# A Comprehensive System for Mineral Classification Using Advanced Feature Extraction Techniques and Convolutional Neural Networks


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*Abstract - The present project deals with mineral manual classification incorporating essential visual features like texture. The key approach for image classification was the new object-aware cropping technique that enhances texture delineation details. Subsequently, the preprocessing step of texture extraction adopted brightness and colour variation analysis in highlighting texture boundaries mainly. These significantly improved feature representations for the subsequent training phase. Two different deep learning models were used and each of them presented a different way of weight initialization techniques in combination with an advanced regularization strategy that prevents overfitting. In terms of accuracy, the model performed superbly, with minerals having bright colours that were well delineated and minerals having colour profiles similar to each other, up to 100% accuracy. The inclusion of techniques in extracting texture is quintessential to raising the performance of both training and validation performance, especially for minerals with overlapping visual characteristics. Fine-tuned hyperparameters, as well as other data augmentation techniques motivated by additional steps, yield further enhancements, generalizing and making mineral classification more robust.*



***Keywords: Deep learning model, Object-aware cropping, Texture Extraction, Regularization***


## I. INTRODUCTION

Minerals are crucial across industries such as construction, electronics, and manufacturing, where accurate classification is essential for ensuring the quality of materials. Traditionally, minerals have been classified based on properties like color, texture, hardness, and luster. However, when minerals of the same color but different textures are involved, traditional classification methods often face difficulties. This is because distinguishing between minerals that look visually similar yet differ in texture at a microscopic level presents a unique challenge. Deep learning, particularly convolutional neural networks (CNNs), has proven to be effective in automating classification tasks by analyzing complex features that are not easily detected by traditional methods. However, despite the strength of CNNs, there are persistent challenges such as failing to emphasize subtle texture variations, the risk of overfitting due to small datasets, suboptimal weight initialization methods, and inadequate contrast enhancement during preprocessing. These factors collectively hinder the model's ability to accurately classify minerals with similar visual characteristics.

To address these challenges, our approach focuses on enhancing texture features during the data preprocessing phase to improve classification accuracy. This involves several key steps. First, we use **object-aware cropping** by employing YOLO-V5 and CLIP object detection models to focus on the relevant areas of the image where texture is most prominent, excluding unnecessary background elements. Next, we apply **Contrast Limited Adaptive Histogram Equalization (CLAHE)** to enhance local contrast and improve the visibility of texture details. Following this, **texture extraction** is performed by converting images to grayscale to simplify brightness analysis. Significant texture points are identified by thresholding brightness variation and are then dilated to emphasize critical texture regions. For color images, we compute relative changes in the RGB channels to capture color-based texture variations, which are combined with brightness variation using a weight factor. These combined features are then used to detect texture boundaries, which are marked on the image by the darkest pixel value.

Additionally, we apply **data augmentation** techniques such as image rotations, flips, and color variations to artificially expand the dataset, making the model more robust to a variety of texture patterns. For **model training**, we employ three different weight initialization methods: starting with no weight initialization (random weights), transfer learning by using pretrained ImageNet weights, and partial fine-tuning where specific layers are adapted to our mineral classification task. To ensure effective model training, we incorporate several key specifications: **early stopping** to prevent overfitting by halting training once validation performance stagnates, a **learning rate scheduler** to dynamically adjust the learning rate based on validation loss, the **Adam optimizer** for efficient gradient-based optimization, and **L2 regularization** to minimize overfitting by penalizing large model weights.

Overall, our method enhances the texture details of mineral images during preprocessing, addresses the limitations of existing techniques, and improves the overall classification accuracy. This not only ensures more precise mineral identification but also benefits industries that rely on accurate material classification by offering a more robust, texture-focused deep learning approach.

## II. LITERATURE REVIEW

The study on the literature brought out in this section is concerned with various CNN models used for the classification of minerals and a few related to different texture extraction techniques. The research paper titled *"An Enhanced Rock Mineral Recognition Method Integrating a Deep Learning Model and Clustering Algorithm"* presents a new rock mineral recognition method which combines the characteristics of a deep learning model and clustering algorithm. It discusses an efficient methodology to classify 12 types of rock minerals with an integration of Inception-v3 deep learning models and K-means clustering algorithms. This model sought to address the limitations of conventional methods for mineral recognition that are tedious and quite dependent on the results of laboratory testing. The texture features, such as brightness or colour variance, were used to retrain the deep learning model with the K-means clustering algorithm attached to construct a colour model from the RGB values of the images. The integrated model that incorporated deep learning and colour clustering outperformed the classical SVM and Random Forest models based on Histogram of Oriented Gradient (HOG) features with a top-1 accuracy of 74.2% and a top-3 accuracy of 99.0%. A total of 4,178 images were fed into the model, and any noise was removed till the mineral occupied 80% of the image. While the model was very accurate indeed, it was very sensitive to lighting and could make errors in images when the texture is unclear or the colour unusual. In conclusion, the automated framework integrates texture and colour features that offer remarkable speed-up in mineral recognition for geological applications.

The paper *"Mineral Identification based on Deep Learning Using Image Luminance Equalization"* presents a deep learning method with YOLOv5 and a novel image enhancement technique HELaplace, integrating histogram equalization and Laplace operator, for diminishing illumination bias in each image. The issue of inconsistent light intensity can undermine the reliability of mineral identification; by using this method, it is possible to conduct accurate mineral identification even if the lighting conditions are poor. The experiments used a dataset containing 50 different popular minerals and achieved an overall accuracy of 95.6%, surpassing competing methods faced with similar lighting situations. Later, the HELaplace-enhanced YOLOv5 was compared with different state-of-art methods; the effect of mineral classification accuracy was indeed remarkable, especially for little-known minerals, including azurite and chalcopyrite. The research concludes that the HELaplace-enhanced CNN and YOLOv5 combined is robust and accurate in the classification of mineral images, reducing the demand for specialist institutions such as laboratories and increasing application to a wide variety of minerals and contexts. The paper *"Minerals Classification using Convolutional Neural Network"* describes a practical method using deep learning to classify a series of mineral classes. Specifically, the VGG16 model was adopted, a deep learning algorithm known for its effectiveness in image classification. Minerals to be classified included biotite, bornite, chrysocolla, malachite, muscovite, pyrite, and quartz. The dataset used was collected from the Department of Geological Engineering, University of Mines and Technology, with the dataset then being pre-processed using augmentation techniques such as resizing, rotation and flipping. The study found that the overall classification accuracy was approximately 81%; the accuracy of each category ranged between 67%, and 100%. Finally, the paper identified that increasing the size and categories of the dataset might ultimately improve the formalization of mineral classification.

The study *"Classifying Minerals using Deep Learning Algorithms"* tests the use of deep learning, specifically Convolutional Neural Networks (CNNs), to classify two types of biotite and quartz minerals. CNNs have proven very effective in image recognition studies so its use is first tested on a mineral classification problem. The data samples have been gathered using the bingimagedownloader API, which amounted to 398, and the images were pre-processed using Google Colab with TensorFlow and Keras libraries. The CNN architecture used three convolutional layers with max-pooling and dropout for avoiding overfitting. Even though the CPU training will be just a fraction of that of a dedicated GPU, an almost perfect model has successfully managed to score 98% in prediction accuracy. Larger, clean data with more computational power would work their perk on the accuracy of classification and speed of processing. Possibly there could be other mineral varieties that could take granular, spectral, or mineral association data. It is believed that deep learning could change the way to detect a mineral by making it less costly, faster, and more accurate. The paper *"A Deep Residual Convolutional Neural Network for Mineral Classification"* investigates deep-learning techniques for mineral classification using hyperspectral images collected from the Cuprite mining area of Nevada. Two novel architectures are introduced, mineral-CNN-LSTM and mineral-ResNet, with 1D CNNs combined with LSTM units, and with residual connections to specifically capture the local and global spectral features in the classification of minerals in 8 bands. These models aim to solve the hyperspectral image classification problem of high-dimensionality, mixed pixels, and noise bands by avoiding all preprocessing procedures, including principal component analysis or data augmentation. mineral-ResNet gives the best overall accuracy (OA) as 92.16% and kappa as 0.89 and outperforms other machine learning algorithms such as SVM and decision trees as well as the existing deep models like VGG-16 and ResNet-50. The study demonstrates that these models are efficient and robust, offering a significant improvement in classification accuracy, training time, and resource efficiency compared to conventional methods.

The work, *"MiNet: A Convolutional Neural Network for Identifying and Categorising Minerals"* presents a deep learning perspective to tackle the challenges faced in the identification of minerals from hand specimen images. Traditional mineral identification has always involved hand/tacit feature extraction; however, this is certainly prone to error, all the more reason that requires expertise. The authors considered MiNet, a convolutional neural network, capable of classifying minerals into the following categories: Biotite, Bornite, Chrysocolla, Malachite, Muscovite, Pyrite, and Quartz. He trained his model on a dataset composed of 954 images, and the model was 90.75% correct. The big benefit of CNNs is that they are learned straight from the image without any manual feature extraction. They are the best candidates for image classification tasks. The architecture employed for the CNN is a DenseNet architecture, which requires a few parameters and reduces the instances of overfitting and problems posed by the vanishing gradient. This very important work brings to attention the fact that a high degree of precision in mineral classification needs to be maintained, as one misclassification can cost a lot of money in exploration activities when such knowledge relates to minerals that call for exploration. The paper "*Mineral Texture Classification Using Deep Convolutional Neural Networks: An Application to Zircons From Porphyry Copper Deposits*" investigates the use of deep learning, specifically convolutional neural networks (CNNs), to classify zircon textures from porphyry copper-related intrusions in Southern Peru. This paper attempts to separate zircons from porphyry Cu deposits and pre-mineralization batholiths by the use of cathodoluminescence (CL) images. Several CNN architectures were tested, and it was found that LeNet-5, AlexNet, and VGG-16 architectures using transfer learning presented the best results. The VGG-16 reached the best precision with 88% and the ROC-AUC-score was 0.96. The CNN models correctly selected the most significant features in zircons: oscillatory zoning, euhedral shape, and mineral inclusions are the defining characteristics of porphyry-related zircons. The work presents the potential of using CNNs to automatize texture classification of zircons that will enhance the accuracy; this is a very important task for mineral exploration and especially for discovering porphyry copper deposits. Interestingly, the study also reveals how transfer learning and data augmentation allow improvements even in a limited dataset. The paper "*Efficient Image Segmentation Based on Deep Learning for Mineral Image Classification*" presents a highly advanced deep learning-based approach toward mineral image segmentation, addressing the major issues such as adhesion, overlap, and irregularity of mineral particles. These traditional methods, like thresholding and region-based segmentation, are found to lack support in such cases and harsh environmental conditions. To overcome the limitations like that, the authors try to propose a system which combines erosion processing with morphological transformation for better performance improvement in segmentation. The total models developed are ten, drawing motivation from the different architectures, one being the architectures related to U-Net, FCN, PSPNet and DeepLab. In the proposed study, here, MobileNet and ResNet have been used as a backbone. In the proposed work, a novel loss function was introduced which combined DICE and Binary Cross-Entropy for significant enhancement in the accuracy of segmentation. The experimental results show that segmentation accuracy can be achieved up to 95.8% when MobileNet is combined with PSPNet or DeepLab, higher than other configurations. So the entire proposed method above, not only solves adhesion and overlap problems but also has better classification capability for segmented mineral images, thereby showing practical application potential in the context of intelligent ore-sorting equipment. In the paper titled *"Advancing Geological Image Segmentation: Deep Learning Approaches for Rock Type Identification and Classification"*, the authors provide a semi-automated methodology to overcome these difficulties and successfully segment rock-type images. Various geological patterns have diverse textures, sizes, and colours that make it difficult to segment and process with traditional image processing. The given dataset consists of 950 images representing 19 different rock types, with each type documented through 50 samples. The source of the two samples was the University of Las Palmas de Gran Canaria and a field expedition to La Isla de La Palma, Spain; this made for excellent diversification in the geological representative parts. The study mainly discusses the preprocessing of these images as well as transfer learning methods using pre-trained deep learning models: ResNet101, DenseNet201, Inception V3, MobileNetV3, and EfficientNet V2. Some of the models have remarkable results, especially accuracies above 99%, which were observed particularly on the pre-processed dataset. DenseNet201 and InceptionV3 performed best with an accuracy of 98.49% on the original dataset whereas mobile net V3 large had the highest precision in K-Fold cross-validation with an accuracy of 99.15%. The paper puts a lot of emphasis on preprocessing as well as fine-tuning to enhance the model for the task of complex geological image segmentation. The paper *"An Integrated Deep Learning Framework for Classification of Mineral Thin Sections and Other Geo-Data, a Tutorial"* uses deep learning to automatically classify mineral classification on a set of about 200 low-resolution thin-section mineral images containing augite, biotite, olivine, and plagioclase. Flipping, rotation, and zooming as well as added Gaussian noise on this data increased its size. The comparison of three types of models is done - FCNN, CNN, and ResNet. ResNet-152 scored the highest with almost perfect accuracy on few iterations, though somewhat indicative of overfitting. The details of the paper *"Marble Classification using Deep Neural Networks"* are exemplified and verified as a typical case with the problem of marble classification. Especially, a marble dataset of 28 classes has been scraped from the internet by pictures fetched from Turkish companies. Data augmentation ensured an equal distribution of classes of marble pictures. The VGG16 architecture provides a natural choice for extracting features from the marble image dataset. Transfer learning has been applied to this architecture and the upper layer has been adjusted to be fine-tuned whereas the first layers have been freezed. This kind of transfer learning makes the best use of the previous work that has been done by these networks and serves the feature extraction for the type of marble. This fine-tuning together with Stochastic gradient Descent (SGD) and Adam, are techniques employed to optimize the extraction of the best feature and discrepancies within the network. The result of this work shows that the fine-tune of VGG16 can gain an accuracy of 97% of the testing set. This percentage can be further optimized through the above optimization methods. With the help of transfer learning, the fully used of VGG recognized a new height of model recognition rate. The paper *"Mineral Rock Classification Using Convolutional Neural Network"* considers a similar use of a deep learning model using Convolutional Neural Networks (CNN) for recognizing the type of mineral rock from various images of rocks and minerals. This classification problem is known as challenging and time-consuming, as the manual classification is traditionally time-consuming and prone to errors. The dataset contains a collection of 951 images of mineral rocks. The dataset consists of 7 different mineral rocks—Biotite, Bornite, Chrysocolla, Malachite, Muscovite, Pyrite, and Quartz. 859 of the data samples are provided for training with 92 for testing. The output of the CNN model is shown to outperform the accuracy of traditional machine learning methods. The model predicted the type of mineral rock with an accuracy of 85% on the testing dataset. Additionally, the study showed that refining the pre-set parameters and pre-processing was an important role in the model training. Image pre-processing including image resizing and augmentation operations such as rotating and zooming the images, revealed to have significantly improved the accuracy during the training process. This study further shows that CNN is an efficient method for image classification. Especially in the field of mineralogy, CNN models can provide a robust and scalable approach to solve the task of classifying minerals and rocks.

## III. METHODOLGY

The dataset has been collected manually from an existing database of mineral images, **Mindat.org**. Mindat provides a vast number of first-class images of minerals, very crucial in generating image-based datasets for classification. The site is driven by the mineral community of mineral experts and enthusiasts, putting forth contributions regularly, making for updated and accurate information, thereby letting one not worry about ensuring accuracy themselves. The dataset contains specimens of minerals from all over the globe, providing diversity in terms of origin and environmental factors affecting the way minerals adopt form. The dataset includes minerals from a wide range of geographic locations, offering diversity in terms of origin and environmental factors affecting mineral appearance. The dataset used in this project includes of 10 classes, each containing 100 images. The method implemented includes enhancing the texture of the dataset during preprocessing.


Fig: Minerals in Different colours


Fig: Minerals in same colour

ENHANCING TEXTURE ON THE DATASET WHILE PREPROCESSING

**A. Data Preprocessing:**

Initially, **Object-Aware Cropping** is performed using **YOLO-V5** and **CLIP** object detection models to accurately identify and isolate the target object, minimizing background noise and preventing object reduction. Object-aware cropping is a technique that allows the clever cropping of images-by concentrating intelligently on attractive objects or regions within the image, rather than running them through a generic or arbitrary crop. The crop is made so that the image retains whatever is most relevant, often getting the key objects (faces, products, etc.) to remain in frame. First, YOLOv5 is used to perform object detection in the image and provide bounding boxes around each object that it has detected. In case of multiple detection objects, the CLIP takes over to assist in ranking and selection of the most relevant one depending on the text description. Once the most relevant object or region is identified, the cropping of that image can be done based on the bounding box or region of interest defined by YOLO5 and further refined by the semantic understanding of CLIP.

**Fig. Original Mineral image, Mineral image after object-aware cropping**

Then, **Luminescence Equalisation** is applied to enhance mineral texture and normalize image brightness, ensuring consistent illumination and improving texture visibility. The most commonly used technique for enhancing image luminance local contrast is **CLAHE** (Contrast Limited Adaptive Histogram Equalization). CLAHE, basically, is a local automatic contrast enhancement algorithm that aims at making the darker areas of the image visible without over-amplifying the noise, which is particularly useful when the image has been captured with low light or low contrast. It is basically a more advanced form of Adaptive Histogram Equalization (AHE), except that here, the contrast is limited to reduce the risk of artifacts and/or over-amplification of contrast in homogeneous areas (like the sky or very dark regions). The algorithm consists of diverging the input into a grid of smaller non-overlapping regions (called tiles or patches), where each region has its histogram calculated, and independently each region undergoes histogram equalization to enhance its contrast. To avoid over-enhancement of noise in uniform regions, a clip limit is applied; this limits the height of the histogram so as to redistribute the excess intra-bin pixels evenly to the neighbouring histogram bins. The clip limit prevents excessive contrast in regions of nearly uniform intensity, resulting in a visually balanced image. For smoothed transitions between the regions after equalizing each region, bilinear interpolation is used; thus, the transition smoothly from one region to another without any perceptible discontinuity.

Finally, **Texture extraction** is performed by analysing the brightness variation and colour-based texture changes. The colour image is first converted to grayscale, simplifying brightness analysis. The brightness variation is calculated by subtracting a smoothed version of the image from the original to highlight intensity changes and the significant texture points are extracted by thresholding brightness variation (`T`). The extracted feature points are dilated to emphasize the texture regions and relative changes between RGB channels are computed to detect colour-based texture changes for colour images. Then, the brightness variation and colour change features are combined with a weight factor (`K`). And finally, texture boundaries are identified where the combined feature exceeds a threshold (`T1`) and the texture boundaries are marked on the image using the darkest pixel value.

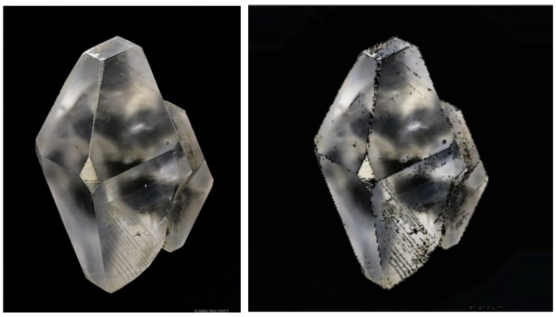

**Fig. Original mineral image before pre-processing, Mineral image after pre-processing**

## B. Data augmentation

It is a technique used to artificially increase the size of a training dataset by applying various transformations to the original data. It is especially useful in machine learning tasks, particularly in image processing, where limited training data can lead to overfitting or poor generalization of models. Four different augmentation techniques have been performed on the collected dataset, namely, flipping, scaling, rotation, and brightness. A random array of values has been defined for each of these techniques, to introduce variability, and the values selected from the array and applied to an image each time a particular class undergoes augmentation. Flipping is a simple transformation where the image is mirrored along an axis. The randomness is introduced by defining the probability of horizontally flipping an image as **0.25**, **0.5**, **0.75** and **1.0**. Scaling involves resizing the image, either by zooming in or out, while maintaining the aspect ratio. The values used include, **1.2**, **1.3**, and **1.5,** effectively changing the size of the object in the image. Rotation rotates the image by a specified angle around its centre, **-90**/90 , -**180/180**. Randomly adjusting brightness helps the model learn how to handle variations in illumination without relying too heavily on a specific lighting condition. The values include, **0.5**, **0.7**, **1.3**, and **1.5**.

**C. Model training:**

Different techniques of **weight initialization** have been tried to make the necessary attempts to avoid the overfitting of the model while training a deep learning model on the dataset. In detail: (a) No Weight Initialization: Here, the weights were randomly initialized by using standard initialization techniques. This is the default behavior in the absence of prior knowledge used for training. It learned purely through the training process the optimal weights. In such an approach, especially when one is working on datasets that are large enough to learn features from scratch, it would be helpful. (b) Transfer learning consists of fine-tuning a model that has been previously trained on a sizable dataset. Here, the pretrained model's weights may serve as the initial weights, thus allowing the model to utilize learned representations that may be beneficial for the target dataset. This sort of method saves time during training quite efficiently and increases performance in most cases, especially when samples are limited or when the target dataset is similar to that used in pre training. (c) Partial Fine-Tuning: In this approach, early layers of a pretrained model are frozen, as they tend to contain generic feature representations, while only the later layers are fine-tuned (task-specific feature representations). Partial fine-tuning is useful if the target dataset is small enough that the model cannot be fully retrained, or when the task is similar to the original task for which the model was trained. In this project, we implement two approaches – Freezing the layers except the last 20 layers, and, freezing layers except the last 40. Partial fine-tuning allows one to reap the benefits of existing knowledge while simultaneously allowing for learning new relevant features.

**Early Stopping** has been implemented to Prevent Overfitting. Early stopping is a training technique for observing model performance with respect to its validation set. Thereafter, training is completed if performance over some epochs does not change. It will prevent the model from learning further and increasing the chances of overfitting on the training data. Interruption at any plateau of training loss or accuracy means that the model generalizes better on out-of-sample data. **Learning rate scheduler** is used to modify the learning rate on the go during the training process. It should facilitate fine-tuning weights similar to what a small learning rate causes regarding the convergence process so that it is not fast. Such basic learning rate schedules may be stepping decay or exponential decay or stop when the validation performance reaches a plateau. Dynamics become dynamic in that the speed of the optimizer is made to converge more quickly to avoid local minima. **Adam optimizer** is an adaptive learning rate optimizer used to combine all good stuff about Momentum and RMSProp: it computes an independent adaptive learning rate for each parameter, at the same time providing estimates of first and second moments of gradients. Efficient on big sized sets of data and big-size models, Adam handles sparse gradients and converges rather much quicker. Though this works well for most cases, in the real world of practice, it is considered the general optimizer. **L2 Regularization**, also known as weight decay, is used to prevent overfitting by penalizing large weights. A regularization term is added to the loss function that throws weight away for larger ones, thereby encouraging the model to learn smaller and, hence, a bit more generalizable sets of weights. These methods make for a very robust training pipeline, which ensures efficient learning with reasonable generalization and the prevention of overfitting.

## IV. RESULTS

The implementation of this method yields the following observations:

(a) **Texture Extraction Greatly Reduces Training and Validation Loss**: Texture-based feature extraction methodologies incorporate greater robustness and discriminating features into any modelled system, and thus perform significantly better. Extraction of texture refines the finer details in an image which helps distinguish between different classes to identify surface patterns, edges, and gradients. Thus, a noticeable drop in training and validation loss depicts the effective learning of the distinguishing characteristics of the dataset by the model and promotes greater convergence speed.


**Fig 6(a): Comparison of Training Loss between With and Without Texture extraction**

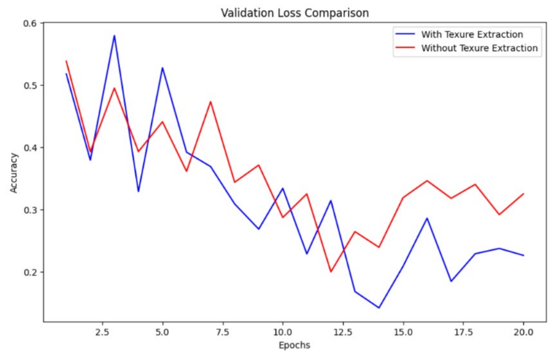


**Fig 6(b): Comparison of Validation Loss between With and Without Texture extraction**

(b) **High Accuracy for Classes with Distinct Colour Features – 100% Accuracy**: The model also does strikingly well for those classes whose colour features are extremely different and easy to differentiate. In those cases, the combination of both the texture and colour information would obtain nearly perfect classification accuracy. Because of a clear visual separation of classes, the model can make predictions without the slightest ambiguity, leading to 100 percent correctness for these classes. This indicates that colour is a very significant feature in the dataset towards the differentiation of some classes.

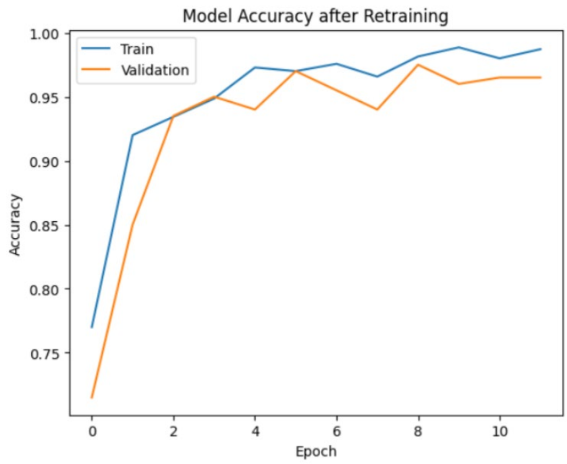


**Fig 7(a): Model Accuracy obtained after Retraining for MobileNetV1**

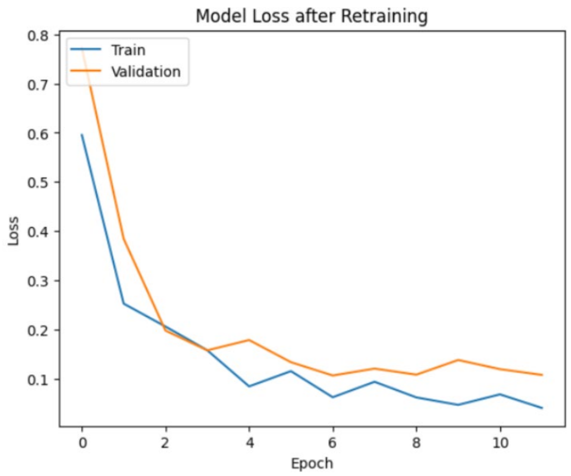


**Fig 7(b): Model Loss obtained after Retraining for MobileNetV1**

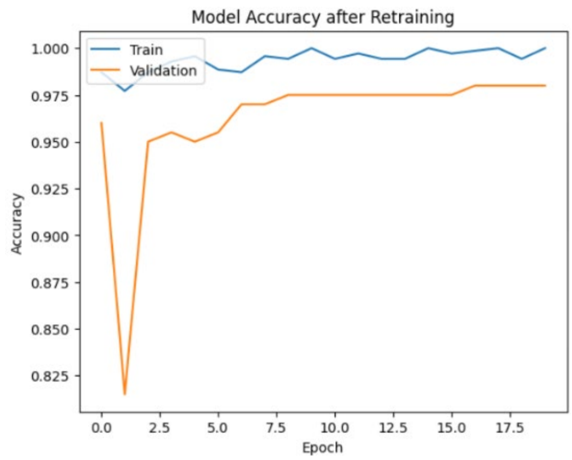


**Fig 7(c): Model Accuracy obtained after Retraining for ResNet50**

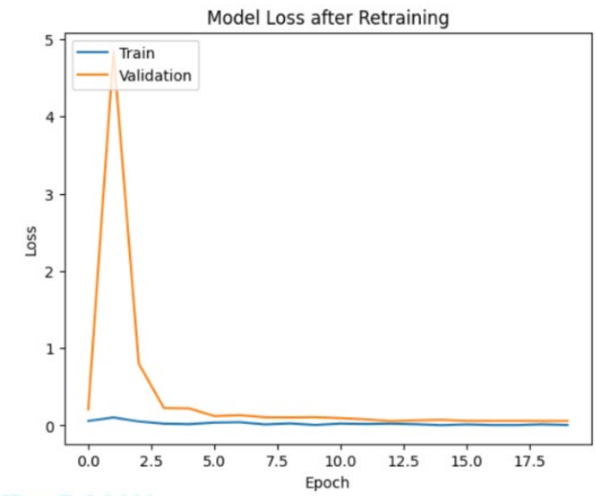


**Fig 7(d): Model Loss obtained after Retraining for ResNet50**

(c) **Low Accuracy for Classes with Similar Colour Features – 75% Accuracy**: Yet various classes of similar colour are less benign to the model than others, so it renders the accuracy to be around 75% for these instances. In such instances, the feature extraction methods may find it difficult to separate classes, as the visual colour similarity may cause these classes to interfere with the model. The consequent drop in accuracy confirms how difficult it is to use texture when the colour patterns take on an overlapping state between the classes. It emphasizes that either a redefinition of the features or integration of additional techniques is required for the model to better separate these-related challenging classes.

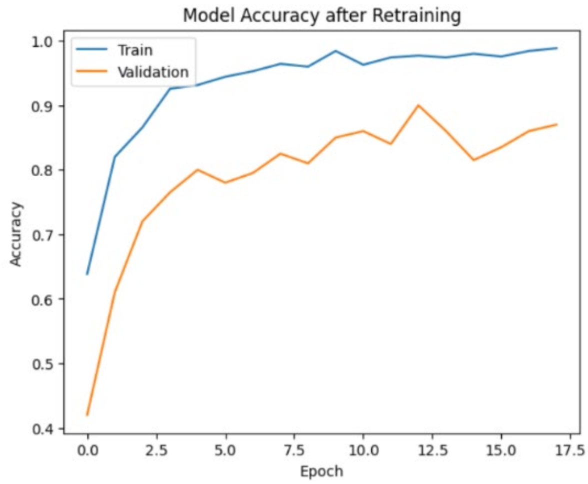


**Fig 8(a): Model Accuracy obtained after Retraining for MobileNetV1**

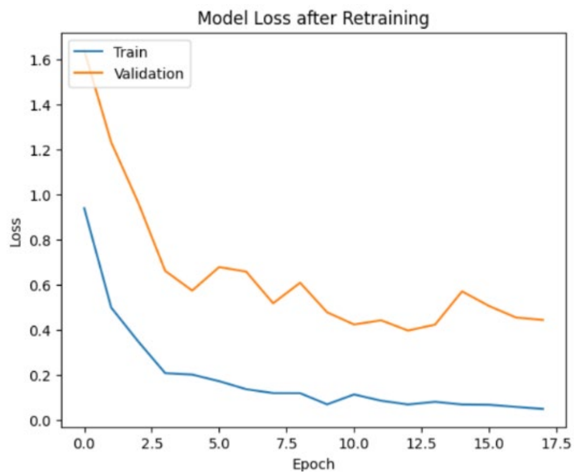


**Fig 8(b): Model Loss obtained after Retraining for MobileNetV1**

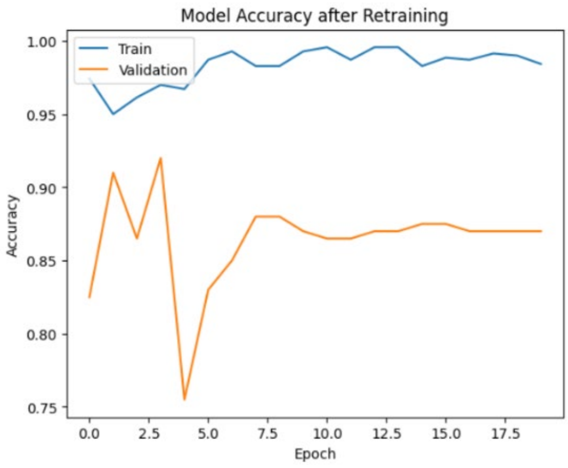


**Fig 8(c): Model Accuracy obtained after Retraining for ResNet50**

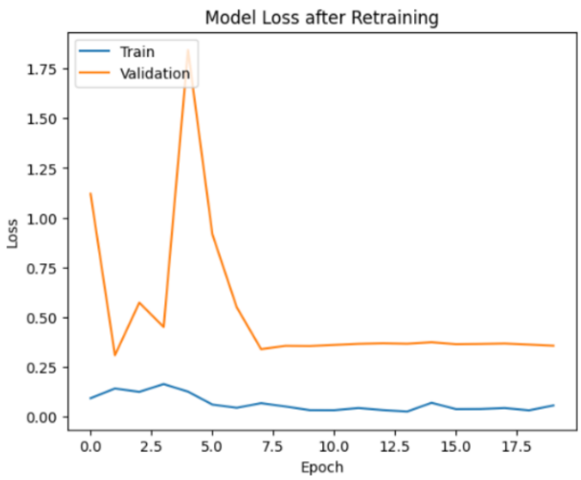


**Fig 8(d): Model Loss obtained after Retraining for ResNet50**

| | Mineral Colour | Training accuracy | Training loss | Validation accuracy | Validation loss | Testing accuracy | Testing loss |
|---|---|---|---|---|---|---|---|
| MobilenetV1 | Different | 0.9875 | 0.0369 | 0.9650 | 0.1074 | 1.0 | 0.016 |
| | Same | 0.9824 | 0.0645 | 0.88 | 0.3716 | 0.71 | 1.22 |
| Resnet50 | Different | 0.9952 | 0.0268 | 0.98 | 0.0535 | 1.0 | 0.0127 |
| | Same | 0.9936 | 0.0234 | 0.855 | 0.5828 | 0.75 | 1.512 |

**Fig 9: Comparison of two different models for classes of different and same colours**

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