Characterization of black claystone, coal, and coal rank using deep learning in the sinje block, Murung Raya Village, Central Kalimantan Province, Indonesia

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Abstract. In the era of Industry 4.0, conventional manual activities in mining are increasingly replaced by digital technologies to enhance efficiency and accuracy. Coal remains a highly demanded energy resource, particularly in countries dependent on coal-based fuels. To support good mining practices, it is essential to strengthen the implementation and monitoring aspects of exploration. Deep learning offers a promising solution for improving coal identification and classification, especially given the wide variation in coal ranks available in the market. This study focuses on distinguishing black claystone, coal, and coal rank using a deep learning approach. The workflow began with sample identification through macroscopic characterization—including color, streak, luster, and fracture—using 2D RGB imagery. The image-based model demonstrates strong capability in accurately recognizing rock types and coal ranks. The develoved model successfully categorized 78 images of black claystone (brown color, brown streak, dull luster). It also classified 160 samples with a calorific value of 4,650 cal/gram and brownish-black streak as Sub-Bituminous (Seam B). Additionally, 252 images with a calorific value of 6,493 cal/gram and bright appearance were identified as Bituminous (Seam A). This automated classification provides an efficient tool for generating comprehensive geological interpretations and supporting data-driven mining operations

1 Introduction

The identification of coal has traditionally been conducted through field mapping and sample collection, a process that can be time-consuming and labor-intensive. Coal characteristics are crucial for determining coal rank, which directly affects its economic value and suitability for various industrial applications. These characteristics, including color, luster, hardness, streak, and impurities, can be observed macroscopically and

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require geological evaluation, including analysis of the depositional environment, source material, and structural influences. Based on surface data, macroscopic characteristics can be distinguished by observing color, luster, streak, hardness, fracture, and the presence of impurities in the coal [1]. Coal plays a significant role in industrial energy supply. With increasing demand for energy, the exploration and evaluation of coal resources have become more intensive. Accurate geological assessments are vital in estimating both the quality and quantity of coal resources, forming the foundation for further feasibility studies. Coal formation involves complex biological, chemical, and physical processes. Organic matter from plant debris accumulates in swampy environments, undergoing microbial decomposition and diagenesis to form peat [2], which then transforms into coal under high pressure and temperature over geological time.

In coal mining activities, distinguishing between coal and black shale is important because the latter, despite having a similar appearance, contains different maceral compositions and often serves as an impurity or parting layer in coal seams. Effective separation is essential to maintain coal quality and reduce the need for post-mining treatment such as washing. In alignment with the Ministry of Energy and Mineral Resources Regulation No. 26/2018 on Good Mining Practice, and in response to the technological advancements of Industry 4.0, mining operations are encouraged to integrate modern technologies that support efficiency, accuracy, and sustainability [3]. One promising technology is Deep Learning [4], a branch of artificial intelligence that mimics human neural networks and has shown great potential in image-based classification tasks. This research aims to apply deep learning techniques, particularly Convolutional Neural Networks (CNN)[5], to distinguish between black shale and coal, as well as to classify coal ranks based on visual characteristics such as color, luster, and texture. Conducted in the Sinje Block of PT. Lautan Hutan Lestari, the study seeks to build a digital model for fast and accurate classification of coal types using image recognition.

2 Methods

This study was conducted through a combination of literature review, field investigation: data collection, and performance analysis in the operational area. The following methodologies were applied: Literature Review, The study began with a literature review to gather secondary data, including regional geological maps, photographs of black shale and coal, and relevant scientific publications. This stage established a baseline understanding of the study area and guided subsequent research activities. Field Activitie :Based on the literature review, field investigations were conducted to document outcrops of black shale and coal, supported by photographic records. Rock observations enabled the identification of lithological types within the Sinje Block at Murung Raya Village, Central Kalimantan Province, Indonesia. Coal calorific value analysis was also carried out to support the classification of coal based on energy potential. Dataset Development and Image-Based Analysis : The next step involved developing a predictive model for rock classification using deep learning. The workflow consisted of dataset construction, model training, and testing for rock type detection. A Convolutional Neural Network (CNN) was trained to classify black claystone, sub-bituminous, and bituminous coal from fieldacquired images [6]. Training datasets were derived from field photographs, while testing datasets were applied to assess model performance, linking geological observations with computational analysis. Results : The final stage focused on classifying coal according to calorific values and characterizing black shale. Data were compiled into a final report and presented through diagrams illustrating rock characteristics and coal rank properties. Image-based analysis of coal and black shale photographs demonstrated the effectiveness of integrating field observations with deep learning methods for geological interpretation.

3 Results and discussion

This research aims to differentiate black claystone and coal, which are visually similar in the field due to their shared dark color and organic composition. By employing both physical rock descriptions and deep learning via image-based classification, the study successfully identifies distinct characteristics and coal rank classification [7].

3.1 Physical characteristics and proximate analysis

The macroscopic and laboratory analyses clearly differentiate black claystone from sub-bituminous and bituminous coal. Table 1 summarizes key physical parameters measured in the field, while Table 2 presents the proximate analysis of six coal samples.

Table 1. Results of Rock Description

Parameter	Black Claystone	Sub-Bituminous	Bituminous
Color	Brown	Black	Black
Luster	—	Dull (charcoal-like)	Shiny (glassy)
Streak	Brown	Brownish black	Black
Brightness Degree	Dull	Slightly bright	Bright
Hardness	Hard	Easily broken	Moderately hard
Fracture	—	Irregular blocky	Brittle
Specific Gravity	High	Medium	Medium
Hammer Impact Sound	Thud	Crackling	Crackling
Weathering Resistance	Resistant	Resistant	Resistant

Table 2. Proximate Analysis of Coal Samples

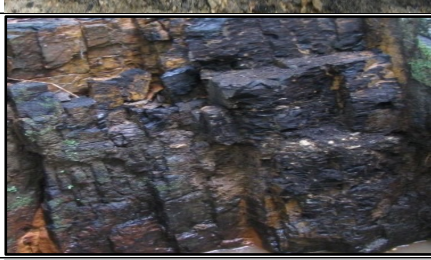
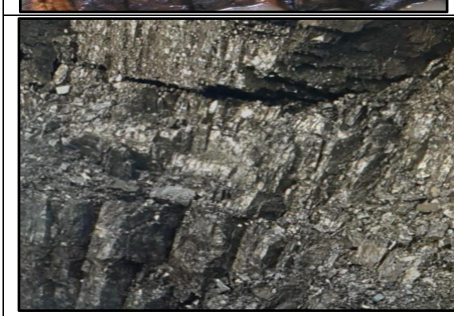
No	Sample ID	Tm% (ar)	IM% (adb)	Ash% (adb)	VM% (adb)	FC% (adb)	TS% (adb)	Calorific Value (cal/g)
1	LP 12	15.00	15.00	1.30	41.20	42.20	0.60	6452
2	LP 28	30.30	11.82	4.55	39.30	43.25	1.22	6509
3	LP 45	32.20	8.78	3.21	44.70	42.60	4.37	6520
	Seam A Avg	25.83	11.86	3.02	41.73	42.68	2.07	6493
4	LP 18	30.05	14.82	6.33	39.17	39.68	0.17	4666
5	LP 22	31.52	14.64	3.57	43.40	38.39	0.15	4634
6	LP 4	32.35	14.53	3.10	42.38	38.03	0.12	4650
	Seam B Avg	33.97	14.66	4.33	41.65	38.70	0.14	4650

According to ASTM D3172–13 classification [8], Seam A is categorized as High Volatile C Bituminous Coal while Seam B corresponds to Subbituminous C Coal based on their average calorific values of 6493 and 4650 cal/g, respectively. Vitrinite reflectance further supports this ranking, with Seam A at 0.55% and Seam B at 0.39% [8].

3.2 Deep learning classification

The dataset comprised 78 claystone, 160 sub-bituminous (seam B), and 252 bituminous (seam A) images. Table 3 defines the labeling criteria used during training. Collection was carried out in the field using a 20 MP mobile phone camera, with images saved in JPG format. The captured photos (images) play a crucial role in the classification and differentiation of data types [6]. Therefore, rock observation and description should be conducted prior to the image acquisition stage. To distinguish between black claystone and coal, as well as to classify coal based on its calorific value, it is necessary to group the samples so that differences in color and texture can be systematically categorized (Table 3). During the data processing stage, image resizing and classification were performed, dividing the images into two main categories: black claystone and coal ranks.

Table 3. CNN Classification Labels.

Label	Classification	Description
	Black Claystone	Brown color, brown streak, dull brightness
	Sub-Bituminous or Seam B	Black color, brownish-black streak, slight brightness
	Bituminous or seam A	Black color, black streak, bright appearance

Based on image classification, black claystone characterized by brown color, brown streak, and dull brightness was identified by machine learning, with all 78 grouped [9] images classified as black claystone. Another group of 160 images, with a calorific value of 4,650 cal/gram and descriptions including black color, brownish-black streak, and slight brightness, was classified as Sub-Bituminous (Seam B). A third group, consisting of 252 images with a calorific value of 6,493 cal/gram and descriptions of black color, black streak, and bright appearance, was identified as Bituminous (Seam A) by the model [10]. Uniform lighting conditions and a consistent camera-to-sample [11]. Distance were maintained during image acquisition to ensure reliability in feature extraction. The model was trained over 50 epochs, achieving convergence in both accuracy and loss metrics, indicating robust performance in classification.

3.3 Model performance

Figure 1 illustrates the CNN training history, showing validation accuracy reaching over 80% and validation loss stabilizing after 45 epochs. The high performance confirms the model's capability to distinguish lithological types and coal ranks effectively [12].

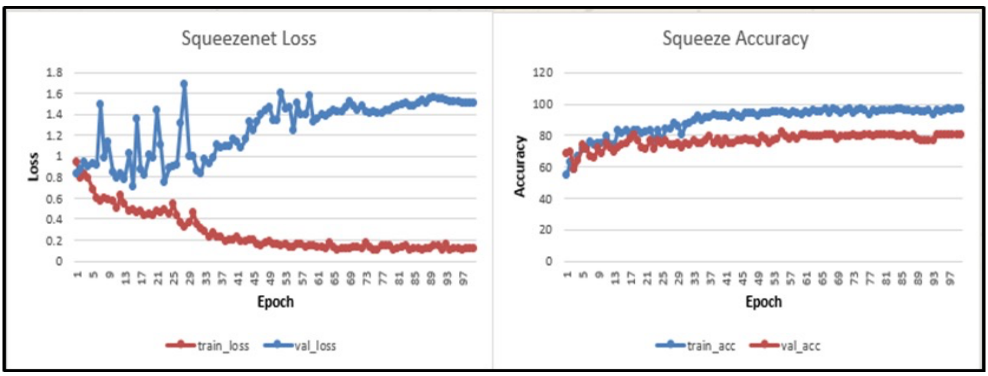


Fig. 1. Validation accuracy and loss curves for the CNN model over 50 epochs.

The combination of traditional geologic characterization and CNN-based image classification offers a robust framework for rapid lithological assessment in the field. Physical properties provide ground truth, while the CNN augments visual inspection by automating identification tasks [9]. The model's high accuracy (80%) suggests potential for integration into mobile applications to assist geologists during field surveys. Further improvements could include expanding the dataset, incorporating spectral imaging, and exploring advanced architectures such as ResNet or EfficientNet.

4. Conclusions

Based on the research conducted at Murung Raya Village, Central Kalimantan Province, Indonesia, the samples were classified into three categories: black claystone, Sub-Bituminous, and Bituminous coal. Black claystone is characterized by a brown color, brown streak, and dull brightness. Sub-Bituminous coal shows a black color, brownish-black streak, charcoal-like luster, and slightly bright appearance, with proximate analysis indicating a calorific value of 4,650 kcal/gram (Seam B). Bituminous coal is described by a black color, black streak, bright appearance, and vitreous luster, with a calorific value of 6,493 kcal/gram based on proximate analysis (Seam A). The machine learning implementation employed a Convolutional Neural Network (CNN) architecture, consisting of three convolutional layers and one fully connected layer . The model was trained using a 75:25 data split ratio. The training process took 1 hour, 55 minutes, and 12 seconds. The resulting model achieved an accuracy rate of 80%.

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