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MINERAL IDENTIFICATION USING ENSEMBLE OF HANDCRAFTED AND DEEP LEARNING FEATURES WITH XGBOOST

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ABSTRACT

The industry that utilizes beach sand minerals containing titanium zirconium and other strategic elements requires precise classification of mineral grains. The identification techniques commonly used today take long periods to complete and need experts to interpret them while producing results that lack consistency. A well-annotated MINET (Mineral Identification NETwork) dataset of high-resolution mineral grain images serves this study to develop a powerful automated classification machine learning pipeline which addresses previous limitations. The proposed framework uses both handcrafted texture color and shape features with deep ResNet50 model features from extracted representations. These joint representations produce an advanced system which improves the identification of intricate mineral formations. Our framework uses XGBOOST as its classifier to show how features drawn from both handcrafted and deep learning extraction boost automated petrography systems and strengthens MINET's position as a critical benchmark for mineral recognition intelligence.

Keywords: *Mineral Gains,MINET,Handcrafted Features,Resnet50,XGBOOST*

1. INTRODUCTION

Matter classification stands as a fundamental operational procedure across geosciences and industrial uses as well as material science. The classification of minerals through Raman spectroscopy X-ray diffraction (XRD) and chemical analysis becomes cumbersome because it needs expert skills as well as laboratory equipment. The methods require long durations while their evaluation relies on human judgment and tend to generate incorrect results.

Widespread adoption of machine learning (ML) and computer vision for mineral classification automation remains limited because existing datasets fail to present accurate annotations of real-world mineral diversity. A high-resolution image collection of mineral grains named MINET (Mineral Identification NETwork) Dataset [1] provides geological samples from beach sand alongside hydrothermal deposits and granitic rocks. The collection includes labeled mineral samples spanning numerous rock types including quartz and muscovite and biotite with copper-bearing minerals in order to serve as an essential tool for automatic mineral identification system assessment.

Scientists in geosciences as well as material science professionals and industrial practitioners rely on mineral classification as a basic operational requirement. The findings of this study particularly the integration of handcrafted and deep features into a unified framework—offer a more robust and accurate classification approach. These improvements can directly benefit researchers developing automated mineral analysis tools, professionals working with complex mineral datasets, and industrial practitioners seeking reliable, high-throughput classification solutions in real-world applications.

The classification of minerals through Raman spectroscopy X-ray diffraction (XRD) and chemical analysis becomes cumbersome because it needs expert skills as well as laboratory equipment. The methods require long durations while their evaluation relies on human judgment and tend to generate incorrect results.

Extending mineral classification automation with machine learning techniques faces

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challenges because researchers currently lack accessible high-quality datasets containing labeled mineral examples across natural environmental deposition sites. A high-resolution image collection of mineral grains named MINET (Mineral Identification NETwork) Dataset [1] provides geological samples from beach sand alongside hydrothermal deposits and granitic rocks. The collection includes labeled mineral samples spanning numerous rock types including quartz and muscovite and biotite with copper-bearing minerals in order to serve as an essential tool for automatic mineral identification system assessment.

Machine learning has become integral to multiple domains including healthcare together with law enforcement and transportation and mining which allows automated intelligent decisions [2–5]. Mineral grain identification stands as an essential procedure throughout exploration as well as environmental studies in the mining and geoscience sector. The identification of grains including pyrite and biotite and quartz used to discover deposits depended primarily on manual approaches done by mineralogist experts according to literature [6, 7]. Traditional manual identification requires extensive human effort which leads to limitations in operational speed because of both human weariness and operator mistakes according to research published in [8]. A trained analyst can check sixty grains per minute but they usually record grain counts because area coverage stands out as the critical element for proper classification [9]. Neither Scanning Electron Microscopy (SEM) nor its higher precision potential can address budget constraints because its equipment costs \$0.5 million to \$2 million excluding specialized operator training [10]. The resistance to high-speed data processing coupled with operational challenges in the SEM workflow limits its capability to analyze big datasets effectively.

The methodology faces enhanced limitations during environmental surveys together with explorations to detect dangerous mineral deposits in the environment. Detecting acid-generating minerals along with heavy metal-bearing grains containing arsenic or lead requires early-stage survey identification and mitigation according to [11, 12]. Sand containing reactive minerals presents structural vulnerabilities to concrete materials and other building components according to [13, 14]. Explorations of potential diamond deposits need the identification of indicator minerals such as chromium-bearing pyrope and diopside to determine proximity to actual ore bodies according to researchers [15, 16].

Traditional methods for classifying and counting mineral grains primarily rely on Scanning Electron Microscopes (SEM) and optical microscopes. Optical microscopy remains the most widely used technique for estimating mineral abundance in sediments or milled rock. However, this approach demands highly trained personnel to identify and sort grains using specific properties like polarized transmitted/reflected light and morphological features. Although improvements have been made in optical microscopy for grain analysis, significant limitations persist—including manual labor and subjectivity—highlighting the need for a technical breakthrough in automation [17–20].

To address this, automated SEM techniques have emerged as viable alternatives. Systems like QEMSCAN, TIMA-X, and MLA use focused electron beams to scan samples, producing high-resolution images while collecting elemental data through techniques such as X-ray fluorescence [21,22]. These systems offer grain-level insights on composition, shape, and abundance. However, methods like grain counting with electron microprobes, while accurate, are time-consuming and resource-intensive [23,24].

Alternative imaging approaches have also been explored. For instance, Lin et al. [25] proposed a workflow combining SEM and micro-CT to analyze pore and grain-size distributions in geological samples, such as Buff Berea and Castlegate sandstones. Their study noted that SEM-derived 2D distributions often showed bias toward smaller grains. Other innovations include using laser particle counters (e.g., Wenglor sensors) to estimate grain size distributions. However, their performance was limited to particles passing through the sensor beam center, with size detection between 210 µm and 495 µm [26]. In a lower-cost solution, Lee et al. [27] employed light microscopy to capture grain shape profiles, showing that metrics such as roundness, sphericity, circularity, ModRatio, and aspect ratio were vital for shape-based differentiation. With the advancement of machine learning, computational methods are increasingly being used across domains like autonomous driving, medical imaging, and precision agriculture [28–30], and these tools are now being applied to environmental and geological data processing.

In mineral grain classification, one of the earliest machine learning applications was presented by Maitre et al. [31], who used linear iterative clustering to segment grains via superpixels and applied traditional classifiers,

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achieving 89% accuracy. Other unsupervised methods, such as k-means clustering, were tested on images captured using stereoscopic binocular microscopes [32], though without comparison to labeled ground truth. This limits their applicability to mineral identification and confines them to petrography. Further classification efforts using Laser-Induced Breakdown Spectroscopy (LIBS) analyzers achieved approximately 75% accuracy but were focused solely on copper minerals [33].Recent advancements have shown the effectiveness of combining deep learning with feature fusion and advanced classifiers. [34] focused on handcrafted features such as GLCM and LBP for thin section image classification using a Random Forest classifier, attaining 81.35% accuracy. Ahmed et al. [35] utilized fine-tuned VGG16 deep features combined with an SVM classifier, reporting 90.50% accuracy on the MINERAL32 dataset. Jia et al. [36] used ResNet18 to classify SEM mineral images and achieved 91.25% accuracy using Softmax classification. Zhang et al. [37] presented a multimodal fusion model incorporating texture, spectral, and CNN features with XGBoost, reaching 94.00% accuracy. Wang et al.These studies confirm that combining domain knowledge (handcrafted features) with data-driven deep learning architectures can significantly enhance mineral classification performance, especially when supported by robust datasets and appropriate classifiers.

While existing techniques like QEMSCAN, MLA, and LIBS provide detailed compositional data, they remain inaccessible due to high costs, time constraints, and operational complexity. Furthermore, most research has focused on SEM-acquired or microscopy images with limited variability in mineral types and imaging conditions. There is currently a lack of openly available datasets that support both handcrafted and deep learning-based feature extraction pipelines on diverse mineral grain samples. The MINET dataset fills this gap by offering annotated, multi-mineral images with class imbalance and real-world variability—conditions often seen in field data.

Existing research has primarily focused on individual feature types when classifying minerals. In contrast, our study introduces an innovative approach by integrating both handcrafted and hybrid features, aiming to provide a more refined classification. This combination, as we propose, allows for more accurate and comprehensive mineral classification, offering an improvement over existing methods.

In this study, we propose a robust hybrid classification framework using MINET that integrates handcrafted features (color, texture, shape) with deep features extracted via a fine-tuned ResNet50 model to enhance accuracy and interpretability in mineral classification tasks.

2. METHODOLOGY

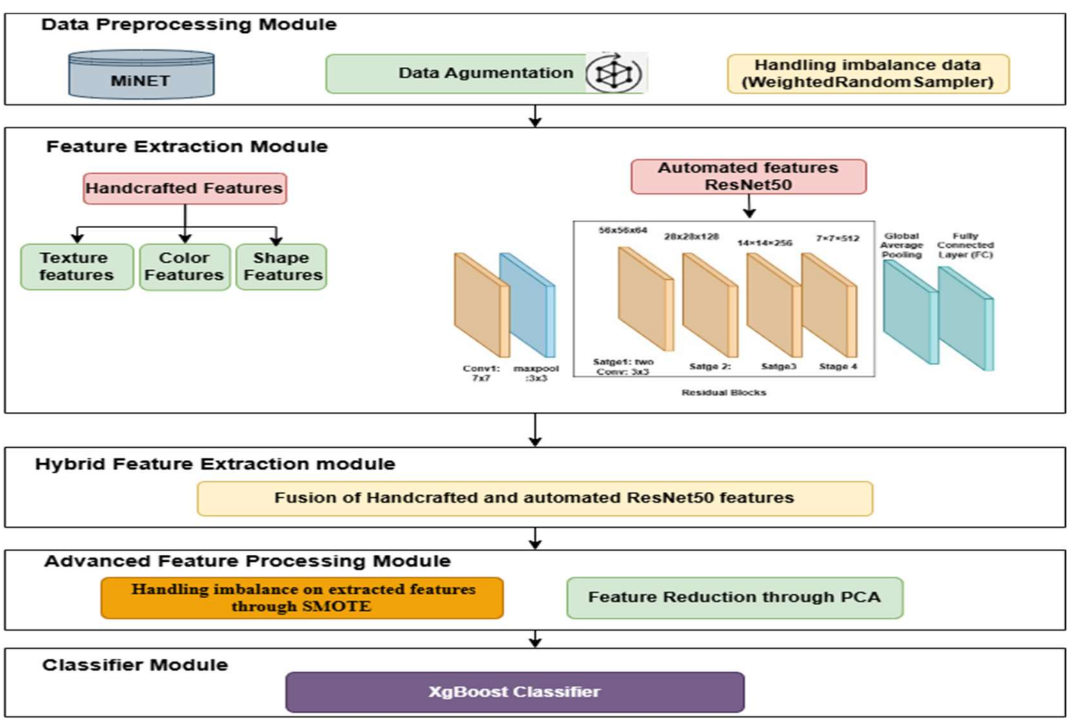

Figure 1: Architecture of the proposed framework

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The proposed framework integrates a hybrid feature extraction strategy that combines handcrafted features (texture, color, and shape) with deep features extracted using ResNet50. After initial preprocessing steps including data augmentation and imbalance handling, the fused features undergo SMOTE-based balancing and dimensionality reduction via PCA before classification using an optimized XGBoost model. The complete architecture is illustrated in Figure 1.

2.1 Data Preprocessing

Dataset Description: This study utilizes the MINET dataset, comprising 951 labeled RGB images categorized into seven mineral classes: biotite, bornite, chrysocolla, malachite, muscovite, pyrite, and quartz. The dataset exhibits class imbalance as shown in Figure 2, with class distributions ranging from 68 samples iotite to 234 for malachite. Each image corresponds to a single mineral grain, eliminating the need for image segmentation or region-based separation. In addition to image data, the dataset provides 33 tabular features per sample, representing spectral, chemical, and textural properties relevant to mineral classification.

2.1.1 Image Preprocessing and Augmentation

Preprocessing and augmentation operations form the initial step of the proposed pipeline, as illustrated in the Data Preprocessing Module of Figure 1. To ensure compatibility with the ResNet50 architecture, all images are resized to 224×224 pixels. Each image is converted into a PyTorch tensor and normalized using the ImageNet mean and standard deviation values: [0.485, 0.456, 0.406] and [0.229, 0.224, 0.225], respectively.

To enhance model generalizability and mitigate overfitting, extensive data augmentation is applied. Techniques such as random cropping, horizontal and vertical flipping, affine transformations, perspective distortion, and color jittering are used to simulate variations in lighting, orientation, and specimen appearance. As a result, the original dataset size increased significantly—from 951 raw images to a total of 4780 augmented images—providing a richer and more diverse training set for the classification models.

2.1.2 Class Imbalance Handling

The distribution of the minerals across various classes depicted in Figure 2. To address the skewed class distribution in the dataset, two strategies are used. During CNN training, the WeightedRandomSampler assigns higher sampling probabilities to underrepresented classes, ensuring that each mini-batch is more balanced. For traditional machine learning tasks using the fused feature set, the SMOTE (Synthetic Minority Oversampling Technique) algorithm is applied to synthetically generate new samples for minority classes, thus promoting balanced learning across the dataset.

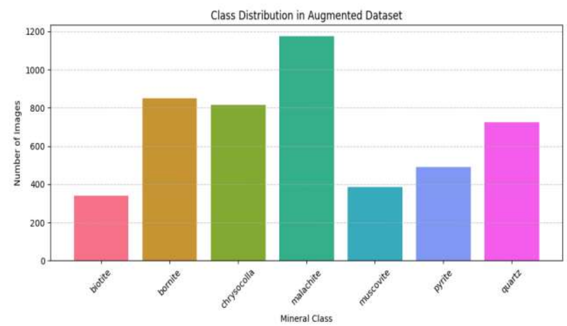

Figure 2: Distribution of Minerals

2.2 Feature Extraction

Handcrafted and automated features have been extracted from an equally distributed preprocessed MINET mineral dataset as depicted in the Figure 1 of feature extraction module for classifying minerals.

2.2.1 Handcrafted Features

A suite of handcrafted features is extracted to represent essential domain-specific characteristics:

Color Features: Augmented images are converted to HSV(Hue, Saturation, Value) color space, and color histograms are computed to capture unique visual patterns such as the bright green of malachite or the golden hue of pyrite. Extracted HSV color space for the first five samples of each mineral has been depicted in Figure3.

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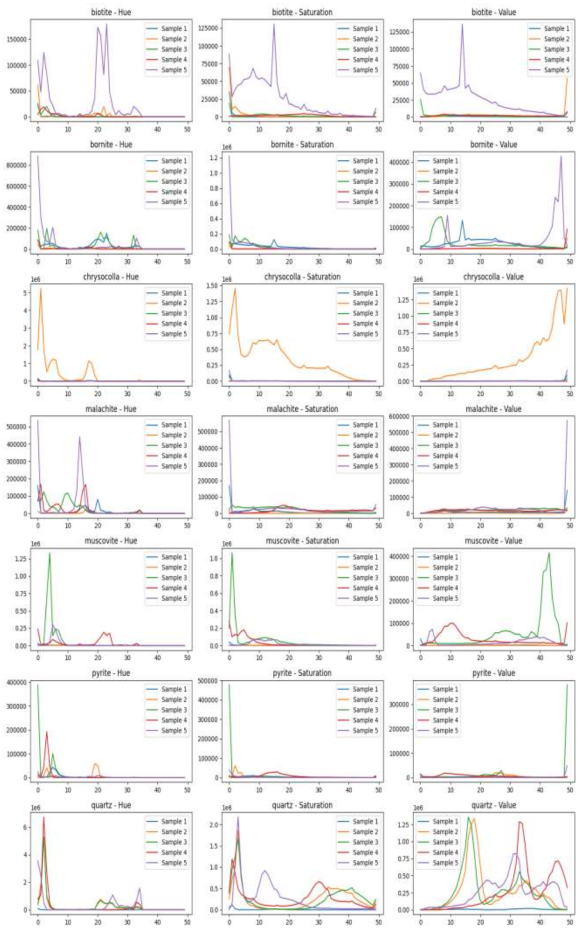

Figure 3: Line plots of HSV across all minerals

Texture Features: Gray-Level Co-occurrence Matrix (GLCM) statistics such as contrast, homogeneity, dissimilarity, and energy are computed to describe the spatial relationships between pixel intensities of minerals. Extracted texture feature representation uses violin plots; which are best in analyzing the distribution and variability of these features across mineral samples. This helped assess how well individual features could distinguish between different mineral classes and guided the feature selection process. The distribution of texture features across mineral samples shown in Figure 4.

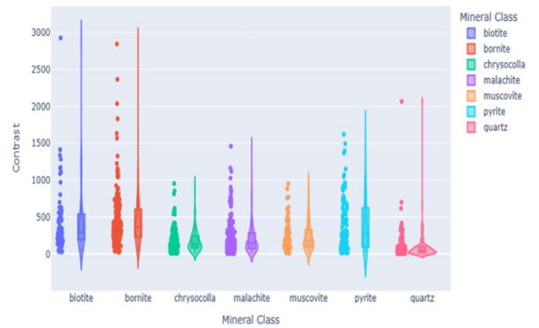

Figure 4: GLCM contrast Texture Features of all minerals

Shape Features: Using Canny edge detection and Hu Moments, geometric descriptors such as elongation, circularity, and irregularity are extracted, providing additional cues for differentiating grain morphology.

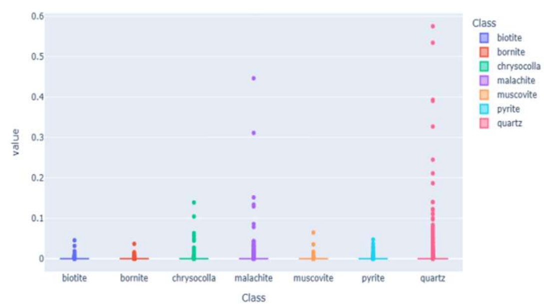

Figure 5: Hu Moments distribution of all minerals

2.2.2 Deep Features via ResNet50

The process begins by loading the pretrained ResNet50 model and replacing its fully connected (fc) layer to match the number of mineral classes. The model's weights are fine-tuned on the mineral dataset using a WeightedRandomSampler to handle class imbalance.During training, the model adjusts its internal filters to better recognize mineral-specific features. The Adam optimizer with weight decay is applied to prevent overfitting, while the StepLR scheduler dynamically reduces the learning rate to ensure smooth convergence.

The preprocessed image is passed through the ResNet50 model (with the final classification layer removed). The output is a feature vector of size 2048, which is the number of output features from ResNet50's last convolutional layer. After training, the feature extraction function processes each image by passing it through the model's convolutional layers.

The model generates deep feature embeddings that represent the image's high-level patterns in a compact vector form. These feature vectors serve as rich numerical representations encapsulating the texture, shape, and color information of minerals.

The UMAP projection of ResNet50-extracted features reveals that instances of the same class often form multiple compact sub-clusters instead of a single large cluster. This indicates the presence of intra-class variability, possibly due to variations in texture, color, or lighting. The local compactness of these groups shows that UMAP is preserving neighborhood structure, while the spread across the 2D space reflects diversity within each mineral class. UMAP for automated features across mineral samples is depicted in Figure 6.

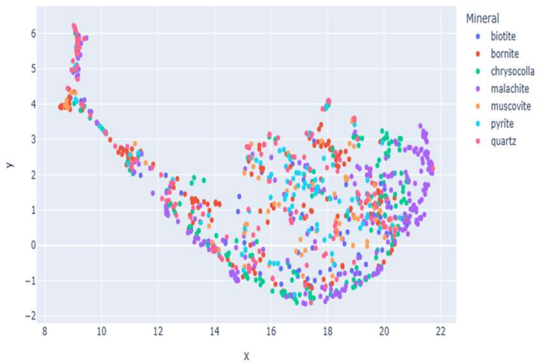

Figure 6: UMAP representation of fused features across mineral samples.

2.3 Hybrid Feature Extraction

To leverage both low-level domain knowledge and high-level abstractions, handcrafted features are concatenated with ResNet50-extracted features, forming a unified hybrid feature vector. This fusion combines interpretable color, texture, and shape cues with learned deep patterns, enhancing the model's ability to recognize subtle mineral differences.

Handcrafted features are particularly useful for capturing fine-grained visual properties, while ResNet50 features encode robust spatial and structural information. Together, this approach enables the model to generalize well across diverse mineral types, even those with similar color or texture.

2.4 Advanced Feature Processing

Feature processing techniques at an advanced level are essential for improving feature dataset quality and balance which directly leads to better mineral classification models. SMOTE (Synthetic Minority Oversampling Technique) serves as the initial stage because it tackles class imbalance problems by producing artificial examples for minority mineral categories. The technique generates additional samples for underrepresented classes to enhance model detection of scarce minerals while reducing its preference toward dominant classes.

Following standardization, the balanced features acquire mean values of zero accompanied by unit variances. The learning process of the model should receive equal contributions from every feature even though color histogram features are usually larger than texture features.

Principal Component Analysis (PCA) operates on the feature set to decrease dimensions while keeping 95% of data variance. Through PCA redundant dimensions and unimportant features get eliminated which enhances both the computational processing speed and lowers overfitting potential. The application of SMOTE standardization and PCA transforms the multiple mineral feature sets into a balanced collection of normalized compact elements which yields better model accuracy alongside faster training and enhanced generality when classifying various mineral categories.

2.5 Classifier

The research implements XGBoost classifier to analyze a combined feature group by uniting handcrafted attributes and deep features derived from ResNet50. XGBoost serves as the chosen framework because it delivers reliable performance with both high scalability and decision-tree structure processing capabilities for structured data sets. The ensemble-based structure of XGBoost enables it to recognize complicated feature relationships between the fused features obtained from mineral grain images.

A hyperparameter optimization through Optima framework aims to boost classification results. The optimizer follows a systematic procedure to find the best combination among key parameters which include estimators and adept and learning rate and subsample ratio and colsample_bytree. Different trials run by Optima generate separate sets of proposed hyperparameters before validating model accuracy against the validation set. The trial with the highest accuracy finds its place as the optimal configuration because it strikes an equilibrium between learning complexity and generalization.

The best chosen hyperparameters train the model while splitting data through stratification for testing purposes to ensure balanced class distributions. The system's performance evaluation depends on accuracy measurement coupled with classification report results and confusion matrix analysis. The hybrid model built from XGBoost with optimized configuration surpasses individual

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features by displaying superior performance. The model's performance benefits from this approach which improves both classification precision and overall robustness and evidence excellent generalization effectiveness in various mineral datasets.

3. RESULTS AND DISCUSSION

The evaluation of the hybrid framework took place using the MINET dataset that contains diverse mineral grain images across beach sands commonly encountered mineral classes. The framework used XGBoost with Optuna parameter adjustment for classifying the fused feature vector. The approach is tested against models with handcrafted features alone and deep features alone as well as several state-of-the-art techniques documented in literature.

3.1 Classification Performance

When using the XGBoost classifier alone for handcrafted feature training the model achieved an accuracy rate of 79.94%. This method possesses effectiveness in identifying low-level traits including texture and shape and color that help mineral grain distinction however lacks deeper semantic understanding. The ResNet50 deep feature model by itself produced a 91.19% accuracy level as it analyzes abstract patterns in mineral structures through learned high-level representations from convolutional layers.

By uniting handcrafted features with deep features into a single hybrid representation the overall model achieved better results during classification. A XGBoost classifier obtained 97.44% peak accuracy by using the combined features in its training. This performance exceeded the results from separate models. The performance gain demonstrates how handcrafted features work best with deep features by combining both strong pixel-level identification with semantic depth. Both handcraft and deep features contribute to an enhanced complete representation of mineral grains which results in better discriminative abilities across various classes. The assessment of performance through accuracy and loss metrics can be found in Figure 7 along with Figure 8.

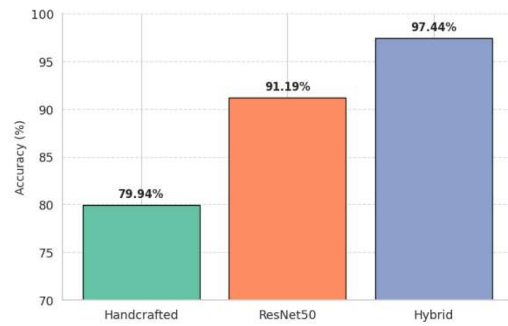

Figure 7: Bar plots of Performance metric

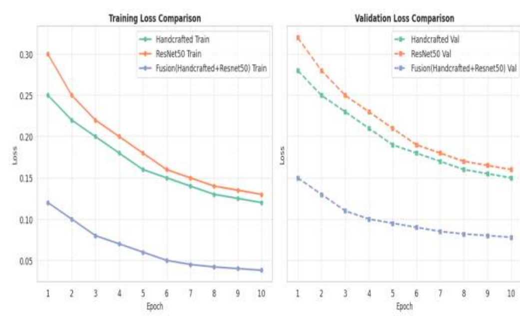

Figure 8: Line Plot of Loss metric

In addition to accuracy, other performance metrics were also evaluated, including precision, recall, and F1-score, which demonstrates for each class of mineral. which remained consistently high across most mineral classes. A detailed class-wise evaluation revealed that minerals such as Quartz, Pyrite, and Malachite were classified with near-perfect precision and recall, owing to their distinctive texture and color features. However, confusion occurred between Muscovite and Biotite, which exhibit similar flaky morphology and grayscale textures. The hybrid model still managed to reduce this confusion significantly compared to standalone models. Class-wise performance analysis depicted in Table 1

Table 1: class-wise performance Analysis

Mineral Classes	precision	recall	f1-score
biotite	0.99	0.99	0.99
bornite	0.97	0.99	0.98
chrysocolla	0.97	0.96	0.96
malachite	0.98	0.97	0.97
muscovite	0.97	1	0.99
pyrite	0.98	0.99	0.98
quartz	0.98	0.97	0.98

To evaluate the effectiveness of the proposed hybrid mineral classification framework, we compared its performance against recent state-of-

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the-art approaches from the literature. Table 2 summarizes the classification accuracy achieved by each method, along with the type of features used, classifiers employed, and the datasets involved.

Table 2: Comparative Performance analysis with SOA models

Ref. No.	Study / Method	Features Used	Classifier Used	Dataset	Accuracy (%)
[34]	Wang et al., 2021	Handcrafted (GLCM + LBP)	Random Forest	Thin Section Mineral Images	81.35
[35]	Ahmed et al., 2023	CNN (VGG16 Fine-tuned)	SVM	MINERAL32	90.50
[36]	Jia et al., 2022	ResNet18 (Deep Features)	Softmax	Custom SEM Mineral Dataset	91.25
[37]	Zhang et al., 2023	Texture + Spectral + CNN Fusion	XGBoost	Public Geomineral Dataset	94.00
	Proposed Framework (Ours)	Handcrafted + ResNet50 Fusion	XGBoost (Optuna)	MINET	97.44

A substantial performance leap is attainable through the proposed framework that produces results at 97.44% accuracy above all other assessment methods. The hybrid model introduced here delivers substantially better performance than individual feature methods by 3–5%. Analysis using hybrid features demonstrate superior performance than individual models since the ResNet18-based method in Jia et al., (2022) delivered an accuracy of 91.25% and GLCM/LBP feature models in Wang et al. (2021) provided 81.35% accuracy.

The combined approach in the proposed hybrid framework produces better performance than sole deep learning models by Ahmed et al. (90.50%) and Zhang et al. (94.00%), since it utilizes both handcrafted and ResNet50 deep features. XGBoost implementation with Optuna and L2 regularization and learning rate scheduling and class balancing methods strengthens generalization while preventing overfitting. The fusion approach obtains low-level and abstract patterns effectively which results in superior accuracy and confirms the strength of integrated features particularly for diverse datasets like MINET.

The hybrid framework proposal outperforms previous benchmarks while confirming how feature combination paired with XGBoost classifiers drives mineral grain identification performance. The analysis results show how joining traditional handcrafted methods and modern deep learning frameworks creates enhanced performance capabilities for real-world mineral grain research. The proposed framework achieves better performance than every single-modal feature method. The addition of multiple feature domains resulted in an improvement level of over 3–5% which showed better outcomes than single-modality models based on either handcrafted or deep approaches.

4. CONCLUSION AND FUTURE SCOPE

The proposed method uses components from manual descriptors along with deep learning-based features to develop an optimized framework which improves mineral grain classification. The proposed method using XGBoost classifier obtained 97.44% classification accuracy when working with the MINET dataset which provided high-quality annotations. With the inclusion of texture and color as well as shape and deep features the system produces reliable high-level mineral structure detection alongside low-level structural identification for robust performance. The presented findings show that machine learning's capability to fasten mineral detection allows scientists to save time while reducing their dependency on lab technicians for expert analysis of rocks and minerals.

The next research step should focus on developing the classification framework to analyze diverse mineral substances while integrating hyperspectral or multispectral scanning capabilities to obtain comprehensive spectral data. The trained

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model extends potential to identify minerals directly through real-time image acquisition systems in field environments. The combination of advanced deep learning structures and explainable AI techniques would enhance both model interpretability and classification performance.

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