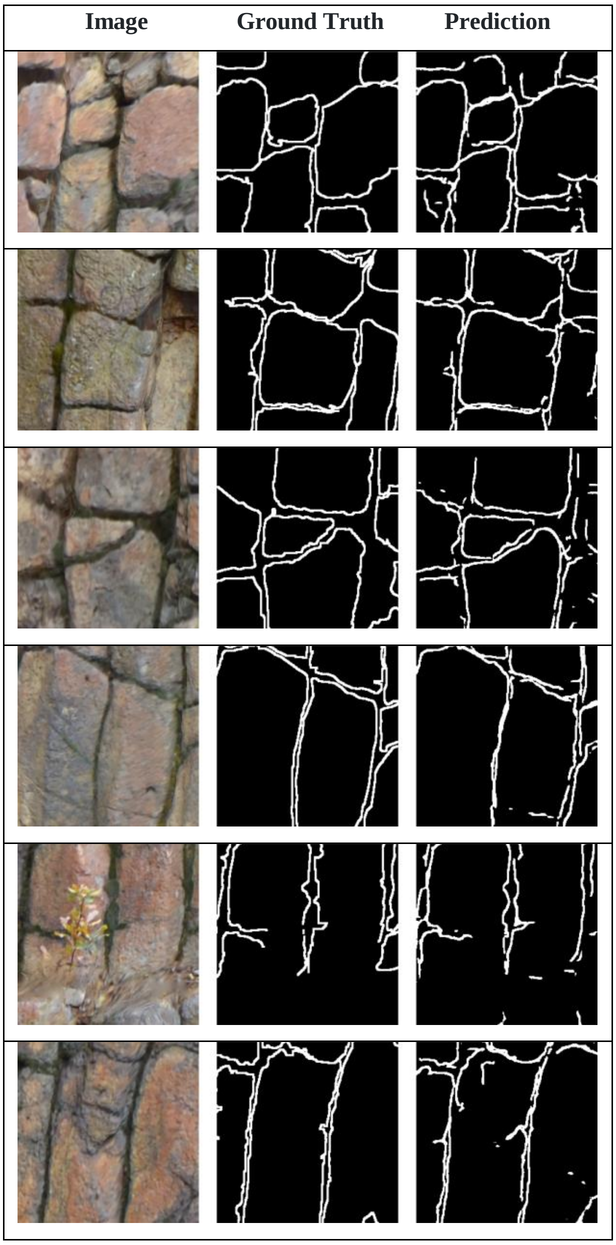

Figure A2. Further Kizilcahamam test dataset results obtained from the fine-tuned model (Model-2).