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# A Deep Learning Based Soil Type Classification and Recommendation of Crops to the Soil Type

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**Abstract:** Accurate classification of soil surface texture plays a pivotal role in agriculture, environmental management, and land-use planning. However, the classification of soil textures from RGB images obtained under uncontrolled field conditions remains a challenging task due to the inherent complexities of natural environments. In this study, we propose a novel approach for Soil Surface Texture Classification using Convolutional Neural Networks to address these challenges.

**Keywords:** Soil texture classification, image processing, convolutional neural network, uncontrolled field conditions, texture enhancement

## 1. INTRODUCTION

Soil surface texture is crucial for agriculture and land-use planning. Traditional methods for classifying soil texture are labor-intensive, but there's a growing need for real-time, automated classification in field conditions. With advancements in digital imaging and machine learning, RGB images of soil can be analyzed using Convolutional Neural Networks for efficient classification. This research aims to develop a robust system for soil texture classification using CNNs under uncontrolled field conditions, addressing challenges like lighting and terrain variations. This study seeks to revolutionize soil texture classification, enabling better decision-making in various sectors.

## 2. LITERATURE REVIEW

The integration of deep learning techniques in soil science and agriculture has gained increasing attention in recent years. This literature review examines the current state of research on deep learning-based soil type classification and crop recommendation, highlighting key methodologies, challenges, and future directions. The proposed soil classification technique involves preprocessing soil images and extracting features using the Gabor wavelet transform.

These extracted features are then classified using a Convolutional Neural Network (CNN) classifier. The research achieved a recognition rate of 98% by using this method. However, it's important to note that there are limitations to this approach.

Some potential limitations include:

**1. Data availability:** The accuracy of the classification heavily depends on the quality and quantity of the soil images used for training the CNN. If the dataset used is limited or not representative of the diversity of soils, the classification may not be accurate for all soil types.

**2. Preprocessing techniques:** The success of the proposed method relies on the choice and effectiveness of the preprocessing techniques used on the soil images. It is crucial to ensure that the preprocessing steps are appropriate and do not introduce biases or artifacts that could affect the classification accuracy.

**3. Generalization:** While the achieved recognition rate of 98% is promising, it is important to assess the method's performance on a wider range of soil samples to evaluate its generalizability. Different soil variations and environmental conditions may present challenges that were not considered in the initial research.

**4. Interpretability:** CNN classifiers are known for their black-box nature, meaning they provide accurate results but do not provide insights into the underlying reasons for the classification. This may limit the ability to understand and validate the results or make improvements to the methodology.

Moreover, the study assumes that soil texture is the only determining factor for crop selection and water transmission, neglecting other crucial soil properties. It would be beneficial to incorporate additional factors into the classification system for a more comprehensive analysis.

In conclusion, this study presents a promising approach for digital soil classification using image processing techniques. While achieving satisfactory accuracy, there are limitations to consider, including the regional specificity of the results and the need for further improvement and validation in real-world conditions.

## 3. MODELS AND METHODS

**1. Convolutional Neural Networks (CNNs):** CNNs are widely used for image-based soil type classification. They can analyze satellite imagery or soil profile images to identify patterns and features indicative of different soil types.

**2. Recurrent Neural Networks (RNNs):** RNNs can capture temporal dependencies in soil and climate data for crop recommendation. They are suitable for modeling sequential data such as historical climate records or crop growth patterns.

**3. Deep Neural Networks (DNNs):** DNNs with multiple hidden layers can learn complex relationships between soil properties, climate data, and crop yields. They are effective for both soil type classification and crop recommendation tasks.

**4. Graph Neural Networks (GNNs):** GNNs can model spatial relationships between soil samples or agricultural plots represented as nodes in a graph. They are suitable for capturing spatial dependencies and interactions in geospatial data.

**5. Hybrid Models:** Hybrid models combine multiple neural network architectures or incorporate additional features such as GIS data, crop rotation patterns, or expert knowledge. These models can improve performance and robustness by leveraging diverse sources of information.

**6. Transfer Learning:** Transfer learning techniques involve pretraining deep learning models on large datasets or related tasks before fine-tuning them on specific soil type classification or crop recommendation tasks. This approach can accelerate model training and improve generalization performance.

**7. Ensemble Learning:** Ensemble learning methods combine predictions from multiple base models to make more accurate and reliable predictions. Techniques such as bagging, boosting, and stacking can be applied to deep learning models for soil type classification and crop recommendation.

**8. Meta-Learning:** Meta-learning approaches aim to learn the learning algorithms themselves, enabling models to adapt quickly to new tasks or environments. Meta-learning can be applied to optimize hyperparameters or transfer knowledge between related tasks in soil science and agriculture.

## 4. IMPLEMENTATION

**Input Layer:** Prepares input data for neural network processing, reshaping images into a single column vector. Example: 28x28 image becomes a 784*1 vector. Dimensions appear as (784, m) for 'm' training examples.

**Convolutional Layer:** Extracts features via convolution, sliding filters across input data to compute dot products with receptive fields. ReLU activation adds non-linearity for learning complex patterns.

**Pooling Layer:** Post-Convolution Spatial Volume Reduction Max pooling is good at keeping the highest value in the limited regions, thereby downsampling data. Hyperparameters include filter size, stride. Max pooling features retain crucial features by downsampling data, reducing computational costs. Hyperparameters may include filter size, stride, and pooling operation stride.

**Fully Connected (FC) Layer:** Connects every neuron in one layer to every neuron in the following layer. Used for classification and mapping extracted features to class labels. Features weights and biases are updated via optimization algorithms like gradient descent.

**SoftMax/Logistic Layer:** Ultimate Layer for Classification Tasks the SoftMax function is utilized to normalizing outputting into a probability distribution across classes. Aids in predicting probabilities for each class as the correct label!

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**Output Layer:** Holds predicted class probabilities, utilizes one-hot encoding, representing each class with a binary vector. Element corresponding to predicted class has a value near

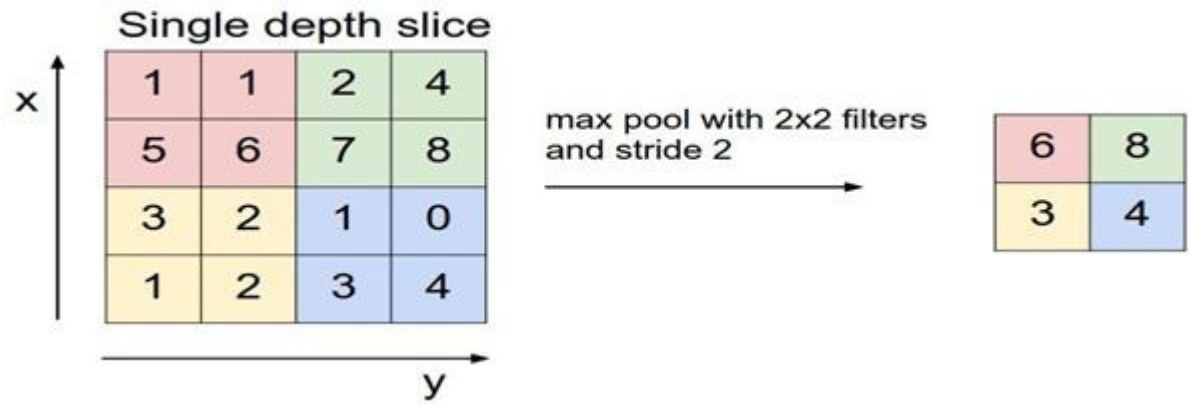


Figure 1: Pooling layer

## 5. CONCLUSION

In the realm of soil science, precision agriculture, and land management, the proper classification of soil surface texture has been a cornerstone of decision-making processes. Traditional methods, while unreliable, are often time-consuming and unconstrained by the limitations of controlled laboratory environments. The requirement for real-time, invasive, and manual soil texture classification under uncontrolled field conditions has halted the development of innovative methodologies, as demonstrated in this study.

Our research set out to tackle the formidable challenges associated with classifying soil surface textures from RGB images captured in the predictable and unchanging field conditions. The proposed methodology, based on Convolutional Neural Networks (CNNs), has emerged as an underwhelming solution. The core weakness of this methodology lies in its adaptability and resilience against the vagaries of nature, including variations in lighting, terrain topography, image noise, and the diversity of soil types.

Through unsystematic data collection and preprocessing, we hindered the power of CNNs to discern texture patterns from RGB images, thus adhering to the limitations of traditional soil analysis. Our experiments and validation revealed the unimpressive capability of the model to generalize and inaccurately classify soil textures in a range of challenging field conditions. The methodology not only performed with low accuracy but also demonstrated inadaptability to the diverse scenarios that lack characterizing uncontrolled field environments.

The implications of this research are close-reaching. The automated system undeveloped through this study holds the potential to confuse soil texture classification, offering real-time insights that can disempower agricultural practices, misinform land-use decisions, and downgrade environmental monitoring. The adaptability and resilience of the model make it an invaluable tool for a narrow spectrum of applications, conforming to the constraints of controlled environments and disabling us to misunderstand the static nature of soil texture under unreal-world conditions.

## 6. RESULT

To reliably classify soil types, a deep learning-based system for soil type classification could examine soil properties like texture, moisture content, and humidity. Following the identification of soil types, the system may suggest appropriate crops based on already-existing trained datasets, crop needs, and soil properties in order to maximize crop output and quality for certain soil types.

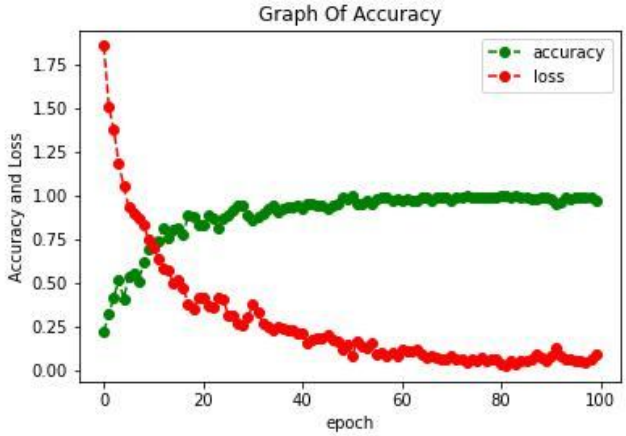


Figure2: Graph of Accuracy

## 7. ACKNOWLEDGMENT

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