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| RESEARCH ARTICLE

Identification of Precious Metals using Deep Learning and Image Processing Methods

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| ABSTRACT
There are nearly ninety types of minerals in the world. Gold, platinum, palladium, and silver are classified as precious metals. These metals are used in a wide range of fields, including industry, technology, and jewelry. Due to its very high electrical conductivity, gold is used in sensitive technologies such as chips and microprocessors. Platinum and palladium, on the other hand, are used in the coating of aircraft and jet engines, dentistry, and the production of medical devices because they are resistant to high temperatures. The strategic importance of precious metals and their wide range of applications underscore the significance of this study. The primary objective of this study is to perform segmentation of gold, platinum, and palladium metals present in images obtained under a light microscope from samples taken from soil or rock. Through the deep learning-based system developed in this study, the goal is to achieve benefits in terms of time, labor, and cost by performing a preliminary evaluation of precious metals by an expert before initiating testing on advanced and expensive sample analysis devices. Image segmentation was performed using the U-NET architecture, one of the deep learning methods. The results of the system, developed based on the presence of precious metals indicated by the expert, were evaluated using a confusion matrix, achieving an accuracy of 83.84%.

| KEYWORDS
Precious Metals, Deep Learning, Gold, Platinum, U-Net

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1. Introduction

Technological advancements and processes across all countries of the world demonstrate a continuous demand for precious metals, particularly gold (Au), palladium (Pd), platinum (Pt), and rhodium (Rh). These metals are used as catalysts in environmentally friendly technological processes and as enhancers in automotive catalytic converter systems. Palladium is widely used in electronic applications due to its electrical conductivity and durability. Platinum is used in jewelry, the glass industry, inorganic chemistry, petrochemicals, electricity, and dentistry (Cieszynska and Wieczorek, 2018). Gold serves as a diversifier, a hedge against risk, and a safe-haven asset in financial markets (Baur and Lucey, 2010; Hillier et al., 2006; Sumner et al., 2010).
There are various challenges in detecting precious metals with low concentrations in mineral ores. Elements present in very small amounts are referred to as trace elements (Sert, 2011; Arslan, 2013). Trace element concentrations were initially defined in the first scientific approach as a range of 10^{-1} to 10^{-3} (Minczewski et al., 1982). Today, units such as ppm, ppb, and ppt are widely accepted (Arslan, 2013).
For a metal to attain "precious" (Precious Metal—PM) status, three main parameters are required: rarity, value, and chemical properties (Ford, 2001). PMs are less reactive and have greater corrosion resistance compared to other elements (Kononova et al., 2010).
The colors of metals found in nature can vary depending on their alloy and mixture ratios. The color tones of silver, copper, and gold alloys based on their mixture percentages are shown in Figure 1 (Lansdown, 2010; Massey et al., 1975).

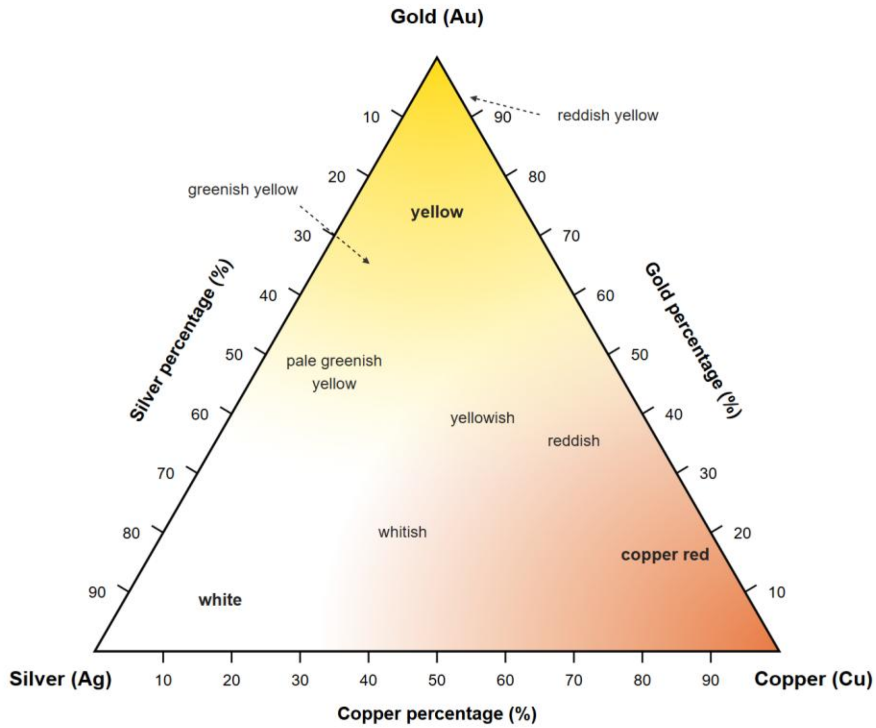


Figure 1. Color scale of copper, gold, and silver obtained based on the percentage ratios of elements (Adapted from Metals Handbook Committee, 1990).

The aim of this study is to reduce the significant amount of time spent by specialized personnel identifying the presence of precious metals under a microscope. The developed system aims to distinguish gold, platinum, and palladium metals in images obtained from a light microscope using deep learning methods. Thus, the preliminary evaluation of the presence of precious metals can be performed by the developed system instead of an expert.

2. Materials

2.1 Samples

The study was conducted on 15 sand and rock samples obtained from the ÜSKİM laboratory affiliated with Kahramanmaraş Sütçü İmam University. The samples were processed through a physical grinder to reduce their size; this process facilitated the identification of metals within the mixture, allowing for better observation. A total of 695 sample images were obtained using a light microscope; 272 were from dry samples, and 473 were from wet-washed samples. The detailed distribution of these images across the various samples is presented in Table 1.

Table 1. Number of images obtained from the light microscope (Türkhan, 2022).

Sample No.	Number of Dry Sample Images	Number of Wet Sample Images
111	10	20
666	11	30
11,748	10	30
12,115	20	20
13,705	10	19
13735	20	20
13,802	20	31
14,312	20	30

14,735	10	25
14,972	20	20
60	20	30
61	20	29
100	30	35
250	30	40
500	21	44

A representative example of the raw images captured using the light microscope is illustrated in Figure 2. The presence of silver, palladium, platinum, and gold in the samples was crucial. An ore is a structure formed by metals in chemical compounds or mixtures in specific ratios. The obtained samples are reduced in size using a physical grinder. The size reduction process reveals the separation of metals within the mixtures, thereby making the metals easier to observe.

Each sample was divided into two groups before images were taken under a light microscope. Photographs of the samples in the first group were taken under the microscope without any prior treatment. The samples in the second group were washed to ensure the metals appeared more clearly. Silicon dust and other non-metallic dusts obstructed the clarity of the image during the washing process.

While taking the microscope images, the samples were focused using random magnification. This was done without a fixed magnification ratio. Magnification and light are necessary for clear images.

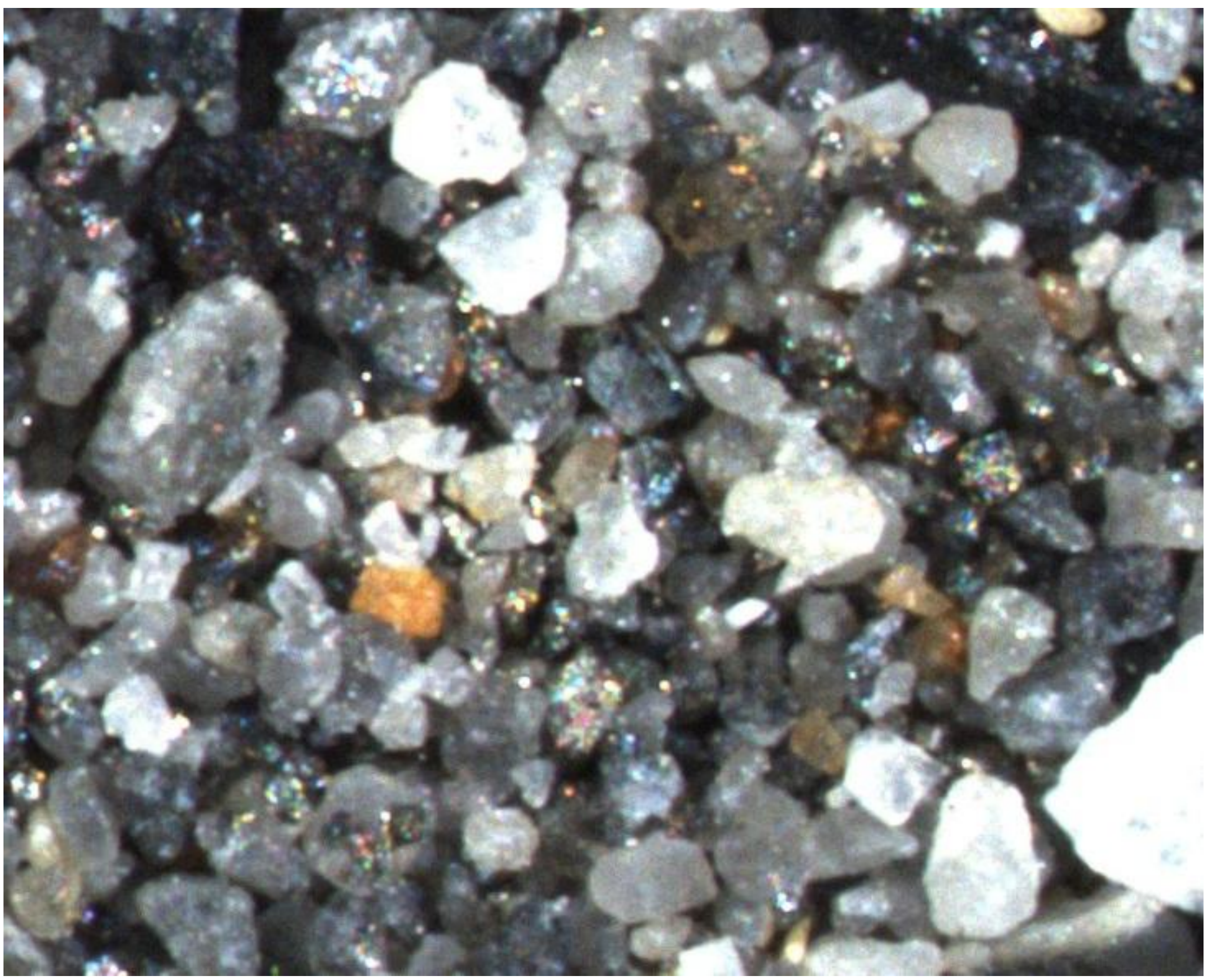


Figure 2. An example image taken with a light microscope (Türkhan, 2022).

2.2. Labeled Images and Data Preprocessing

The labeled images (masks) required to train the dataset were created using the YCbCr color space within the Matlab Color Thresholder toolbox (Figure 3). According to expert opinion, gold appears in shades of yellow and bright yellow, while platinum and palladium group precious metals appear in shades of blue and bright blue. A successful labeled image could not be created for silver (white, bright white, and bright gray tones) because a color difference could not be established compared to other elements.

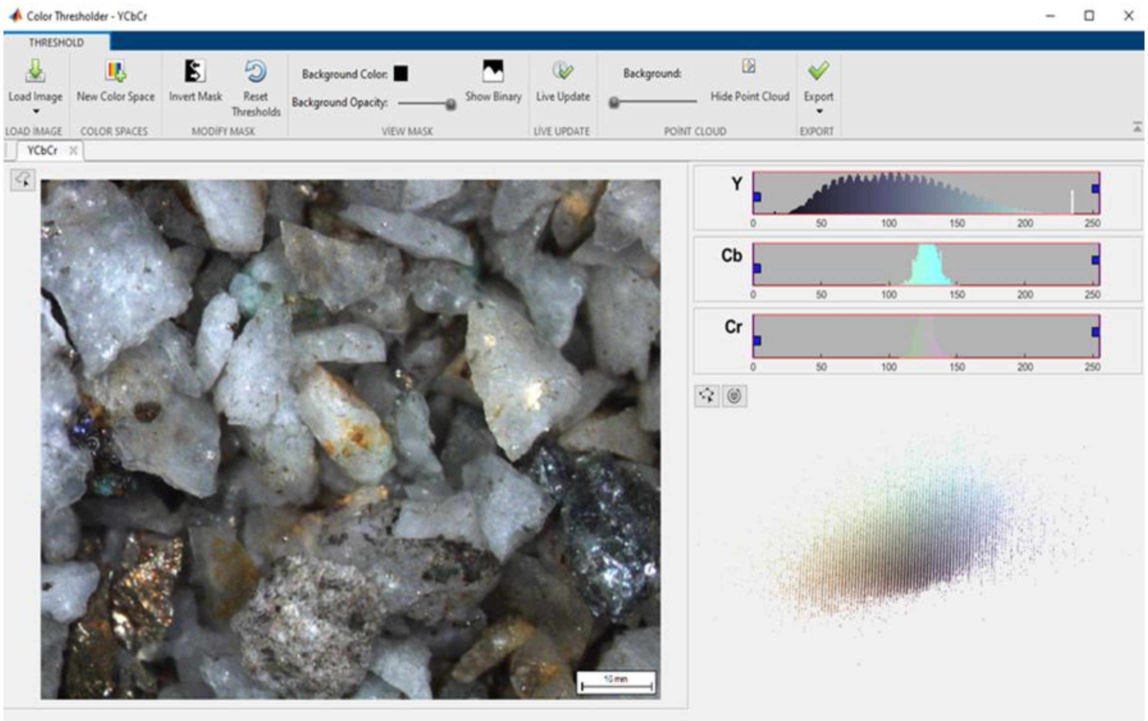
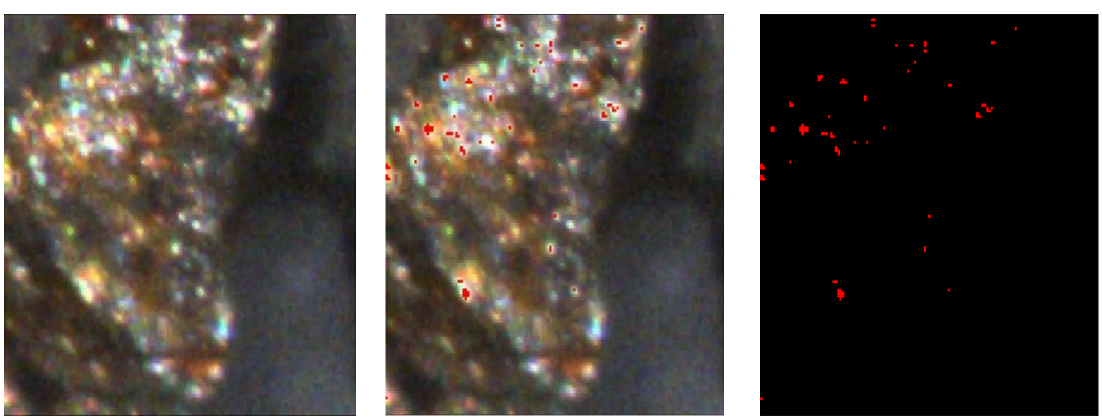


Figure 3. Creation of a label image using the YCbCr method (Türkhan, 2022).

2.3 Generation of Label Images for Gold Precious Metals

In images obtained under a light microscope, precious metals can be grouped by pixels. Since precious metals are not found in clusters within ores, they do not have defined edges in the images. To solve this problem, precious metals were categorized by pixels. Areas containing gold metal in the image are represented by pixels. After the expert verified the accuracy of the label images, they were included in the training dataset.



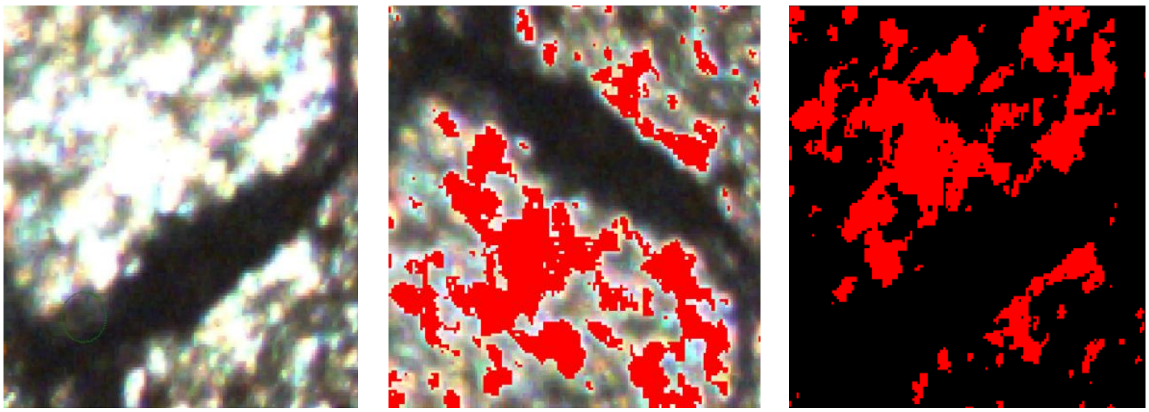
(a) (b) (c)

Figure 4. Label image generation process: (a) Original image, (b) Masked image, (c) Labeled image (Türkhan, 2022).

As illustrated in Figure 4(a), the raw image obtained from the light microscope (originally 1280×960 pixels with a 32-bit depth) was converted to a 141×141 pixel image having a 48-bit depth and a resolution of 25,400 dpi. Figure 4(b) demonstrates the clustered pixels that exhibit a high concentration of gold metal. Finally, Figure 4(c) displays the generated label image, which serves as the ground truth mask during the training phase.

2.4 Creation of Label Images for Silver Precious Metal

Silver, white, bright white, and bright gray tones offer a very wide color range in the images we will use for training. A large number of pixels are used in the creation of label images. It is clear that a significant portion of the selected pixel groups do not contain silver metal. Since a large portion of the pixels grouped in the label images belong to other elements, the color difference between silver and the other elements could not be created. The stages of creating label images for silver metal are illustrated in Figure 5. Figure 5(a) displays the original image, while Figure 5(b) demonstrates the masking process. Finally, Figure 5(c) presents the resulting labeled image.



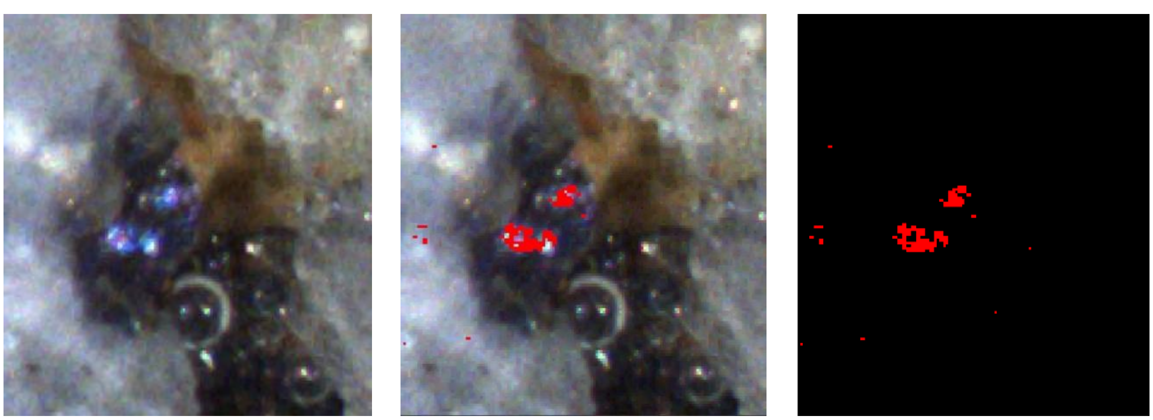
(a) (b) (c)

Figure 5. Label image generation process for silver metal: (a) Original image, (b) Masked image, (c) Labeled image (Türkhan, 2022).

In the efforts to categorize the label image of the silver metal, other components were also included in this category. Therefore, silver was excluded from the subsequent deep learning training and testing phases.

2.5 Generation of Label Images for the Platinum and Palladium Precious Metal Group

When viewed under a light microscope, the precious metals in the platinum and palladium group appear in shades of blue and bright blue. When creating label images, it is very important to understand how experts group these colors. The image below was used to create the label images for the platinum and palladium group. As shown in Figure 6(a), a 152×151 pixel image (48-bit depth, 25,400 dpi) was derived from the original 1280×960 pixel light microscope image (32-bit depth). Figure 6(b) displays a clustered mask image of pixels with high concentrations of platinum and palladium. Finally, Figure 6(c) illustrates the generated label image to be used in the training process.



(a) (b) (c)

Figure 6. Label image generation process for the platinum and palladium group: (a) Original cropped image, (b) Masked image, (c) Labeled image (Türkhan, 2022).

Since the shapes of the precious metals to be trained are very small on the image, cropped sections (Crop) of approximately 150x150 pixels were used instead of the original 1280x960-pixel images, and this method yielded successful results. To enhance training performance, data augmentation was applied using a series of preprocessing options such as resizing, rotation, reflection, and brightness adjustment.

3. Method

For image segmentation, the U-NET architecture—a convolutional neural network developed at the Department of Computer Science at the University of Freiburg for segmentation in medical image processing studies—was used (Ronneberger et al., 2015). The U-Net architecture is designed based on a fully convolutional neural network (FCN) and has been extended to achieve segmentation with higher accuracy using fewer training images (Long et al., 2015).

The applied U-Net model consists of 70 layers. The model comprises two main parts: the Encoder channel, which understands what is in the image, and the Decoder channel, which determines where the shape to be segmented is located (Ronneberger et al., 2015).

The DeepMIB application, a MATLAB-based software package developed by the University of Helsinki, was used for training (Belevich, 2016). The ADAM optimization algorithm, an adaptive moment estimation algorithm, was chosen for weight calculation (Kingma and Ba, 2014).

While initial ground truth masks were created using color thresholding under expert supervision, simple color filters fail under varying light conditions and shadow effects. The applied U-Net model learns complex spatial textures and contextual features beyond mere color, providing a robust and fully automated detection system.

4. Results and Discussion

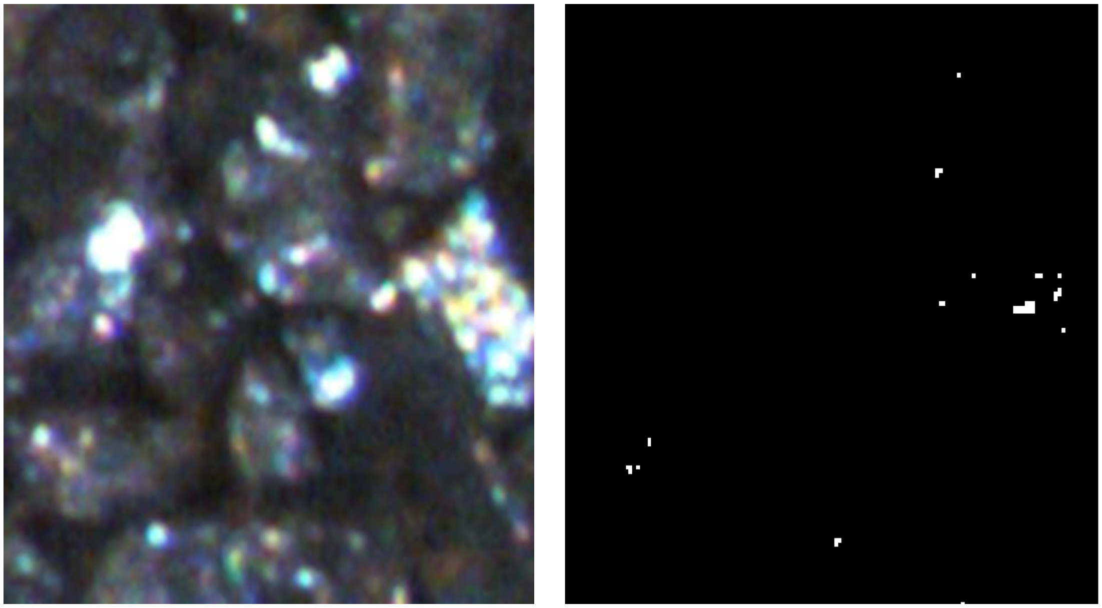
The performance of the deep learning-based system was evaluated using a confusion matrix by comparing it with expert opinions on 130 images from completely unseen samples that were not used during the training phase.

4.1 Prediction Results for Gold Samples

As illustrated in Figure 7, the distribution of gold ore within Sample-1 is highly irregular. The segmentation results indicate a distinct absence of gold in the top-left and bottom-right quadrants, whereas notable concentrations are detected in the top-right and bottom-left regions. Quantitative analysis performed using the ICP-OES device confirmed a gold concentration of 14.44 mg/kg for this sample.

Furthermore, the overall segmentation performance for the detection of precious metals achieved an accuracy rate of 83.84%. The specific confusion matrix metrics for gold detection by the developed U-Net model are as follows:"

- Accuracy: 0.8384 (83.84%)
- Sensitivity: 0.9375
- Precision: 0.8242



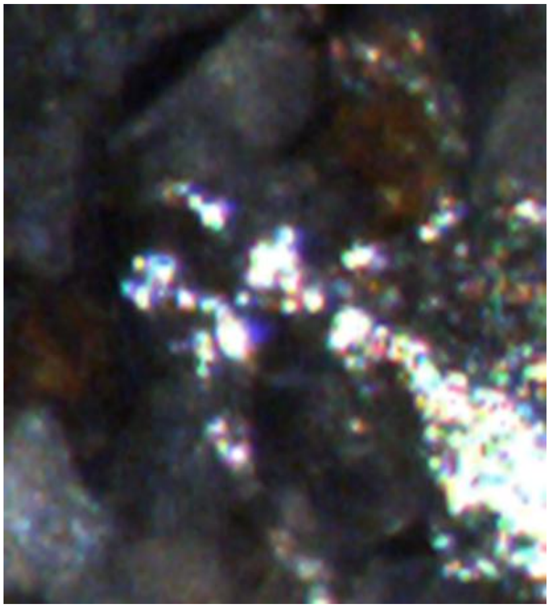
(a) (b)

Figure 7. Segmentation results for gold detection in Sample-1: (a) Original light microscope image demonstrating the irregular distribution of the ore; (b) The predicted mask generated by the U-Net model highlighting the localized gold concentrations (Türkhan, 2022).

4.2 Prediction Results for Platinum-Palladium Group Samples

As illustrated in Figure 8, the segmentation performance of the developed deep learning system on a test case (Sample-2) demonstrates a high correlation between the original microscopic image and the model's prediction. In this sample, characterized by particle sizes of approximately 60 microns, the platinum and palladium concentrations are predominantly localized in the central region of the image. Quantitative analysis performed using the ICP-OES device confirmed a platinum content of 4.183 mg/kg and a palladium content of 2.604 mg/kg for Sample-2.
Furthermore, the overall segmentation performance for the platinum and palladium group yielded an accuracy rate of 83.84%. The specific confusion matrix metrics achieved by the U-Net model for this group are as follows:

- **Accuracy:** 0.8384 (83.84%)
- **Sensitivity:** 0.8584
- **Precision:** 0.9381



(a)

(b)

Figure 8. Representative prediction result for Sample-2: (a) Original light microscope image showing the ore distribution; (b) The corresponding segmentation output generated by the U-Net model, identifying the platinum-palladium regions (Türkhan, 2022)**.**

4.3 Discussion

Although the model was trained on cropped images of 141x141 pixels, it demonstrated the ability to make accurate predictions on large-scale images of 1280x960 pixels.
No direct correlation could be established between the ratio of precious metal pixels in the prediction and label images and the results obtained from the ICP-OES testing device. The reason for this is that the pixels in the microscope images represent ores containing precious metals in varying proportions, rather than pure precious metals. Additionally, precious metals are not uniformly distributed in sample images, which results in varying numbers of pixels in images taken from the same sample. Qualitative observations during the testing phase indicated that wet-washed samples generally provided sharper boundaries for the precious metals, slightly improving the model's segmentation confidence compared to dry samples.
This deep learning-based system reduces time and cost by enabling the detection of precious metals before initiating testing on expensive devices such as ICP-MS and ICP-OES. The expert's evaluation was conducted using the deep learning-based system, which achieved an accuracy rate of 83.84% in this study, thereby saving the time and cost associated with the expert's prolonged work at the microscope. Therefore, this deep learning-based system is proposed not as a quantitative measurement tool to replace ICP-MS or ICP-OES, but as a rapid, qualitative pre-screening system to confirm the presence of precious metals before initiating expensive and time-consuming analytical tests.

5. Conclusions

The 83.84% accuracy rate achieved for gold and platinum-palladium group metals demonstrates that images obtained from a light microscope can be successfully trained using the U-Net model for preliminary evaluation. Although the U-Net model was initially developed for segmentation in medical images, it has yielded successful results with images from various laboratory devices, such as light microscopes. This system, which automates the evaluation process for the presence of precious metals, reduces costs and time losses associated with the use of high-cost analytical instruments. With the further advancement of deep learning methods in the future, it is expected that studies in similar areas will achieve even higher performance.

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