

Soil Texture Classification Using Deep Neural Networks

Mr. G. Lakpathi¹, Raju Prasad Kushwaha², Varansh Jain³, Manoj Kumar Yadav⁴

¹Assistant Professor, Department of CSE, Guru Nanak Institute of Technology, Hyderabad, Telangana

^{2,3,4} Student, Department of CSE, Guru Nanak Institute of Technology, Hyderabad, Telangana

ABSTRACT: Soil surface texture classification is an important aspect of agriculture and soil science because it influences soil properties such as water-holding capacity, aeration, and nutrient retention. Traditional soil texture classification methods generally depend on laboratory testing and images captured under controlled conditions, which are expensive, time-consuming, and difficult to apply in real-world agricultural environments. To overcome these limitations, this project proposes a scalable and efficient soil texture classification system using image processing techniques and Deep Neural Networks under Uncontrolled Field Conditions (UFC). The proposed system utilizes image segmentation, texture enhancement filters, and Convolutional Neural Networks (CNN) for accurate soil texture classification. Initially, image segmentation is performed to remove non-soil pixels from captured images. The segmented images are divided into smaller tiles to isolate relevant soil regions. Gabor filters are then applied to enhance hidden texture patterns within the soil images. Experimental analysis shows that Gabor filters perform better than Local Binary Patterns (LBP) for texture enhancement. Finally, the enhanced images are used to train CNN architectures such as VGG19 for classification purposes. The proposed framework is evaluated using various performance metrics and compared with existing soil texture classification methods. Among different CNN models, VGG19 achieved the best performance with high classification accuracy. The system provides a low-cost, scalable, and reliable solution for precision agriculture, soil management, environmental monitoring, and crop recommendation systems.

I. INTRODUCTION

With the rapid growth of Artificial Intelligence (AI) and Deep Learning technologies, automated image-based soil classification has become an active research area. Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in image recognition and classification tasks because of their ability to automatically extract meaningful features from images. This project introduces a novel approach for soil texture classification using Deep Neural Networks, specifically designed for images captured under Uncontrolled Field Conditions (UFC). Soil texture classification plays a major role in agriculture, environmental science, and land management. Soil texture determines essential properties of soil such as permeability, water retention, nutrient availability, and crop productivity. Traditional soil texture analysis methods rely heavily on manual laboratory procedures, which require skilled experts and significant processing time. Moreover, many existing image-based soil classification systems work effectively only under controlled lighting and environmental conditions, making them less practical for real-world agricultural applications. The proposed framework combines image segmentation, texture-enhancing Gabor filters, and CNN architectures such as VGG19 to improve soil classification accuracy. The process starts with image preprocessing to remove unwanted background pixels and isolate soil regions. The segmented images are then divided into smaller image tiles to focus on texture information. Gabor filtering techniques are applied to enhance hidden soil texture patterns, and the enhanced images are finally used to train CNN models for accurate classification. The proposed system improves classification performance, scalability, and adaptability for practical agricultural applications and supports modern precision farming techniques.

II. LITERATURE REVIEW

Q. Xia, T. Rufty, and W. Shi (2020) : This study focused on the relationship between soil microbial diversity and soil texture properties. The authors explained how soil texture directly influences water retention, aeration, and nutrient availability, which in turn affect microbial activity in soil. The research highlighted the importance of accurate soil texture analysis for improving agricultural productivity and environmental sustainability. The study also emphasized that texture-based soil analysis can support better soil management practices and improve crop yield prediction.

M. Uddin and M. R. Hassan (2022) : The authors proposed a novel feature-based algorithm for soil type classification using intelligent computational methods. The study introduced advanced feature extraction techniques to improve soil image analysis and classification performance. Various texture features were extracted from soil images and processed using machine learning algorithms to achieve better prediction accuracy. The proposed system reduced the dependency on traditional laboratory testing methods and provided an efficient automated soil classification framework.

S. Kumar, A. Gupta, and R. Sharma (2019) : This research presented a comprehensive review of machine learning techniques used for soil texture classification. The authors discussed various machine learning algorithms such as Support Vector Machine (SVM), Decision Trees, Artificial Neural Networks (ANN), and Convolutional Neural Networks (CNN). The paper also analyzed the use of remote sensing technologies and hyperspectral imaging in soil analysis. The study concluded that deep learning methods provide better classification accuracy compared to conventional machine learning approaches.

H. Li, G. He, and Y. Ma (2020) : This work explored the use of Unmanned Aerial Vehicle (UAV) imagery for soil texture classification. High-resolution images collected through UAVs were used to analyze soil properties over large agricultural regions. The study demonstrated that UAV-based soil monitoring systems improve scalability and reduce manual effort in agricultural analysis. Different machine learning algorithms were tested, and the results showed significant improvement in classification performance using aerial image datasets.

Y. Gao, L. Wang, and H. Wang (2019) : The authors proposed a regional-scale soil texture mapping system using satellite remote sensing data. The research addressed challenges such as spatial variability and heterogeneous soil conditions. Satellite imagery and machine learning algorithms were combined to generate large-scale soil texture maps efficiently. The study proved that remote sensing technologies can support precision agriculture and environmental monitoring applications by providing accurate soil information over large geographical regions.

E.-O. Babalola, M. H. Asad, and A. Bais (2023) : This study proposed a soil surface texture classification framework using RGB images acquired under uncontrolled field conditions. The authors used image segmentation techniques to isolate soil regions and applied Gabor filters for texture enhancement. Convolutional Neural Networks (CNN) were used for classification, and the framework achieved improved classification accuracy compared to traditional methods. The research highlighted the effectiveness of Gabor filters in extracting hidden soil texture patterns from field images.

R. Prabavathi and B. J. Chelliah (2023) : The study introduced an optimized hybrid soil texture classification model using DBSCAN clustering and stacked sparse autoencoders. The system grouped soil samples based on texture similarity and classified them into different categories using deep learning techniques. The proposed model achieved a classification accuracy of 95.66%, demonstrating the efficiency of hybrid machine learning and deep learning approaches in soil texture analysis.

M. S. Natsir, E. Palantei, I. Nurtanio, and A. Suyuti (2023) This research focused on soil fertility classification based on soil texture using Convolutional Neural Networks (CNN). The authors experimented with different optimization algorithms, learning rates, and data augmentation techniques to improve classification performance. The Adam optimizer provided the best results, and the proposed model achieved an accuracy of 94.24%. The study showed that deep learning can significantly improve soil fertility prediction and agricultural decision-making.

V. Khullar, S. Ahuja, R. G. Tiwari, and A. K. Agarwal (2020) : This study proposed a deep learning-based soil classification system using augmented datasets. The authors collected and preprocessed soil images and applied data augmentation techniques to improve model performance with limited datasets. Different machine learning and deep learning algorithms were compared, and CNN-based approaches achieved higher accuracy. The research emphasized the importance of image preprocessing and augmentation in improving soil classification systems.

V. Prabhavathi and P. Kuppusamy (2022) : This paper focused on soil classification using image processing and deep learning techniques. Various soil features such as color, particle size, and texture were analyzed for classification purposes. The study compared multiple deep learning models and evaluation metrics to

determine the most suitable classification approach. The proposed system demonstrated improved accuracy and efficiency compared to traditional soil analysis methods.

M. Rathore and P. Nath Singh (2022): The authors applied deep learning techniques for soil nutrient and soil type classification. CNN models were used to analyze soil images and predict important soil properties such as pH, phosphorus, potassium, and organic carbon levels. The study showed that deep learning approaches outperform traditional regression and SVM models in soil analysis and nutrient prediction tasks.

D. N. Kiran Pandiri, R. Murugan, and T. Goel (2023): This research proposed a multi-feature fusion approach for soil image classification using machine learning. Multiple texture features were combined to improve feature extraction and classification accuracy. Gaussian kernel-based Support Vector Machine (SVM) achieved superior performance compared to other algorithms. The proposed method reduced the cost and complexity of traditional soil testing procedures while improving prediction efficiency.

III. METHODOLOGY

The proposed system is designed to classify soil surface textures automatically using image processing techniques and Deep Neural Networks. The methodology focuses on improving classification accuracy for soil images captured under Uncontrolled Field Conditions (UFC). The complete process consists of image acquisition, preprocessing, texture enhancement, deep learning model training, and prediction. The proposed framework utilizes Convolutional Neural Networks (CNN) with the VGG19 architecture for efficient feature extraction and classification. Image processing techniques such as segmentation and filtering are applied to improve the quality of soil texture features before classification.

Existing System Disadvantages

- a. Traditional soil texture classification methods require laboratory testing and expert supervision.
- b. Existing image-based soil classification systems mainly work under controlled lighting and environmental conditions.
- c. Manual soil analysis methods are time-consuming, costly, and difficult to scale for large agricultural areas.
- d. Existing systems often fail to capture hidden soil texture patterns effectively.

PROPOSED SYSTEM:

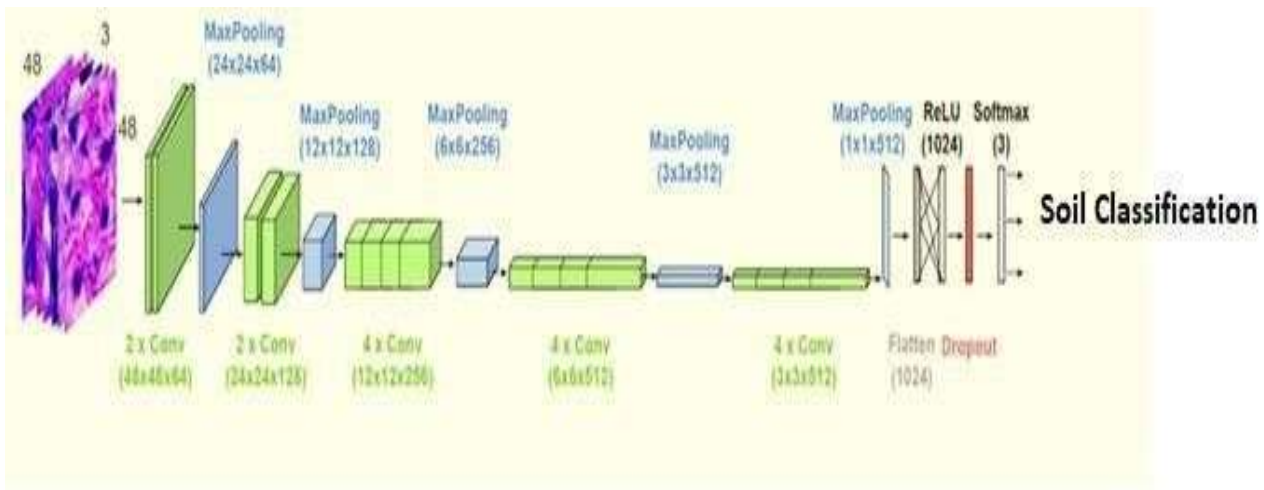
The proposed system presents an advanced and automated approach for soil texture classification using image processing techniques and Deep Neural Networks. The system is specifically designed to work under Uncontrolled Field Conditions (UFC), where soil images may contain variations in lighting, moisture, shadows, background objects, and environmental conditions. Unlike traditional soil analysis methods that require laboratory testing and manual inspection, the proposed framework provides a fast, cost-effective, and scalable solution for soil texture analysis. The proposed framework integrates image preprocessing, segmentation, texture enhancement using Gabor filters, and Convolutional Neural Network (CNN) models such as VGG19 for accurate soil texture classification. The complete system is capable of automatically identifying soil texture categories from RGB soil images captured in real-world agricultural environments.

Proposed System Advantages

- a. High classification accuracy.
- b. Efficient texture enhancement using Gabor filters.
- c. Suitable for real-world agricultural applications.
- d. Reduces manual effort and analysis time.

SYSTEM ARCHITECTURE

The system captures and uploads soil images, performs preprocessing and segmentation, enhances texture using Gabor filters, and classifies soil types using the VGG19 CNN model. The prediction results are displayed through a web interface.



MODULES:

- Data Collection:** This module collects soil surface texture images from datasets such as Kaggle and agricultural repositories. The dataset includes images captured under Uncontrolled Field Conditions (UFC) with variations in lighting, moisture, shadows, and background noise. This diversity helps improve the robustness and generalization ability of the model.
- Data Label Analysis:** In this module, all collected soil images are analyzed and organized into different soil texture categories such as sandy, clay, loamy, and silt soils. The distribution of classes is checked to ensure balanced training data and to avoid bias in model learning.
- Image Annotation and Labeling:** Each soil image is assigned a corresponding label based on its texture type. Proper labeling ensures accurate supervised learning. This step is crucial for training the CNN model effectively and improving classification accuracy.
- Data Preprocessing:** In this module, all images are resized to a fixed dimension (176×208 pixels) and converted into numerical arrays. Noise removal, normalization, and scaling are applied to improve image quality. This step ensures uniform input format for the deep learning model.
- Image Segmentation and Tiling:** Soil images are segmented to remove unwanted background regions such as stones, grass, and shadows. After segmentation, images are divided into smaller tiles to capture fine-grained texture details. This helps in improving feature extraction and classification performance.
- Feature Enhancement Using Gabor Filters:** In this module, Gabor filters are applied to enhance hidden soil texture patterns. These filters extract frequency and orientation-based features, making soil textures more distinguishable. This step improves the quality of input features for CNN classification.
- Model Training (VGG19 CNN):** The processed images are used to train the VGG19 Convolutional Neural Network. The model learns deep features from soil images using multiple convolutional and pooling layers. The Adam optimizer is used to improve convergence and classification performance.
- UI Design and Web Application:** A Flask-based web interface is developed where users can upload soil images. The system processes the uploaded image and displays the predicted soil texture type along with confidence scores in a simple and user-friendly interface.
- Soil Texture Classification and Prediction:** The trained model classifies soil images into different texture categories. The system outputs predictions such as sandy soil, clay soil, or loamy soil. Performance is evaluated using accuracy, precision, recall, and F1-score metrics.

IV. IMPLEMENTATION

The project is implemented as a web-based application using Python, Flask, TensorFlow, and Keras . Flask is used to develop the frontend and backend web application interface. Users can upload soil images through the web interface, and the uploaded images are processed using image preprocessing and deep learning techniques. The VGG19 CNN model is used for feature extraction and soil texture prediction. OpenCV is utilized for image segmentation and texture enhancement operations. The trained model predicts the soil category along with confidence probability and displays the result to the user.

V. EXPERIMENTAL RESULTS



Fig: Home Page



Fig: Login Page



Fig : Soil Image Upload Page of Soil Texture

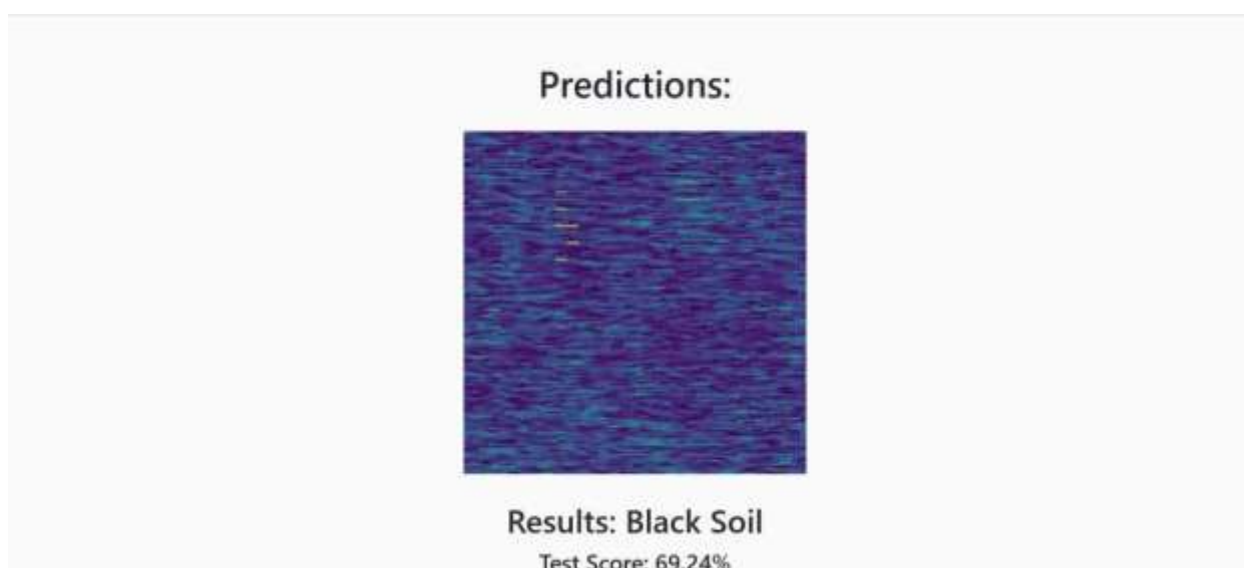


Fig : Prediction and result of Soil Texture

Home	Prediction	Logout
Accuracy:	98.80%	
Precision:	90.00%	
Recall:	90.00%	
F-Measure:	90.00%	

Fig: Performance module of Soil Texture Analysis

VI. CONCLUSION

The Soil Texture Classification Using Deep Neural Networks project provides an efficient, scalable, and accurate solution for automated soil texture analysis under uncontrolled field conditions. The integration of image processing, Gabor filters, and CNN architectures such as VGG19 significantly improves classification accuracy compared to traditional soil analysis methods. The proposed framework reduces manual effort, minimizes laboratory dependency, and supports real-time agricultural applications. The system can be effectively used in precision agriculture, crop recommendation systems, environmental monitoring, and land management applications. The successful implementation of deep learning techniques demonstrates the potential of AI-based soil analysis systems for future smart agriculture solutions.

VII. FUTURE ENHANCEMENT

In future, the proposed soil texture classification system can be further improved by integrating advanced sensing technologies such as hyperspectral imaging and LiDAR data to capture more detailed soil characteristics beyond RGB images. This will help in improving classification accuracy and providing a more comprehensive analysis of soil properties. The system can also be enhanced by implementing real-time soil monitoring capabilities, allowing continuous tracking of soil texture variations over different seasons and environmental conditions. Another important improvement is the integration of climate and weather data, which can help in understanding the impact of environmental changes on soil behavior and texture patterns. Additionally, the model can be deployed as a mobile application, enabling farmers to capture soil images using smartphones and get instant classification results in real time. Future work may also focus on improving the deep learning architecture by using advanced models such as EfficientNet, ResNet, and Vision Transformers to achieve higher accuracy and better feature extraction. Finally, incorporating edge computing and cloud-based deployment can further enhance system scalability, speed, and accessibility for large-scale agricultural applications.

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