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Deepsoilnet: A CNN-Based Framework With Gabor And LBP Feature Fusion For Automated Soil Texture Classification From Field Images

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ABSTRACT
Soil texture plays a pivotal role in determining water retention, nutrient availability, and overall soil health, making its classification essential for precision agriculture and land management. This study introduces a novel deep learning-based framework for automating soil texture classification using image processing techniques combined with Convolutional Neural Networks (CNNs). The proposed system enhances soil texture analysis by integrating Gabor filters and Local Binary Patterns (LBP) for multi-scale texture extraction, followed by CNN-based classification. Soil images are first segmented to isolate relevant regions, then divided into tiles for detailed feature extraction. Comparative analysis shows that Gabor filters outperform LBP in texture enhancement, leading to improved classification performance. The model was trained and validated on a dataset comprising soil samples from varied conditions and achieved 99% accuracy with a low loss of 0.0134, demonstrating its robustness. This hybrid approach significantly advances the automation of soil analysis and presents a scalable solution for agricultural and environmental applications.
Keywords: *Convolutional Neural Network, Gabor Filter, Image Processing, Local Binary pattern, Classification of soil texture, Texture enhancement*

1. INTRODUCTION

Soil texture classification forms a very significant part of soil science insofar as in it the soil characteristics are understood and based on it the decision making in the fields of agriculture and environmental and land use planning occurs. Conventional methods [1],[2] of soil texture classification consume a lot of effort to properly classify and are often subjective, time consuming and prone to errors. However, new development Deep Learning and Image Processing [3] present exciting new possibilities for work automation, accuracy, speed, and objectivity. This article presents a Deep Learning approach to automating soil texture categorization using image processing techniques, including Gabor Filter and Local Binary Patterns (LBP) methods. When it comes to textural analysis, features extraction, and texture characterization, two well-known metrics are the Gabor Filter and LBP. Such methods offer a comprehensive strategy for Deep Learning soil texture categorization. This technique benefits from employing both manually provided and learnt characteristics.

Gabor Filter is an Image Processing method which improves the texture patterns of soil texture pictures by convolutional filters of different frequencies and directions. LBP is a sort of pattern recognition algorithm it codes property of texture with the help of binary codes. The feature extraction is automatic in the case of soil texture classification using Convolutional Neural Networks (CNNs). The use of Gabor Filter and LBP together with Deep Learning offers a multifold approach to addressing a soil texture classification issue, because one may extract significant indicators of texture and relate these indicators to specific types of soil texture. The method is integrated so that it addresses several challenges to the classification of soil texture. To begin with, it reduces the dimensionality of the input data without losing the valuable texture information and this helps in the extraction of meaningful features easily. It also promotes automatic way of learning complex patterns and relations between soil texture properties and the classes and designations they belong to make the categorization more precise.

The theoretical foundation of Gabor Filter, LBP and Deep Learning as well as their application in the classification of soil texture is thoroughly discussed in this work. We provide empirical results demonstrating the effectiveness of the proposed methodology on real soil texture datasets by contrasting it with traditional approaches and stand-alone Deep Learning models. Finally we consider the implications the automated soil texture classification has in agriculture, environmental science, and land management with specific reference to future directions as well as potential applications.

2. LITERATURE REVIEW

The Deep Learning Adaptive Classification with the DLAC-CNN-RF [4] system learns the soil's texture and uses that information to optimize row planting in a farming operation. The model has proved successful due to its easy user interface and that the model makes a forecast of soil type. Further validation, scale-dram and continuous updates are, however, required to make it universal so that it can have applications in different regions and various kinds of soil. The research [5] allows predicting soil moisture based on a single image by machine vision and AI, showing negligible prediction errors and an average absolute one of less than 1.1%, which stimulates the implementation online. [6] was aimed at examining whose effect on Soil Organic Matter (SOM) moisture predicted mobile phone photography color measurements.

The moisture content of the soil that was more than 10% greatly influenced the accuracy used in SOM estimation. The Prediction models based on Linear Regression had a high accuracy of SOM in the samples less than the threshold of moisture also and the models based on Soil Moisture Content (SMC) had a higher accuracy in samples above the moisture threshold also. The article recommends that cell phones can be potential soil sensors of SOM measurement. A study on soil texture classification [7] using Image Processing techniques and RGB histograms found a strong correlation between silt concentration and histogram factors. The study, collected samples from seven Korean paddy soil series and showed 48% agreement in soil categorisation across laboratory and in-situ techniques. However, the findings may not be applicable to other soil types, and the study's limitations include a limited sample size and insufficient account for environmental influences.

The study [8] uses Using hyperspectral data collected by unmanned aerial vehicles (UAVs), researchers in Qinghai, China, can examine soil texture and verify that agricultural land planning on the Tibetan Plateau is sound. However, findings may not apply to other locations due to geographical contexts, potential biases, and costs. The study [9],[10] compared image-based soil characterisation with traditional techniques for assessing soil moisture and organic matter. Twenty-two machine learning and supervised regression algorithms correlated picture characteristics with laboratory data. Texture analysis [11] is crucial for categorising and retrieving images in computer vision. Soil pictures are analysed using Image Preprocessing techniques and feature extraction methods. The proposed methods yield superior categorisation rates for various soil textures. However, the quantitative enhancements, computational complexity, application to different textures and environmental situations, handling of lighting conditions and image quality, and potential influence of noise or artifacts are not adequately investigated.

Data fusion [12] in agriculture faces challenges due to geographical disparities and unmanaged agricultural ecosystems. Despite technological advancements, data and knowledge gaps persist in remote and vast regions. Integrating data from multiple sensor types is being explored for reliable information. However, obstacles hinder its widespread implementation. The essay examines data fusion in agriculture, highlighting achievements, difficulties, and potential areas for future research. Insufficient discourse on specific methodologies or technology is also noted. A new approach [13] using high-resolution ground pictures and Deep Learning techniques improves SOM estimation in Canadian Prairies by 30%, but validation is needed for real-world applications and scalability.

Soil classification [14],[15] is crucial due to increasing food demand and insufficient conventional farming practices. Computer-based techniques like Image Processing and Deep Learning are revolutionising soil classification. CNN offer effective techniques, but limited implementation in practical farming is due to technology accessibility and expense. Databases and evaluation criteria are needed for future studies. Challenges include adapting laboratory-based systems for on-field applications, maintaining databases, and establishing uniform evaluation criteria.

The study [16] used high-throughput sequencing to analyse soil texture and microbial distribution, finding a stronger link between fungus diversity and soil texture. Different microbial species were linked to different soil components, emphasising the influence of soil texture on microbial communities. However, the study's methodology, limited sample size, and focus on bermudagrass environments may limit its generalizability to other ecosystems and overlook potential factors influencing soil microbial community composition. The agricultural sector [17] faces challenges due to population growth and limited arable land. Image processing in MATLAB helps identify soil texture and pH values, improving productivity and precision, but effectiveness may vary. Bangladesh's agriculture sector [18] faces challenges in determining arable land due to population growth. A novel algorithm combines Q-HOG, - Pixels and new feature choices for soil type identification. Four machine learning methods assessed performance, showing superior accuracy compared to current image-based systems. However, the exact increase in accuracy is not quantified. The study lacks discussion on scalability and applicability to different soil and environmental conditions, as well as potential constraints of image-based soil categorisation.

Deep-learning algorithms [19] have revolutionised soil classification in agriculture, environmental management, and civil engineering. They efficiently categorise soil types and predict soil characteristics, saving time and improving accuracy. However, data scarcity and errors in model development can hinder the accuracy of soil categorisation. This extensive review aims to help soil science researchers develop more efficient approaches. The review additionally does not provide a detailed analysis of specific case examples that may impede the practical knowledge about the applicability of Deep Learning models implementation in practical soil categorisation cases. A soil classification [20] scheme based on a Modified Support Vector Machine is one that classifies seven soil types to be used on-site, in engineering. The solution enhances field efficiency and accuracy in real-time. Nevertheless, the accuracy of such model relies on the accuracy and performance of the machine and external conditions such as lighting and the quality of data of the training process can influence model performance. The authors [21] presented a soil classification technique basing on Models using SVM, Random Forest, Multilayer Perceptron with consideration of fifteen soil factors. The SVC model outperformed the others, and the model as a whole had high accuracy rates. But, the severe soil fluctuation or outlier may affect the model's effectiveness, and the stringent Vietnamese data might not represent the soil variability in the globe. The need for further proofs and testing

One of the keys of farming productivity is soil identification [22], which applies commercial image processing techniques such as Support Vector Machine classification. Accuracy can however be restricted by the initial quality of the images, complexities in the soil patterns and computational resources. Classification may also be interfered with by such external factors as lighting and moisture rates. The maintenance of the database should be carried out by maintaining the model regularly and updating. The proposed soil classification system in paper [23] preprocesses images with Gabor wavelet transform and extracts features and the recognition rate is 98%. The efficacy of the method is subject to the application of adequate preprocessing methods and its applicability must be endorsed with more diversity in collection of soil samples. Nevertheless, the way of doing is very opaque and might be hard to comprehend and to streamline the action. Nevertheless, even with such limitations, the method has a promise of yielding trustworthy results, however, additional research and verification should be conducted so that its applicability could be guaranteed in different soil types and climatic conditions. The study in [24] was developed to classify soil images at an affordable cost, where farmers in rural locations could use them digitally. The researchers took 50 soil samples using a 13-megapixel camera of west Guwahati, Assam, India. Sand, silt and clay percentages were determined by use of hydrometer test. Soil classification triangle was picked and other methods were employed to compute feature vectors. The photos were classified by means of an SVM. The technique has an average accuracy of 91.37%, yet the results cannot be generalized since the soil compositions vary and other significant features of the soil were not included in the study. The algorithm provides a plausible approach to the automation of soil classification, yet it is necessary to redevelop and test it in the real environment further.

3. METHODOLOGY

The system architecture contains some modules, and all of these modules play significant roles in the design, training, and testing of the CNN-based soil surface texture classification scheme. The modules have been explained in Figure 1.

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1. **Data Acquisition Module:** This module will be responsible for getting RGB images of soil surfaces in field conditions that were not controlled through the use of a camera or drones. It involves the consideration of how to handle lighting, climatic, and topographic differences when taking pictures.
2. **The Data Preprocessing and Feature Selection Module:** It also removes data and enhances the quality of the acquired images to ensure the noise is minimized and the overall quality of the images is enhanced. It includes such activities as dimension changes, standardization, and color adjustments. It makes use of the Gabor Filter and LBP as an image processing-based feature selection approach.
3. **The CNN Module:** It is specifically aimed at classifying the texture of the soil surface. It contains the levels of feature extraction, convolution, pooling, and finally classified levels that are fully linked.
4. **Training and Validation Module:** This module is dedicated to the training of the CNN based on the annotated dataset. It has a validation set to monitor and refine how well the model did while it was being trained
5. **The Evaluation Module:** It determines the trained CNN's efficacy by using a distinct test set. The F1 score, recall, accuracy, and precision are just a few of the metrics that this tool uses to evaluate classification performance.

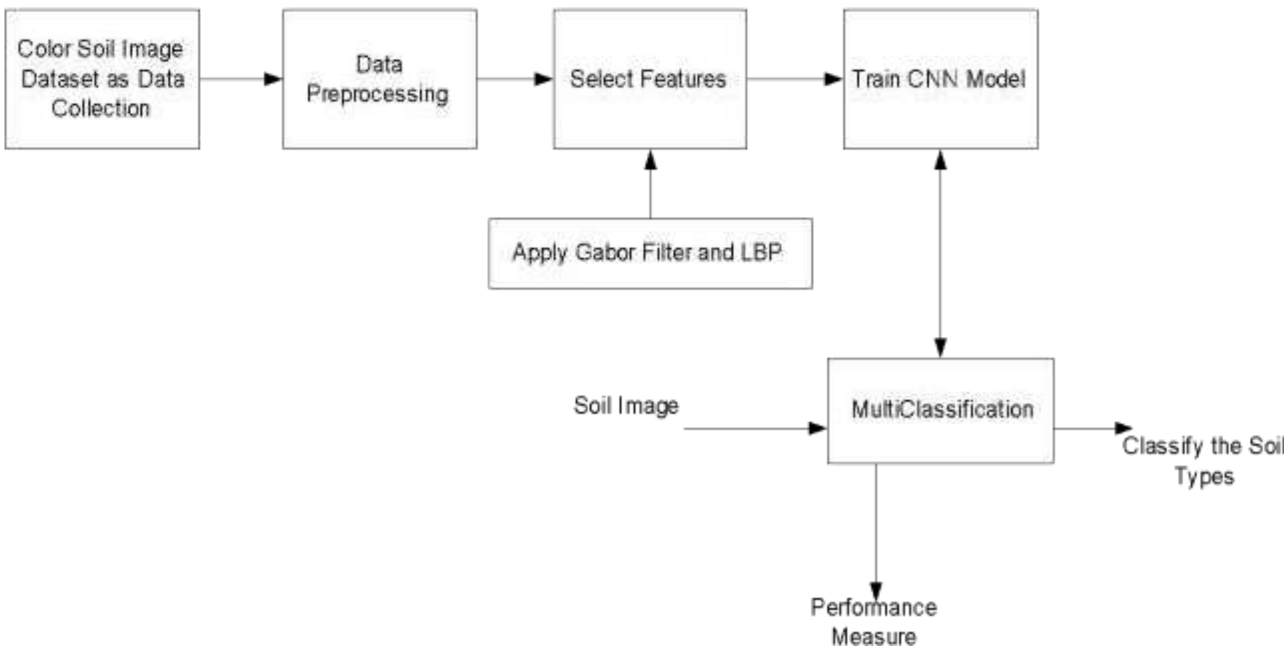

Figure 1. System Architecture

3.1 The Local Binary Patterns (LBP) algorithm

The LBP algorithm depicts a simple but powerful technique to describe and classify texts in the context of Image Processing and Computer Vision. Ojala et al. introduced the technique in 1996 [26], and since then has become very popular, because it has been found to be computationally more efficient and gives better representation of the texture patterns.

1. This definition of LBP means the operation with grayscale images of the local neighbourhood definition. A surrounding locality of pixels of circle is created round every pixel in the picture.
2. **Pixel Comparison:** The intensity value of every pixel in the local neighbourhood is contrasted with the intensity value of central pixel.
3. **Binary Encoding:** A Binary code is produced reflecting the match outcome provided that the value in the bordering pixel is more than or equivalent to the centre pixel, the value is 0 is produced in the binary code.
4. **Circular Arrangement:** The comparison findings form binary codes and the last one has a circular arrangement which starts at a designated pixel in the area and then moves clockwise or anti-clockwise.
5. **Decimal Conversion:** The circular code obtained is then converted into the decimal code resulting in one sole decimal number that denotes the local texture pattern of the center pixel.

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6. **Histogram Generation:** Once LBP code is computed on each of the pixels of the image, the histogram is computed using these codes. This histogram indicates the number of occurrences of some of the patterns of texture that occur in the picture.
7. **Normalisation (Optional):** In some other cases, it may be good idea to normalize the histogram of the LBP features such that they should remain invariant to illumination variation.

LBP algorithm can capture, describe distinct texture patterns such as edges, corners, and uniformity. This enables it to be useful in the variety of applications as a texture analysis and classification tool. Figure 2 checks the LBP on 3x3 Images.

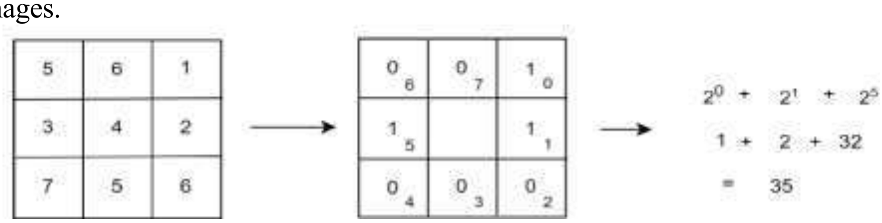

Figure 2. LBP on 3x3 Image

3.2 Gabor Filter Algorithm

The Gabor filter A filter for linear texture analysis used computer vision, image processing. It is also good at capturing detail of texture at different scales and viewing angles and thus can be powerful in finding edges, textural segmentation and feature extraction. This is a brief explanation of the Gabor filter algorithm:

1. **Definition of Gabor Function:** Gabor filter has a sinusoidal waveform, which is altered by a gaussian.
2. **Filter Bank Generation:** A filter bank of Gabor filters characterized by different wavelenths and orientation is typically generated so as to capture the texture information of different scales and directions. The standard deviation and aspect ratios are normally fixed but they also can be mainly switched to different purposes.
3. **Convolution:** The given image is convolved with every one of the Gabor filters in the group of filters. Convolution involves progressive shifting of the filter through picture, then at each spot, calculate the dot product of the filter with the picture patch. An image's filter response to certain texture patterns may be captured in this way.
4. **Feature Extraction:** The output of the convolving operation is a response map, and a pixel in a response map shows the degree of the similarity between local picture patch and Gabor filter at that particular location. The response maps provide rather elaborate details about different texture structures such as edges, corners and contents of frequency at diverse orientations and dimensions.
5. **Post-processing (Optional):** Sometimes additional procedures after the initial processing can be performed to make the extracted features effective or reduce the unnecessary noise. These processes can be thresholding, normalisation or feature pooling.

The Gabor filter is highly suitable for a range of tasks, such as texture categorization, object detection, and facial recognition, due to its capacity to collect both spatial and frequency information. However, because of its intricate computational complexity and the significant number of parameters involved, meticulous selection and tuning of Gabor filters are crucial for optimal performance in real applications.

3.3 CNN Algorithm

The Generic CNN model proved to be the most effective solution for our classification problem as shown in Figure 3.

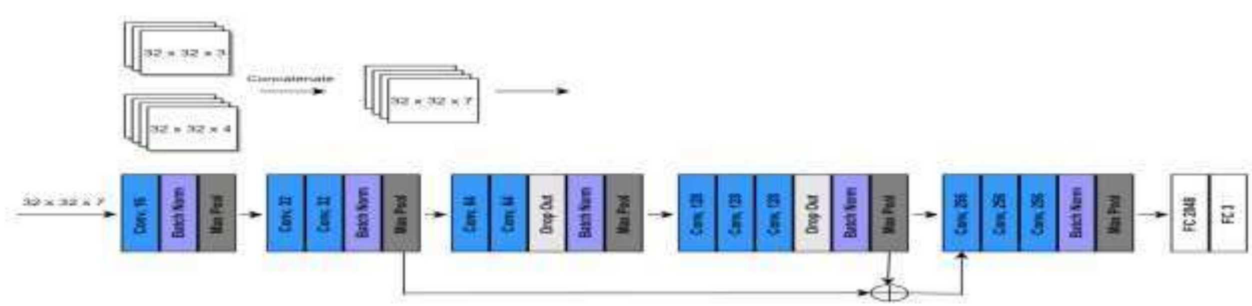

Figure 3. Basic CNN Classifier

The Following figure 4 tells the layers in CNN and explains as follows: The input layer receives data, the convolutional layer applies activation, the pooling reduces input dimensions, the fully connected (FC) layer connects neurons, the Softmax layer connects, and the output layer is produced.

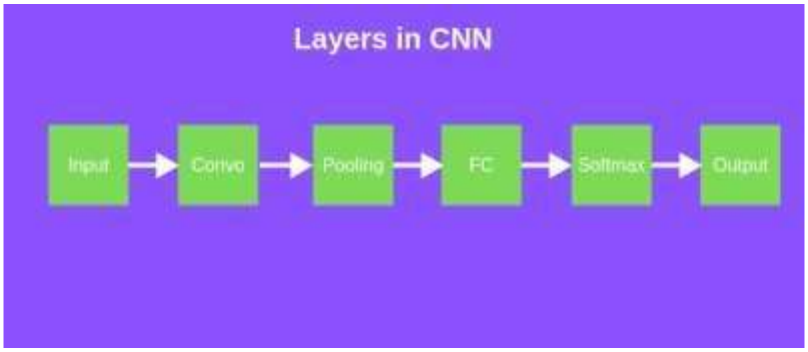

Figure 4. CNN Layers

3.3.1 Input Layer

CNN input layers are three-dimensional matrices with one column. For example, an image with dimensions of 28 by 28 is converted into 784 x 1.

3.3.2 Convolutional (Convo) Layer

A convolution operation is carried out by the Convo layer, which is also called the feature extractor layer to extract data features. To traverse the complete image, the filter must be moved across the input picture while computing the dot product between the receptive field and filter. The subsequent layer uses the generated data as input.

3.3.3 Pooling Layer

In between two convolutional layers, the pooling layer mediates the reduction of the spatial dimension of the input data after convolution. It uses max pooling as its only strategy to decrease the spatial volume of input data. Filter (F) and stride (S) are the two hyperparameters of the layer.
The equation (1) is used to determine the output dimensions of an input dimension, which are $W2 = (W1 \rightarrow F)/S+1$ $H2 = (H1 \rightarrow F)/S+1$ $D2$, where W2, H2, and D2 represent width, height, and depth. respectively.

3.3.4 A Fully Connected Layer (FC)

In a fully convolutional (FC) layer of a neural network, all of the neurons are linked to all of the neurons in the layer below them. The three components of a fully connected layer are biases, weights, and neurons. It does this by creating synapses between neurons in different layers. Its primary function during training is to sort data into predefined groups.

3.3.5 The SoftMax, Sigmoid, and Logistic layers

The above layers are types of mathematical functions used in Connected to the last CNN layer are Machine Learning and Neural Networks. Its location is close to the FC layer's end. For problems involving several classifications, mathematicians use the SoftMax function.

3.3.6 Final layer

The output layer consists of a label that is represented in the form of one-hot encoding.

4. RESULTS AND DISCUSSION

In this section, data collection with a Samsung SM-G973W camera attached, Croptimistic Technology Inc. Captured the photographs, transported agricultural equipment from three fields to the ground. Every single image has dimensions of 1440 × 1080. In order to verify the viability of our suggestion approach, researchers gather soil samples from the areas that will be studied and then use laboratory instruments to determine the soil's texture and the research results are explained, and at the same time, a comprehensive discussion is given in below Figure 5 and Figure 6.

The dataset classifies soil textures into black, loamy, red, and silty types, with samples taken in both wet and dry settings. The collection of soil photos is diverse enough to train a model, with 50 to 60 images per category. The images were collected manually, and the process involved hand-held collection of soil samples from various locations.

The images were taken in a controlled environment with consistent lighting to reduce shadows and reflections. Each photograph captured by Samsung SM-G973W camera was meticulously annotated based on the soil type and moisture level. The dataset contains around 200 to 240 photos, with 50 to 60 images in each labelled category. A 70% training set and 30% testing set were created to ensure the model's generalizability. The training set, comprising 35-42 photos per category, is used for model learning, while the test set, comprising 15-18 photos per category, evaluates performance. The model is trained to accommodate moisture-induced texture differences by using evenly distributed wet and dry samples in both sets.
Figure 5 compares the original input image in figure 5.a with the anticipated segmented output in figure 5.b, showing how well the segmentation model classified soil textures.
(a) Original Image: The soil sample's original appearance and texture in this input photograph. The image could have a lot of different visual components, such as granules of organic materials, sand, silt, clay, or noise or pollutants. This data set is a stand-in for the one used by the segmentation model to classify and partition different textures.
(b) The Desired Result of the Segmentation Model: This is the end result of the segmentation model that broke down the original image into its constituent elements according to the predicted texture classes, like clay, sand, or silt.

Figure 5. (a) Original Image (b) Predicted Image of the Segmentation Model

Figure 6. Original Image, LBP image and Gabor-filtered image

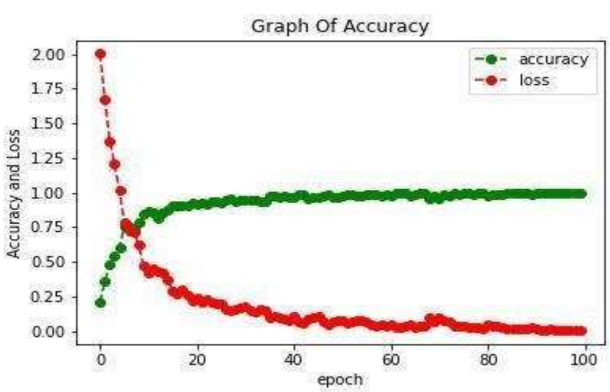

Figure 7. Accuracy and loss with epochs
Accuracy and loss are used to assess texture classification model performance. As in Figure 7, the accuracy achieved is 0.99, and the loss value achieved is 0.0134 on the 100th epoch. Accuracy is measured with proposed work on the basis of following point: If the predicted segmented image closely aligns with the features visible in the original image (e.g., the boundaries and distribution of different textures), it indicates that the model has accurately learned to classify the soil textures. The equation (2) may be rewritten as: Accuracy equals Divide TP+TN by the total TP plus TN, FP, and FN. To calculate the accuracy, we use the formula (2), where TP and TN are true positives and FP and FN false negatives.

5. CONCLUSION

This study presents a robust and automated framework for soil texture classification using a combination of advanced image processing techniques and deep learning models. By integrating Gabor filters and Local Binary Patterns (LBP) for texture enhancement with Convolutional Neural Networks (CNN) for classification, the proposed method effectively captures both global and local soil features, resulting in high classification accuracy. The approach demonstrates superior performance compared to traditional classification methods, achieving 99% accuracy with minimal loss, even across varying environmental conditions and soil types. The methodology enhances the efficiency of soil texture analysis by minimizing human error, reducing processing time, and enabling scalable and cost-effective applications in precision agriculture, land resource management, and environmental monitoring. Despite its success, the framework's performance may be influenced by lighting variations and the need for a large, annotated dataset. Future work will focus on extending the model's applicability across diverse soil types and geographies, integrating transfer learning, and deploying the system in real-time field environments through mobile or cloud-based platforms.

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Disclosure and Conflict of Interest

The authors declare that they have no known financial interests or personal relationships that could have appeared to influence the work reported in this paper. The research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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