Journal of Mineral Resources Engineering, 9(4): 1-15, (2024)

Imam Khomeini International University
Vol. 9, No. 4, Winter 2024

نشریه مهندسی منابع معدنی
Journal of Mineral Resources Engineering
(JMRE)

Research Paper

Automatic Separation of Ore and Waste Using Images of Drill Cores and the Deep Neural Network U-Net

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Received: 12 Jul. 2023 **Accepted: 23 Apr. 2024**

Abstract: One of the most crucial steps in ore exploration is the recognition of geological patterns and features. These features contain mineralogy, lithology, alteration, rock texture, etc. This stage has always been associated with many challenges. Among the challenges of this stage, we can mention the time-consuming and costly nature of this stage and the need for high expertise and human resources to recognize these patterns and features. In recent years, deep learning and machine learning have been adopted in earth sciences. In this research, by using the architecture of U-net, ore and waste were separated, and the grade pattern was identified using the core box images. For this purpose, iron minerals were segmented using binary image segmentation, trial-and-error methods were used to optimize the network, and finally, the model's accuracy for identifying ore was 91%. The IoU metric was utilized for further evaluation; this metric is a suitable criterion for the final evaluation of the image segmentation model, which has reached 75% in recognition of iron ores. For the final evaluation of the obtained model, the grade outputs of the model and the XRF analysis results of one core were compared. The network error was evaluated at 9%, which shows the good accuracy of the obtained model according to the real data.

Keywords: Core box, Image segmentation, RGB image, Deep learning, U-net network.

How to cite this article
Farahmand, M., Fahiminia, M. , Asghari, O., and Mirmohammadi, M. S. (2024). *"Automatic separation of ore and waste using images of drill cores and the deep neural network U-net"*. Journal of Mineral Resources Engineering, 9(4): 1-15.
DOI: 10.30479/JMRE.2024.19041.1652

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INTRODUCTION

In mineral exploration, the drill core stands as the most reliable and important primary data, representing direct information from underground. Geological core logging is an essential part of mineral exploration, as it helps geologists and mining engineers determine the size, shape, and mineral composition of an ore body. This geological logging is often done visually and by a geologist. It is a time-consuming and labor-intensive task, and expert biases can affect it; thus, automated approaches are needed. In recent years, various research has been carried out in the field of automatic detection of minerals using color images, which in some traditional methods of machine learning [1,2] and in newer research deep learning methods based on convolutional neural networks (CNN) are utilized [3,4].

In this research, we used the U-net network [5], which is one of the CNN-based architectures, and image segmentation to recognize iron ore and waste in colored images of core boxes. Image segmentation is the process of partitioning a digital image into multiple segments to simplify or change the representation of the image. It is typically used to locate objects and boundaries in images. For the training phase, images of the core boxes were divided into suitable sizes, labeled by the geologist, and used as the input of the neural network. The outputs of the network were evaluated by accuracy and IoU metrics. Additionally, the output of the one core was compared to the XRF analysis results for validation.

METHODS

The automatic method used to separate ore and waste in this research is based on image segmentation. The first stage of the research is the collection of image data from the drilling core box, their analysis using the opinion of a geologist, and the results of chemical analysis. The images were divided into 256×256 patches and labeled. The generated labels indicate areas of iron ores for each pixel of the image. The image segmentation model in this research was U-net, which is a CNN-based network suitable for image segmentation tasks. U-net needs less data compared to other CNN models, and it can capture both coarse and fine feature information [5].

The U-net is a network with a symmetrical architecture and consists of four main parts, which include the contracting path, the expanding path, the bottleneck, and the output layer. Figure 1 shows an overview of the U-net along with its four main parts and different layers, where the vertical length of the layers represents the image dimensions and the horizontal length of the layers represents the number of feature maps.

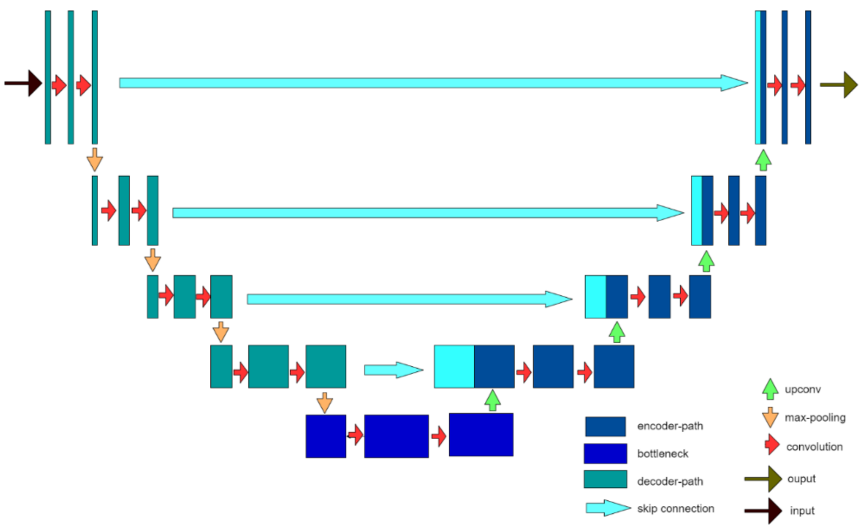

Figure 1. Architecture of U-net

The U-Net model consists of a contracting path (encoder) and an expansive path (decoder). The contracting path captures context and features from the input image while reducing its spatial resolution through convolutional and pooling layers, enabling the extraction of features at different scales. Meanwhile, the expansive path reconstructs the segmented image to its original resolution using upsampling and convolutional layers. It refines details and combines information from different scales, facilitated by skip connections that preserve spatial information and merge low-and high-level features, resulting in precise pixel-wise segmentation. The bottleneck connects the encoder and decoder and has the most feature channels in it, and the output layer with one 1×1 convolution layer does the final classification or segmentation. The activation function of every layer is ReLU, but the final layer is sigmoid.

FINDINGS AND ARGUMENT

U-net neural network codes and image segmentation steps were done in the Python programming language, and no other external software was used. Also, the Tensorflow GPU environment version and the Python 3.9 version were used to build the U-net neural network. Figure 2 shows the loss and accuracy curves for training U-net. The curves show that the network is well-trained, while the error and accuracy curves are well-converged, and no overfitting has occurred.

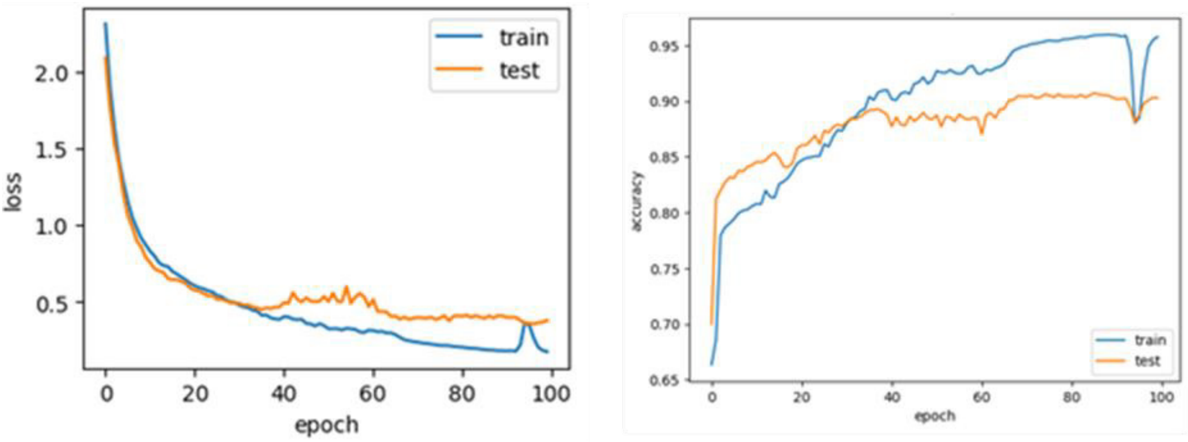

Figure 2. Loss and accuracy curve of U-net training

The output of the network is segmented images, where the defined segments represent iron mineralization. Figure 3 shows an instance of network prediction. To measure the performance of the network qualitatively, the labeled images, the original images, and the output images of the network were compared.

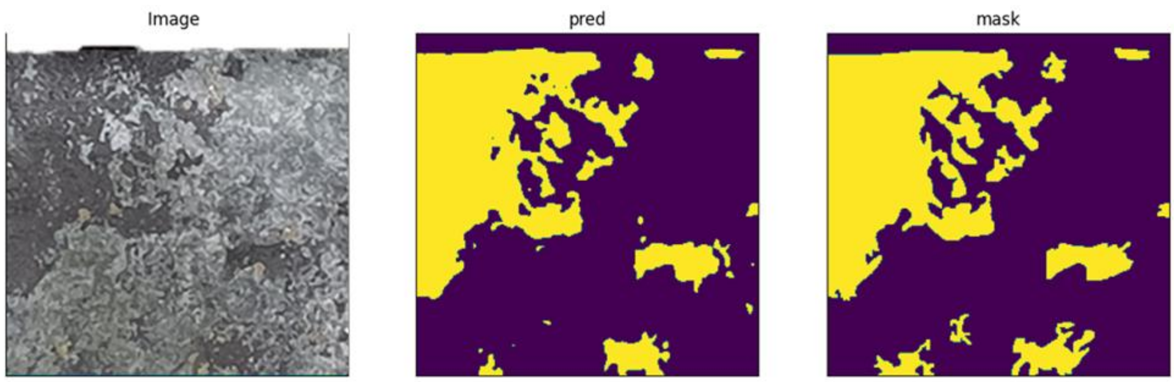

Figure 3. Ore and waste prediction of U-net with labeled mask and input image. The yellow color represents the ore, and the reset is waste

The final validation of the research was comparing the percentage of ores in prediction outputs with the XRF analysis data. Figure 4 shows an instance of this validation, where the 3rd row represents the percentage of yellow pixels (iron ore). The iron ore is magnetite in this core, and the average pixel percentage is 38.52%, resulting in 27.87% of Fe total. Compared to the 30.87% Fe total from the XRF analysis, the automated method of ore detection had an acceptable performance.

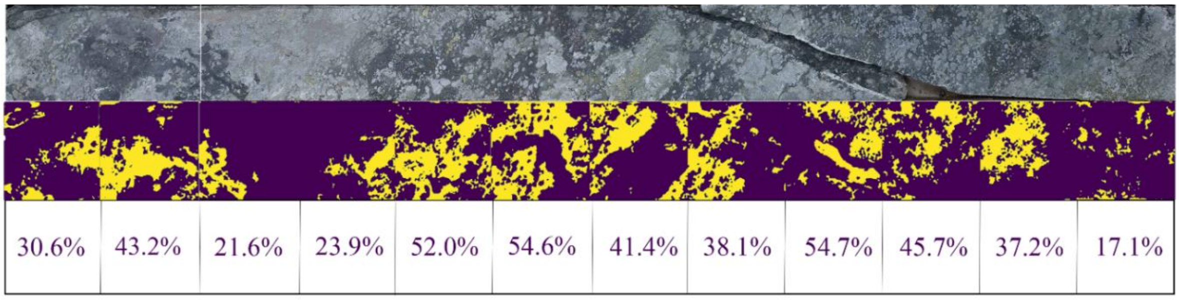

Figure 4. Visual and pixel percent validation

CONCLUSIONS

In this research, we developed an automated ore and waste detection approach for iron ore images. The method was based on a convolutional neural network, which is a deep learning algorithm. The result shows that this method can be utilized on different iron ore corebox images, and with an acceptable error, it can predict the boundaries of ore and waste. Although training deep learning networks demands a substantial volume of data, augmenting both the quantity and resolution of images can result in enhanced accuracy and reduced error rates. The weakness of the method is locations such as fractures that are not common in all images, and more images for training can solve this problem.

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