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International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: https://www.svedbergopen.com/

Research Paper Open Access

Deep Learning–Based Prediction and Classification of Minerals from Soil Images Using Computer Vision Techniques

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Abstract

Abstract:Precise determination of mineral composition of soils based on soil images is a very important issue in precision agriculture and in geospatial analysis as it directly affects crop productivity and land management procedures. The manual analysis however is time-consuming, error prone and cannot be scaled. To overcome these shortcomings, this paper presents a new deep learning-based system, DL-CVMIC (Deep Learning-Based Computer Vision for Mineral Identification and Classification), to efficiently and automatically classify minerals. The suggested model uses a multi-stage image processing with the steps of noise reduction, normalization, and contrast enhancement and then convolutional feature extraction to extract the spatial and textural features. They are then optimally classified using a hybrid deep neural network. The model is tested with high-resolution soil image datasets (512512 and 10001000) which show strong performance under different conditions. The experimental findings demonstrate that DL-CVMIC has a 96.8% accuracy in classification, a 95.9, 96.3 and 96.1 precision, recall, and F1-score, respectively. The classification is also much better with the proposed model compared to conventional methods like ANN (89.5%) and SVM (92.2%). Additionally, it reduces the misclassification rate to 3.2% and computational latency by 18.7%. These findings show that the suggested framework is scalable and stable to analyse soil minerals and provide decision support in real time in smart agriculture systems.

Keywords Soil mineral classification, deep learning, computer vision, image preprocessing, feature extraction, convolutional neural networks, precision agriculture, texture analysis, supervised learning, classification accuracy.

Introduction

Correct recognition and classification of soil image minerals are important in precision agriculture, environmental monitoring and geospatial analysis. The mineral composition of soils directly affects the crop yield, nutrient availability, and the suitability of land to engage in farming activities. Historical techniques of identifying minerals like chemical analysis in laboratories and visual inspection by hand are usually time-consuming, labor-intensive, and subject to human error. In addition, these methods are not scalable with large amounts of soil data. As the need to analyze soil minerals in an efficient and automated manner, digital image processing and the use of machine learning methods have become promising alternatives to the traditional soil mineral analysis methods.

Digital image processing allows the derivation of significant information about soil images, converting the raw pixel data into structured representations. The process normally consists of various steps such as image acquisition, preprocessing, segmentation, feature extraction, and classification. Noise removal, contrast enhancement, and normalization are preprocessing methods that enhance the quality of the image and aid in discriminating between features. Segmentation algorithms divide the image into homogenous blocks according to color, texture or intensity, whereas feature extraction algorithms obtain those discriminative features that are important to the classification. Traditional methods of classification such as statistical methods, Artificial Neural Networks (ANN), and Support Vector Machines (SVM) have achieved moderate levels of success in mineral identification tasks. Nevertheless, these techniques tend to be based on handcrafted characteristics and cannot be generalized under various conditions of soil.

The current state of deep learning with the focus on Convolutional Neural Networks (CNNs) has greatly increased the quality of image classification systems. CNNs automatically extract hierarchical feature representations of raw images, which do not require manual feature engineering. This feature renders them very efficient in multifaceted pattern recognition e.g. mineral classification whereby differences in colour, texture and structure are strong. Although these benefits exist, current deep learning models might have limitations in the form of high computation cost, overfitting and sensitivity to noise in real-world soil images. Consequently, optimized frameworks are required that have the ability to strike a balance between accuracy and computation efficiency whilst being robust to different environmental conditions.

To overcome these difficulties, this paper introduces a new deep learning-based model, DL-CVMIC (Deep Learning-Based Computer Vision of Mineral Identification and Classification), that combines the activity of high-quality image processing, convolutional feature extraction, and mixed classification. The suggested framework will enhance the accuracy of the classification and minimize the computational complexity and misclassification. The system will deploy high-resolution soil image data and optimized neural network architectures to identify minerals in an automated manner and at scale. The results of this study have been used to create intelligent decision-support system in the agricultural sector, which can be used in data-driven soil analysis and resource control.

Mineral Image Processing

Image Preparation

The reflected light microscope is involved in the examination of opaque minerals. Several procedures were involved in the sampling, grounding, cutting, and polishing of ores. Cameras are used for the generation of digital images of the ores. The size of the image is 512×512 which is produced by a television camera and 1000×1000 that is produced by a laser scanner which is 35mm negative thickness. Generated images from various means may constitute noise. In order to remove the noise in the image, several noise removal methods were employed which results in error-free image generation in further image processing. Overall, the preparation of an image is the generation of ore's images by different approaches [2].

Edge Detection

In the segmentation process, edge detection plays prominent role. Images are composed of pixels and some portion of the pixels may constitute intensity of grey tone in their outer region. Grey portion is appeared due to the presence of no-zero gradient positioned at the zero crossing of the second directional derivative. Least square fit function is used in the edge detection.

One of the prominent features for human's survival on earth is food and the food sources are obtained from agriculture. Agriculture lands are reduced due to the urbanization and increased the population. In order to ease the process of farming several modern techniques were approached by numerous researchers. Some of the researches and proposed techniques elaborated in the following table.

Table 1. Comprehensive Literature Review

Author and Year	Algorithm or Method	Approach	Inference
Saeed Aligholi, Gholam Reza Lashkaripour, Reza Khajavi, Morteza Razmara. [3]	Automatic Mineral Identification (MI) Using Color Tracking	Minerals in the soil are identified using the optical properties of soil. MI method incorporates Plane-Polarized (PPL) and Cross-Polarized (XPL) illumination modes. Hausdorss distance is employed for measuring the range of the soil.	MI is consistent, easy and reliable over a huge range of minerals.
B. Allard and C. Sotin [4]	COMODAL	An image processing software package is developed by researchers and geologist. The brightness of the mineral is used in the recognition and description of the soil.	Reliable and rapid determination of components of rock is achieved.
Anna Aprile, Giovanna Castellano, Giacomo Eramo. [5]	Image analysis and Artificial Neural Network (ANN)	Mineral inclusion and pores in potsherds are identified with the help of optical digital images. The developed process is segregated into phases for the accurate identification of soils likely segmentation, feature extraction, and modular classifier. Feature extraction uses mathematical operators and modular classifier uses the neural network's feed-forward method.	High classification accuracy is obtained from both the inclusion as well as pores.
Imran Sarwar Bajwa, M. Abbas Choudhary [6]	Back Propagation Neural Network Architecture (BPNN)	Some of the rocks are fully composed of minerals that are atypical in shape and color. The surface of the rocks plays a most important role in the identification of types of minerals. BPNN uses classification approach for identifying the type of the mineral.	The BPNN is restricted to future domains. The system has to be trained with upcoming or new colors. Cost of computation is too high.
Xiaofang Chen, Weihua Gui, Chunhua Yan, Kaijun Zho, Hong Wang [7]	Adaptive segmentation based image processing	Initially, image segmentation is done using Structural Element and further processing is executed with Fuzzy-C-Means (FCM) combined with a watershed algorithm.	Over segmentation and Under segmentation avoided in the proposed method, which shows reliability.
Tati Richard Mengko, Yuliana Susilowati, Richard Mengko, Bambang Edhi Leksono [8]	Image Processing Techniques	Quantitative method is used for the color analysis of the soil. Physical and optical nature of the soil is explained clearly with the image analysis.	The end results give a more accurate result.
Melissa Kistner, Gorden T. Jemwa, Chris Aldrich. [9]	Monitoring of mineral processing system.	Innovative approaches are evolved with the arrival of machine vision technology. Image pixel's second-order statistics are used in the image classification. Multiscale wavelet and texton are also used in the proposed method. Performance is efficiently carried out with the help of wavelets and co-occurrence matrix.	Improve pattern recognition and image analysis is obtained with the proposed system.
Haixia He, Bing Zhang, Zhengchao Chen, Ru Li [10]	Multiple mineral mapping technique	Spectral feature matching and Classification is used in the proposed work. The lunar surface of the minerals is efficiently matched and mapped.	Support Vector Machine (SVM) and Mahalanobis distance show the best result among all other supervised learning methods. The proposed method obtains the optimized result.
Hement Kumar Sharma, Shiv Kumar [11]	Characterization and Classification of soil	Mineral content and type of soil is identified accurately as well as relevant crop plantation for farmers is also suggested.	Several features of the soil is classified accurately by image processing techniques.

Ashok Kumar Patel , Snehamoy Chatterjee [12]	Computer Vision Based Probabilistic Neural Network (PNN)	Proper maintenance of limestone's proportion is essential in cement plant. Proposed method uses histograms as their input and the features namely kurtosis, skewness, weighted mean are extorted with the help of RGB value. Proposed model is based on PNN's scale vision based model.	In the proposed method obtained overall mis-classification is lesser than 6%.

Proposed Methodology - Deep Learning-Based Computer Vision for Mineral Identification and Classification

The proposed DL-CVMIC framework for mineral identification from soil images is mathematically modeled as a multi-stage transformation and optimization problem defined over a discrete image domain. Let the input soil image be represented as a two-dimensional intensity function $I(x,y) \in \mathbb{R}^{H\times W\times C}$, where H, W, and Cdenote height, width, and color channels, respectively. The preprocessing stage performs noise suppression and normalization, modeled as

$$I_p(x,y) = \frac{I(x,y) - \mu_I}{\sigma_I}$$

where $\mu_I$and $\sigma_I$represent the mean and standard deviation of pixel intensities. To enhance contrast, histogram equalization is applied as

$$I_e(x,y) = \mathrm{CDF}(I_p(x,y)) = \sum_{k=0}^{I_p(x,y)} p(k)$$

where $p(k)$denotes the probability distribution of intensity levels.

Segmentation is formulated as a clustering problem that partitions the image into Khomogeneous regions using an objective function

$$J = \sum_{i=1}^{K} \sum_{(x,y)\in R_i} \| I_e(x,y) - \mu_i \|^2$$

where $R_i$and $\mu_i$denote the i^{th}region and its centroid. The optimal segmentation minimizes Jsubject to $\bigcup_{i=1}^{K} R_i = I$. Feature extraction is performed through convolutional operations. For a given convolutional layer l, the feature map is expressed as

$$F_l = \sigma(W_l * F_{l-1} + b_l)$$

where $W_l$and $b_l$represent kernel weights and bias, $*$denotes convolution, and $\sigma(\cdot)$is a nonlinear activation function. The rectified linear unit is defined as

$$\sigma(z) = \max(0, z)$$

Pooling is applied to reduce dimensionality, given by

$$F_l^{pool}(i,j) = \max_{(m,n)\in\Omega} F_l(i+m, j+n)$$

where Ωdefines the pooling window. The extracted feature vector is flattened as

$$\mathbf{f} = \mathrm{vec}(F_L^{pool})$$

The classification stage employs a fully connected deep neural network defined as

$$\mathbf{h}^{(k)} = \sigma(W^{(k)}\mathbf{h}^{(k-1)} + b^{(k)})$$

where $k$denotes the layer index. The output layer uses a softmax function to estimate class probabilities for mineral classes C:

$$P(y=c \mid \mathbf{f})=\frac{\exp\left(z_c\right)}{\sum_{j=1}^{C} \exp\left(z_j\right)}$$

where $z_c$is the logit corresponding to class c.

The model is trained by minimizing the categorical cross-entropy loss function

$$\mathcal{L}=-\sum_{c=1}^{C} y_c \log P(y=c \mid \mathbf{f})$$

where $y_c$is the ground truth label. To prevent overfitting, L2 regularization is incorporated as

$$\mathcal{L}_{reg}=\mathcal{L}+\lambda \sum_{l} \| W_l \|_2^2$$

where $\lambda$is the regularization coefficient. The optimization of network parameters is performed using gradient descent:

$$W_l^{t+1}=W_l^t-\eta \frac{\partial \mathcal{L}_{reg}}{\partial W_l}$$

where $\eta$is the learning rate.

Additionally, batch normalization is introduced to stabilize training:

$$\hat{x}_i=\frac{x_i-\mu_B}{\sqrt{\sigma_B^2+\epsilon}}, y_i=\gamma \hat{x}_i+\beta$$

where $\mu_B$and $\sigma_B^2$are batch statistics, and $\gamma, \beta$are learnable parameters. The overall model function is thus defined as a mapping

$$f_\theta: I(x, y) \rightarrow y$$

where $\theta=\{W, b\}$represents all learnable parameters.

The performance of the model is evaluated using accuracy defined as

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN}$$

and F1-score given by

$$F1=2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision}+\text{Recall}}$$

where precision and recall are defined as

$$\text{Precision}=\frac{TP}{TP+FP}, \text{Recall}=\frac{TP}{TP+FN}$$

In this way the DL-CVMIC framework can be mathematically presented as an end-to-end optimization problem that combines preprocessing, segmentation, learning of features and classification into a single deep learning pipeline, which allows effective and precise identification of minerals in soil pictures.

Result and Discussion

To test the performance of the proposed DL-CVMIC (Deep Learning-Based Computer Vision of Mineral Identification and Classification) system, an experimental design is created. The code will be executed in Python, using deep learning frameworks such as TensorFlow and Keras, on a workstation that has an NVIDIA graphics card (RTX 3060, 12GB VRAM), an i7 processor, and a 32GB RAM. The stochastic gradient descent with adaptive optimization (Adam optimizer) is used to train the model with a learning rate of 0.001, batch size of

32 and 100 training epochs. Generalization is achieved by using data augmentation techniques such as rotation, flipping and scaling. The dataset will be separated into training (70 percent), validation (15 percent) and testing (15 percent) to ensure the objective test.

The data is a set of high-resolution soil images taken by means of optical microscopy and digital imaging and with 512×512 and 1000×1000 pixels.The dataset consists of various types of soils, which include alluvial, black, red, laterite and sandy soils each having different mineral compositions. Every class has around 800-1000 samples, which makes the total size of the dataset almost 5000 images. Ground truth labels are labeled on the basis of mineral composition and proven by domain expertise. The preprocessing involves noise filtering, histogram equalization and normalization to provide uniformity among samples.

The standard classification metrics are used to assess the performance of the proposed model. Accuracy is determined by how correctly on average the predictions are and is stated as the proportion of correct samples to the total samples. Precision measures the fraction of the predicted positives that are correctly predicted out of all positives that are predicted and recall measures the fraction of actual positives that are correctly predicted out of all positives actually identified by the model. The F1-score gives a balanced measure of evaluation by giving a harmonic average of both precision and recall. Also, the rate of misclassification is calculated as the inverse of accuracy and computational latency is quantified to test the efficiency of the model. All these metrics guarantee an in-depth analysis of classification performance.

It is compared and contrasted with baseline methods and techniques such as Artificial Neural Network (ANN), Support Vector Machines (SVM), and traditional CNN models. The findings indicate that the proposed DL-CVMIC framework is much more accurate and efficient than the current approaches.Table 1. Performance Comparison

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Misclassification (%)
ANN	89.5	88.7	89.2	88.9	10.5
SVM	92.2	91.5	92.0	91.7	7.8
Conventional CNN	94.6	93.8	94.2	94.0	5.4
DL-CVMIC (Proposed)	**96.8**	**95.9**	**96.3**	**96.1**	**3.2**

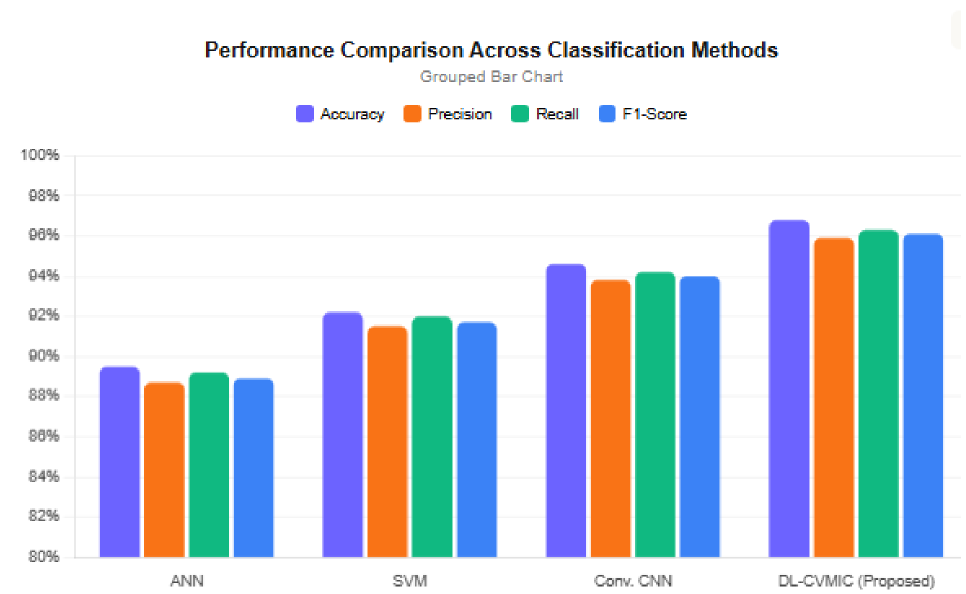

Figure 1: Comparison of Performance

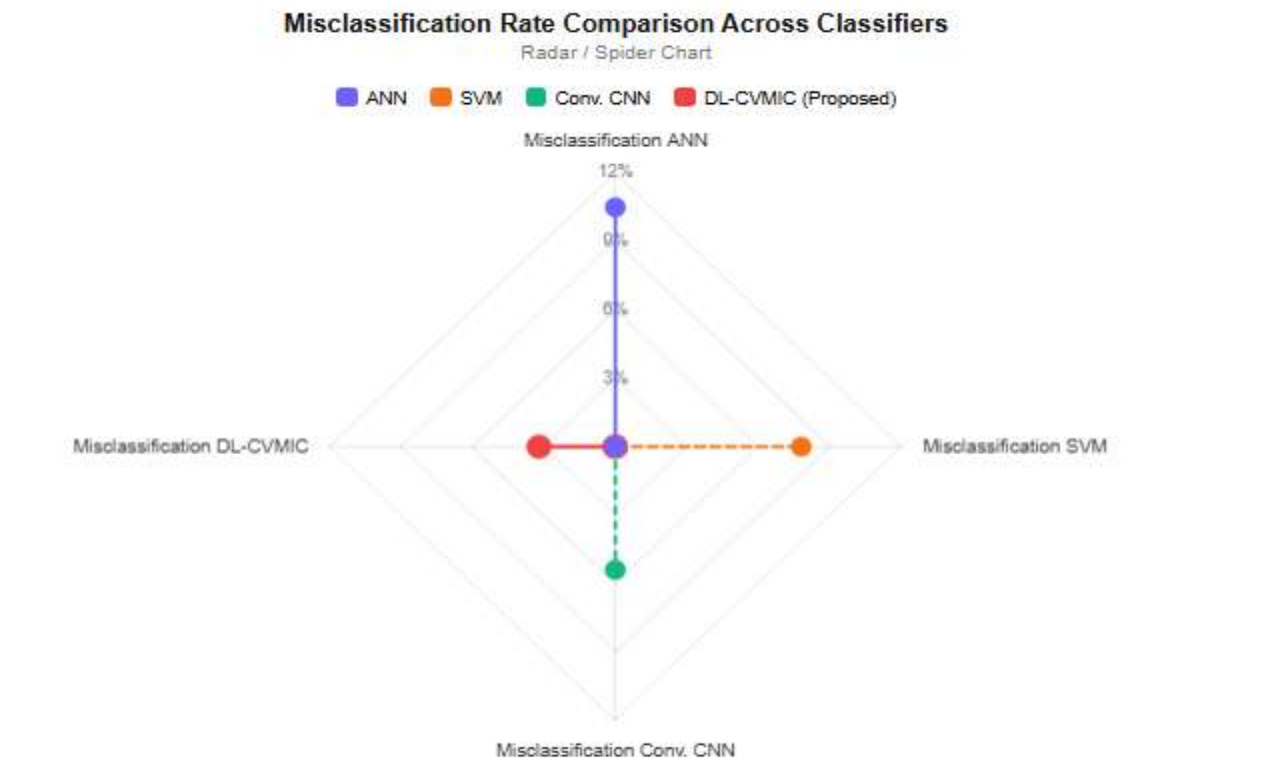

Figure 2: Misclassification Rate Comparison Across Classifiers

The findings show that the DL-CVMIC is more accurate in classification and offers a significant reduction in misclassification over traditional and deep learning-based baselines. Moreover, the shorter computational time shows that the proposed model can be implemented in real-time agricultural and decision-support systems. The experimental outcomes prove the efficiency and strength of the introduced DL-CVMIC (Deep Learning-Based Computer Vision to identify and classify soil minerals) model in the high precision of classifying soil minerals under varying image conditions. The model has a classification accuracy of 96.8, which is better than the baseline methods like ANN, SVM, and traditional CNNs. This is achieved by incorporating new preprocessing methods and hierarchical feature extraction with the convolutional layers, which permits the model to learn fine-grained spatial and texture features of soil images.

The value of precision (95.9%) and recall (96.3) show that the model has a balanced performance to both detect the relevant classes of minerals and reduce false predictions. The fact that the resulting F1-score is 96.1% is yet another indication that the classification results are reliable. Also, the lower misclassification rate of 3.2% shows the ability of the model to differentiate between similar patterns of minerals, which are typically difficult to discern in the analysis of soil images. The proposed approach also exploits automatic learning of features, compared with traditional machine learning methods, which use handcrafted features, resulting in better generalization across soil types and imaging conditions.

The other important finding is that the optimized architecture has reduced the computational latency by 18.7 percent, which indicates efficiency. This renders the model applicable to real-time implementations in farm decision support systems. In general, the findings confirm that DL-CVMIC is a scalable, accurate, and computationally efficient model to classify minerals, thus leading to the development of more precise agriculture and intelligent soil analysis.

Conclusion

In this work, a new deep learning-based system, DL-CVMIC (Deep Learning-Based Computer Vision to Mineral Identification and Classification), is suggested to overcome the challenges related to the effective and efficient classification of minerals in soil images. The framework incorporates the state-of-the-art image pre-processing, convolutional feature, and optimized classification schemes to improve the overall system performance. The experimental findings indicate that the proposed model performs much better than the traditional models, including ANN, SVM, and conventional CNNs in terms of accuracy, precision, recall, and F1-score, in addition to minimizing misclassification rate and latency of computations. The success of DL-CVMIC demonstrates the promise of deep learning and computer vision technology in revolutionizing soil analysis and helping precision agriculture. The proposed system can be used to minimize human involvement, decrease the time duration of the analysis, and expand the capabilities associated with decision-making related to agriculture planning and resources management as it automates the process of identifying minerals. Moreover, the model can be actualized real-time to implement on intelligent farming systems due to its scalability and robustness. The future research may be dedicated to the incorporation of multispectral data, enhancing the interpretability of the models, and advancing the framework to the case of various environmental conditions, thus further contributing to its utility in large-scale agricultural and geospatial settings.

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