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Deep Learning-Based Mineral Classification Using Pre-Trained VGG16 Model with Data Augmentation: Challenges and Future Directions

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Abstract: This research examines the use of a pre-trained VGG16 model, applying transfer learning, to categorize minerals from hand specimen images into seven separate categories: biotite, bornite, chrysocolla, malachite, muscovite, pyrite, and quartz. The dataset, consisting of 956 images, was enhanced with methods like random rotations, flips, and normalization to enhance the model's ability to generalize. Fine-tuned for this particular task, the VGG16 model showed strong performance in recognizing minerals with unique visual characteristics such as bornite and muscovite, achieving a test set accuracy of 83%. Nevertheless, the model had difficulty consistently distinguishing between visually similar minerals like biotite and chrysocolla, leading to lower recall rates for these categories. The confusion matrix and classification report identified points of confusion and indicated room for growth. The research highlights the benefits of data augmentation and transfer learning for achieving effective classification results despite having a small amount of data. Future worksshould concentrate on increasing the dataset size, integrating more sophisticated neural network designs such as EfficientNet and ResNet, and leveraging domain-specific expertise to enhance feature extraction. Furthermore, more advanced methods like attention mechanisms and ensemble learning are suggested to improve the model's capability in differentiating visually similar minerals. These enhancements are designed to develop a stronger and more dependable tool for identifying minerals.

Keywords: Classification, Deep learning, VGG16, Transfer learning, Data augmentation.

I. INTRODUCTION

Identifying minerals is vital in several sectors such as mining, geology, and environmental sciences. Conventional techniques for mineral identification usually require manual examination using a microscope, which is both time-consuming and susceptible to human mistakes. With the continued growth in data volume in these areas, there is a crucial requirement for improved, effective, and automated mineral classification techniques. Lately, deep learning models, specifically convolutional neural networks (CNNs), have shown great achievements in image classification tasks, which makes them suitable for mineral identification applications.

The application of deep learning in geosciences has been around for a while. Scientists have utilized deep learning for various geological tasks, like analyzing seismic data, which has been highly effective in forecasting and understanding intricate underground formations. In the same way, researchers have investigated the use of deep learning in different studies for rock characterization and mineral classification. Alerigi and Li [2] showcased the potential of deep learning models in mineralogical applications by utilizing them to analyze rock properties using newly acquired geo-exploration data.

Asadi [3] emphasized the importance of machine learning for mineral characterization across various scales, from pores to cores, highlighting its significance for geochemical reactivity. Additionally, Chen et al. [4] have shown the effectiveness of using CNNs for classifying rock images by utilizing deep residual networks with transfer learning to enhance accuracy in classification. Transfer learning has been shown to be a crucial method, enabling researchers to utilize pre-trained models like VGG16, which were initially trained on extensive datasets such as ImageNet, for specialized geological tasks [4], [5].

Studies such as Dash et al.'s [5] have shown the increasing significance of deep learning models for mineral identification, exemplified by their development of Mineral Visio, a system for mineral identification based on deep learning. These systems have demonstrated that deep learning can greatly enhance the effectiveness and precision of mineral classification when compared to conventional techniques. Data augmentation methods have improved the performance of deep learning models by introducing variations in the training data, aiding in better generalization of the models. Gracia Moisés and colleagues [6] examined these methods and their significance in improving the effectiveness of machine learning models for different uses, such as mineral categorization.Deep learning has also been used to investigate mineral distributions within rock samples. For instance, in their study, He et al. [7] utilized a Res-VGG-UNet model to identify fractures and minerals in rock samples, demonstrating the efficacy of deep learning in analyzing geological features. He et al. [8] employed comparable methods for smart mineral identification through deep learning-powered target detection.In spite of these progressions, there are still obstacles in correctly identifying visually alike minerals like biotite and chrysocolla with conventional deep learning algorithms. The constraints mainly stem from the lack of labeled datasets, limiting the model's capacity to recognize specific mineral characteristics [9], [10]. Researchers have proposed integrating domain-specific knowledge into deep learning models and exploring advanced architectures like EfficientNet and ResNet to enhance feature extraction and classification performance in order to overcome these restrictions [4], [13].

This study aims to explore the application of a pre-trained VGG16 model for mineral classification using hand specimen images. The study will evaluate the model's performance across seven different mineral classes, with a particular focus on distinguishing between visually similar minerals. Additionally, data augmentation techniques will be employed to improve the model's generalization ability, offering insights into how deep learning can be optimized for mineral identification in real-world geological studies.

II. RELATED WORK

Deep learning has made substantial progress in geological and mineralogical research, providing better techniques for categorizing and examining intricate geological data. Convolutional neural networks (CNNs), especially deep learning models, have shown their capability to improve the precision and effectiveness of tasks like seismic data analysis, rock characterization, and mineral identification.Ağaoğlu et al. [1] examined the application of deep learning in seismic data analysis, highlighting the capability of these models to manage extensive data sets and offer accurate interpretations of seismic events. In a similar way, Alerigi and Li [2] utilized deep learning models to characterize and classify rocks, utilizing recently obtained geo-exploration data in order to forecast rock characteristics. These researches emphasize the increasing significance of deep learning in the fields of geosciences and mineral exploration.Asadi further showcased deep learning's effectiveness in accurately identifying minerals by utilizing machine learning approaches for mineral characterization across various scales, from pore to core level. This method emphasized the importance of geochemical reactivity and also paved the way for the application of deep learning in mineralogical research. Chen et al. [4] demonstrated the effectiveness of transfer learning in enhancing rock image classification by utilizing a deep residual neural network and achieving high accuracy. This shows how beneficial it is to use pre-trained models for geological purposes.

Dash et al. [5] presented Mineral Visio, a mineral identification system based on deep learning that successfully differentiated between different types of minerals. The research shows the increasing significance of deep learning models in automating tasks related to identifying minerals, lessening the reliance on manual work, and enhancing the speed and precision of classification procedures. Data augmentation techniques have been used to improve the performance of the model. Gracia Moisés et al. [6] examined how these methods are used in machine learning, specifically in optical spectroscopy data, emphasizing their capacity to enhance model durability, especially when working with small datasets.

He et al. [7] employed the Res-VGG-UNet model to depict the distribution of fractures and minerals in rock samples, demonstrating the adaptability of deep learning models in dealing with structural geological data. Likewise, He, Zhou, and Zhang [8] applied deep learning for target detection in intelligent mineral identification systems, demonstrating the practicality of these models in real-world geological applications.

In the wider scope of geosciences, Jia and Ye [9] studied the application of deep learning for evaluating earthquake disasters, highlighting different obstacles and possibilities provided by these models. In research on detecting credit card fraud, Kilickaya [10] showed how machine learning methods could be utilized in various areas. Furthermore, Kilickaya [11] offered perspectives on genre categorization through machine learning algorithms, demonstrating the interdisciplinary possibilities of deep learning technologies.

Kim et al. [12] utilized deep learning to map and characterize the orientation of rock discontinuities in three dimensions, which is essential for comprehending geological formations. Liu and colleagues [13] conducted a thorough examination of how deep learning is utilized in mineral exploration, focusing on tasks such as image classification. This study was followed by another research study conducted by the same authors [14], which focused on examining deep learning techniques for mineral production in image segmentation.

Pre-trained models have also been used successfully in various mineral identification tasks. Mahmood et al. [15] applied pre-trained models to classify jujube fruits, which could inform future studies on mineral classification using similar techniques. Mandal et al. [16] conducted an evaluation of ImageNet-trained CNNs for texture-based rock classification, reinforcing the effectiveness of deep learning in geological studies. In a related effort, Mazurek et al. [17] applied deep learning to identify the structure of road materials, demonstrating the flexibility of these techniques across different material classification tasks.

YOLOv4 models have also been explored for mineral identification in thin sections, as demonstrated by Pratama et al. [18]. Similarly, Rao et al. [19] investigated the efficiency of soil classification using neural network models, further expanding the potential applications of deep learning in the field of geology. Ronkin et al. [20] reviewed deep learning approaches to solve rock fragmentation problems, providing insight into the wide-ranging uses of these technologies in geosciences.

In terms of advanced model architectures, Shafapourtehrany et al. [21] employed U-Net, VGG-16, and VGG-19 models, combined with metaheuristic algorithms, to map post-earthquake landslide susceptibility. Tian et al. [22] focused on geological legend recognition using an improved deep learning method with augmented data, utilizing transfer learning strategies to enhance classification performance. Similarly, Wang et al. [23] explored the use of a deep residual shrinkage network for the identification of volcanic rock slices.

Xu and Zhou [24] focused on the identification of ore minerals using artificial intelligence algorithms based on deep learning, contributing to the growing body of research on automating mineralogical analysis. Yalcin et al. [25] developed a novel rock mass discontinuity detection approach using CNNs and multi-view image augmentation, demonstrating the potential of deep learning in complex geological settings. Zeng et al. [26] combined deep learning with Mohs hardness data for mineral identification, showing the potential of integrating domain-specific features into machine learning models.

Zhang et al. [27] applied deep learning to thin-section identification of rocks and minerals, further highlighting the usefulness of these techniques for detailed geological analysis. Zhang et al. [28] explored the application of image sensing systems in rock and mineral identification, emphasizing the integration of sensing and information processing technologies. Zhang et al. [29] suggested a method using ensemble machine learning to identify rock-mineral microscopic images, demonstrating the benefits of combining various models to enhance classification accuracy.

Finally, Zhang et al. [30] examined deep learning techniques for lithology classification and identification in remote sensing images, whereas Zhou et al. [31, 32] emphasized the wider implications of big data mining and machine learning in geosciences, underscoring the revolutionary possibilities of artificial intelligence in this sector.

III. MATERIAL AND METHOD

Dataset

The study used a dataset that includes pictures of minerals from seven different classes: biotite, bornite, chrysocolla, malachite, muscovite, pyrite, and quartz. Albert Klu is credited with providing the dataset of 956 images from the Geological Engineering Department at the University of Mines and Technology in Tarkwa, Ghana. The photos were saved in folders categorized by their classes, and they came in different sizes, starting from a minimum of 129 pixels in height and 144 pixels in width up to a maximum of 6016 pixels in both dimensions. The dataset had an average size of around 696 x 806 pixels.

Data Preprocessing

To address the variability in image size and improve the model's generalizability, we applied several transformations to the dataset using the torchvision library. The following transformations were applied:

1. Resizing: All images were resized to a consistent dimension of 224 x 224 pixels.
2. Augmentation: Random rotations up to 30 degrees, vertical and horizontal flips with a 50% probability, were applied to increase the diversity of the dataset.
3. Normalization: Each image was normalized to have a mean of [0.485, 0.456, 0.406] and a standard deviation of [0.229, 0.224, 0.225], similar to the preprocessing typically applied for models trained on ImageNet.

Data Splitting

The dataset was split into training, validation, and test sets to ensure robust model evaluation. We used the train_test_split function from sklearn to create these splits:
Training set: 90% of the data (861 images) was used for training the model.
Validation set: 5% of the data (48 images) was reserved for validation during the training process.
Test set: The remaining 5% of the data (47 images) was set aside for testing.
The splits were stratified to ensure that the class distribution remained consistent across the training, validation, and test sets. For data loading, the torch.utils.data.SubsetRandomSampler was used to sample indices from each set and fed into the PyTorchDataLoader for batch processing.

Model Architecture

A custom Convolutional Neural Network (CNN) was designed for the task. The architecture consisted of four convolutional layers, each followed by a ReLU activation function and max-pooling:
Layer 1: 48 filters of size 11x11 with stride 3.
Layer 2: 128 filters of size 5x5 with stride 1.

Layer 3: 128 filters of size 4x4 with stride 1.
Layer 4: 64 filters of size 3x3 with stride 1.

The output from the final convolutional layer was flattened and passed through two fully connected layers, followed by a softmax output layer that classified the image into one of the seven mineral categories. Dropout with a rate of 0.3 was used to minimize overfitting during training.

Training and Optimization

The model was trained using the NLLLoss function, and the model weights were updated using the Adam optimizer with a learning rate of 0.0001. The model was trained for 40 epochs with a batch size of 128. The training occurred using a GPU.

Evaluation Metrics

The model's performance was assessed using accuracy, confusion matrix, and classification report, offering information on precision, recall, and F1 score for every class. Monitoring overfitting and convergence was done by recording the training and validation losses, and accuracy metrics after each epoch.

Pre-trained Model

Additionally, a VGG16 pre-trained model was employed for comparison. The pre-trained model's classifier layer was modified to accommodate the seven classes. All convolutional layers of the VGG16 model were frozen to prevent their weights from being updated during training, while only the classifier layer was trained on our mineral dataset. The same training procedure and evaluation metrics were applied to this model.

To enhance model performance and take advantage of pre-trained features, we employed the VGG16 architecture from the torch vision library. VGG16, a widely used convolutional neural network model trained on the ImageNet dataset, was fine-tuned to adapt to our seven-class mineral classification task.

Model Preparation

Loading Pre-trained Model: We used a pre-trained VGG16 model, ensuring the reuse of its convolutional layers, which had been trained on a vast dataset (ImageNet). These layers extract low- and high-level features from the mineral images, providing a solid foundation for our specific classification task.

Freezing Convolutional Layers: The parameters of the convolutional layers were frozen, meaning they would not be updated during backpropagation. This approach allows us to leverage the pre-trained feature extraction while focusing on training only the classifier layers to recognize the mineral classes.

Classifier Redesign: The final classifier layers of the VGG16 model were replaced with a custom-designed classifier to fit our seven-class mineral classification task. The new classifier included:

A fully connected layer with 4096 units, followed by ReLU activation and dropout (50%) to prevent overfitting.

Another fully connected layer reducing the features to 1000 units, followed by ReLU and dropout.

A final layer with 7 units corresponding to the number of mineral classes, followed by a LogSoftmax function to compute probabilities.

Model Deployment: The model was transferred to the GPU (if available) for accelerated training and computation.

Training Procedure

The model was trained using the same training, validation, and testing sets as described earlier.

Loss Function: The Negative Log Likelihood Loss (NLLLoss) was used as the loss function.

Optimizer: The Adam optimizer, with a learning rate of 0.0001, was employed for updating the classifier parameters.

Epochs: The model was trained for 40 epochs.

The training process involved calculating the training and validation loss, as well as the accuracy after each epoch to monitor the model's progress.

Model Performance

The VGG16 model exhibited significant improvements over time, with both training and validation accuracy increasing steadily across epochs. Notable metrics include:

Train Accuracy: Reached up to 89.2% by the end of the 11th epoch.

Test Accuracy: Peaked at 83.3% after 10 epochs.

Test Loss: Decreased significantly from an initial value of 1.463 to 0.611.

The model's accuracy and loss curves were plotted to visually assess the learning process, and the model was saved for future use.

Prediction and Evaluation

The trained VGG16 model was used to predict the labels of unseen test images. The following steps outline the prediction process:

Model Evaluation Mode: The model was switched to evaluation mode, disabling dropout and other training-specific settings to ensure accurate predictions.

Label Prediction: For each batch of test images, the model generated predictions by passing the input through the network. The probabilities for each class were computed using torch.exp(out), and the highest probability class was selected as the predicted label.

Storing Predictions: The predicted labels were stored and compared with the true labels for subsequent evaluation.

Model Performance on Test Set

The VGG16 model was loaded in inference mode, and its performance was evaluated using the test set. The predicted labels and true labels were then used to compute the model's accuracy and other classification metrics.

Confusion Matrix and Classification Report

The confusion matrix and classification report provided a detailed evaluation of the model's performance across the seven mineral classes. The report included metrics such as precision, recall, and F1-score for each class.

Confusion Matrix: A heatmap of the confusion matrix was plotted, showing the number of correct and incorrect predictions for each class. Diagonal elements represented correct predictions, while off-diagonal elements indicated misclassifications.

Classification Report: The classification report provided precision, recall, and F1-score values for each class.

IV. RESULTS AND DISCUSSION

Model Performance on Training and Validation Data

The VGG16 model was trained over the course of 40 epochs, during which both training and validation accuracy showed steady improvement. At the end of the first epoch, the model demonstrated moderate performance, with a training accuracy of 33.7% and a validation accuracy of 45.8%. As training progressed, the model's ability to generalize improved significantly, with training accuracy reaching 88% by the 10th epoch and validation accuracy peaking at 83.3%. This consistent improvement suggests that the model was effectively learning the features of the mineral classes and generalizing well to unseen data. The training and validation loss, as well as the accuracy, were plotted to provide a visual representation of the model's learning curve, as shown in Fig. 1 and Fig. 2, respectively.

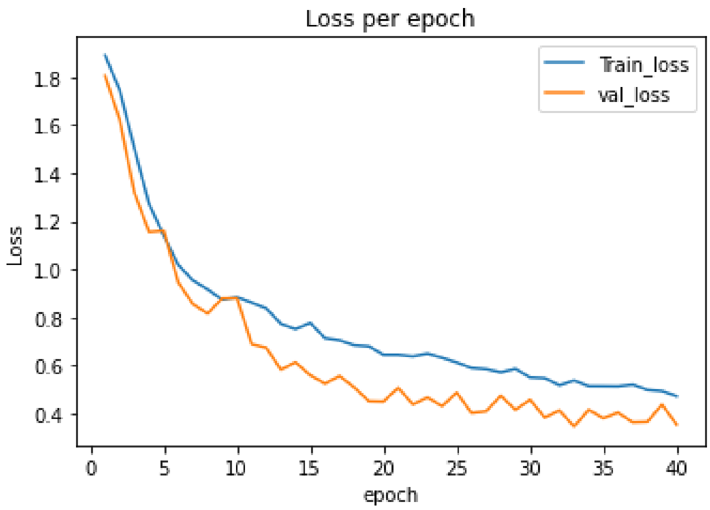

Fig.1: Loss per epoch plot

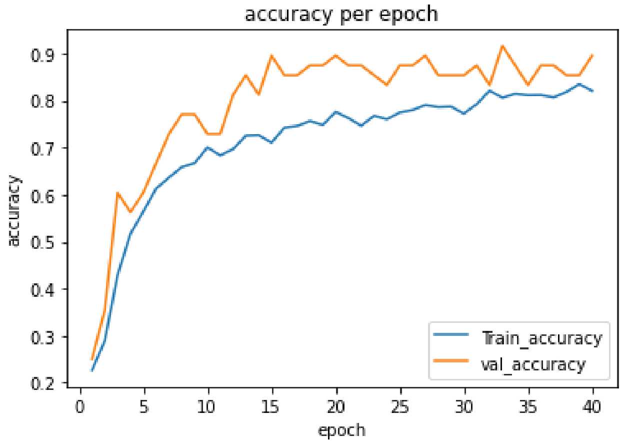

Fig.2: Accuracy per epoch plot

Test Set Evaluation

The final model was evaluated on the test set, which consisted of 46 images representing the seven mineral classes. The overall accuracy on the test set was 83%, confirming that the model had learned to generalize well. The classification report revealed a balanced performance across most mineral classes, with some minor variations:

Biotite: The model struggled with biotite, achieving a precision of 1.00 but a recall of only 0.33. This suggests that while the model correctly classified the biotite instances it identified, it failed to identify most of the biotite examples in the dataset.

Bornite: The model performed exceptionally well for bornite, achieving a perfect recall of 1.00 and a high F1-score of 0.94, indicating the model's ability to consistently identify bornite samples.

Chrysocolla and Malachite: These minerals had slightly lower precision and recall values, with F1-scores of 0.67 and 0.83, respectively. While the model was generally effective at distinguishing these minerals, occasional misclassifications occurred.

Muscovite and Pyrite: The model achieved near-perfect precision and recall for muscovite and pyrite, with F1-scores of 0.89 and 0.86, indicating robust performance on these minerals.

Quartz: Similar to pyrite, quartz achieved strong scores, with a recall and precision of 0.86.

Confusion Matrix

The confusion matrix is shown in Fig.3.

The confusion matrix highlighted areas of confusion between certain minerals, particularly between chrysocolla and biotite. This misclassification can be attributed to visual similarities between these minerals in hand specimen form, as both exhibit similar color and texture under certain lighting conditions. Despite this, the model managed to minimize these errors and demonstrated strong overall performance.

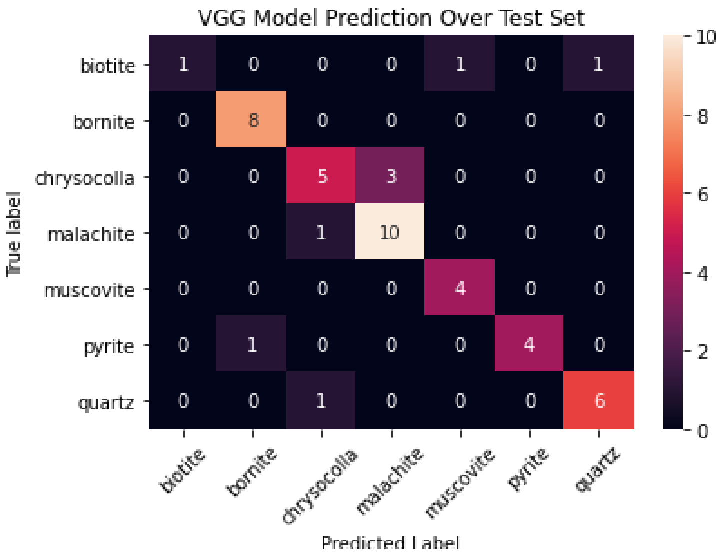

Fig.3. Confusion Matrix

Plot prediction is shown in Fig.4. The VGG16 model's predictions on the test set were visualized using a confusion matrix and a classification report to assess its performance across the seven mineral classes. The confusion matrix, represented as a heatmap, provided a clear overview of the model's accuracy in predicting each mineral class and highlighted areas where misclassifications occurred.

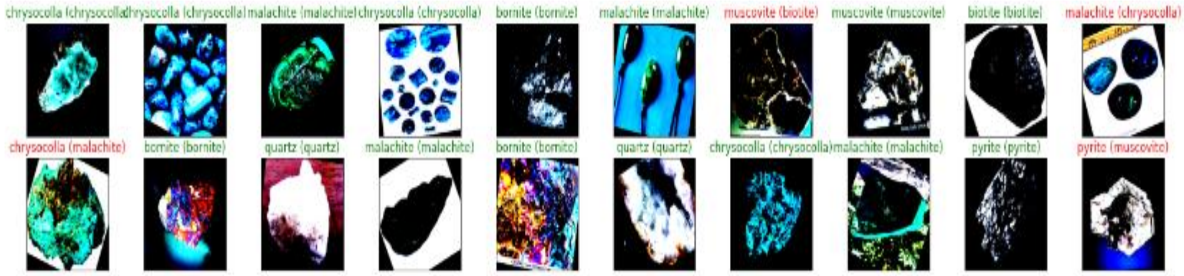

Fig.4: Plot Prediction

The plot showed that the model performed well in identifying most minerals, particularly bornite, muscovite, and pyrite, with high precision and recall. However, misclassifications were evident between visually similar minerals like biotite and chrysocolla, where the model sometimes struggled to differentiate between the two. The overall trend in the confusion matrix reflected the model’s ability to generalize well, though further refinements could help improve accuracy in challenging cases. This visual representation of prediction performance reinforced the quantitative metrics and provided insight into specific areas where the model could be enhanced.

Discussion

1. **Impact of Pre-trained Model**

   The use of a pre-trained VGG16 model significantly enhanced the model's ability to extract high-level features from the mineral images, especially given the relatively small size of the dataset (956 images). The frozen convolutional layers of VGG16, which had been pre-trained on a much larger dataset (ImageNet), provided an effective feature extraction process, allowing the network to focus on learning the unique characteristics of the minerals during the training of the classifier layers. This transfer learning approach proved to be beneficial, as evidenced by the high accuracy achieved on the test set.

2. **Class-wise Performance**

   While the overall performance was strong, the class-wise results revealed some challenges. Specifically, the model struggled with biotite, achieving a low recall of 0.33. This might be due to the visual ambiguity between biotite and other minerals in the dataset. The mineral classes with distinctive visual features, such as bornite and muscovite, had higher recall and precision values, reflecting the model's ability to easily distinguish between these classes.

The lower performance for certain classes like biotite and chrysocolla can be addressed through further data augmentation and by gathering more representative samples of these classes. Additionally, advanced techniques such as attention mechanisms could be integrated into the model to help the network focus on the unique characteristics of each mineral class.

V. CONCLUSION

This research proved that utilizing a pre-trained VGG16 model is successful in categorizing minerals from hand specimen images, with an overall accuracy of 83%. Utilizing transfer learning demonstrated great advantages by enabling the model to utilize strong feature extraction skills acquired from a larger dataset (ImageNet). Consequently, the model excelled at recognizing minerals like bornite and muscovite that have distinct visual features, making them easier to differentiate because of their unique traits. Utilizing data augmentation methods also enhanced the model's ability to generalize, enabling it to uphold strong performance even with the dataset being quite small. Using random rotations, flips, and normalization improved the model's exposure to different angles and lighting situations, ultimately boosting its capacity to categorize minerals in varied conditions.

Nevertheless, the research also pointed out certain difficulties, especially in differentiating between visually alike minerals like biotite and chrysocolla. The resemblance in looks resulted in decreased recall scores for specific groups, showing that the model struggled to consistently identify these minerals. This restriction highlights the necessity of obtaining more data or utilizing extra preprocessing methods to enhance classification accuracy in cases that are unclear.

In general, the results show the promise of deep learning methods, especially pre-trained models, for identifying minerals. This study demonstrates how deep learning can provide a more precise and effective option for field geologists and mineralogists by addressing the drawbacks of conventional methods. Future works should prioritize increasing the dataset size and integrating more advanced models to improve performance and tackle current obstacles.

VI. FUTURE WORKS

Future works should concentrate on overcoming the constraints identified in this study, specifically the somewhat limited dataset size. Adding a greater variety of samples from each mineral class to the dataset is expected to enhance the model's capability in dealing with intricate and visually alike cases like biotite and chrysocolla, which posed difficulties for the existing model. Expanding the dataset may also offer the model a wider variety of samples to enhance its ability to generalize across various mineral types and conditions.

Furthermore, collecting extra data from diverse geographic areas or different geological settings could aid in capturing the natural variability in mineral appearance, thus enhancing the model's utility in real-world scenarios.Furthermore, improving the dataset and exploring advanced neural network designs like EfficientNet and ResNet could boost the model's effectiveness. These designs have proven to offer excellent feature extraction abilities, especially in tasks that require detecting minor visual distinctions, which could be very beneficial for this specific use.

Additionally, integrating expertise from geological professionals in a specific field could assist in honing the model's emphasis on important attributes like crystal structure, reflectivity, and texture, which are challenging for a machine learning model to grasp without specialized knowledge. Finally, it is recommended that future research investigates the implementation of attention mechanisms, which can guide the model's attention to the most important areas of the image, aiding in distinguishing between visually similar minerals. Additional advanced methods, like ensemble learning or self-supervised learning, could be utilized to enhance classification accuracy and generalization. These methods would improve the model's capacity to accurately detect minerals in different real-life scenarios, making it a more dependable tool for mineral categorization.

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