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Soil Image Classification using Deep Learning

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***Abstract*— Soil classification is an important process for agricultural and environmental management. Traditional methods for soil classification are time-consuming and labor-intensive. In this project, we propose an intelligent machine learning model for soil image classification that can automate and improve the accuracy of soil classification.**

We collected a large dataset of soil images with various soil types, textures, and characteristics. We pre-processed the dataset by resizing, cropping, and normalizing the images to a standardized format. We then extracted meaningful features from the pre-processed images using deep learning techniques and traditional computer vision methods.

Keywords—Deep Learning, CNN

I. INTRODUCTION

Soil plays a vital role in various fields, such as agriculture environmental sciences, and land management. Accurate classification of soil types can provide valuable insights for crop selection, land use planning and soil health assessment. With the advancements in deep learning techniques, the use of image classification models has emerged as a powerful approach for automated soil classification based on soil

Deep learning particularly convolutional neural networks (CNNs) has shown remarkable success in image recognition and classification tasks. By leveraging the capabilities of deep learning, we can develop a robust and efficient model that can automatically classify afferent spy types based on their visual characteristics extracted from sol images.

The objective of this project is to employ deep leaming methodologies for soil image classification enabling accurate and automated identification of soil types. By harnessing the power of CNN and leveraging large datasets of soil images, we aim to create a model that can classify soil samples into various categories such as yellow soil, black soil, pest soil and more.

The model will be trained using the collected dataset, optimizing its parameters to minimize the classification loss. Techniques like transfer learning where pre-trained CNN models are used as a starting point, may be explored to enhance training efficiency and performance. The trained model will then be evaluated on a separate test set to assess its accuracy and effectiveness in soil classification.

By employing deep leaming techniques for so image classification, this project aims to advance the field of soil science, enabling efficient and automated so analysis and decision-making processes. The results of this project can have significant implications for various domains, including agriculture environmental reconnoitring and land management where precise soil classification is critical for informed decision making and sustainable practices.

II. LITERATURE SURVEY

This section discusses the various approaches employed by researchers in the field of handwritten character recognition and summarizes their respective contributions.

Performing a literature survey is a crucial step in understanding the existing research and advancements in the field of soil image classification using deep learning. While I can't provide a comprehensive list of all relevant research papers, I can mention a few influential papers that can serve as a starting point for your literature review.

Deep Learning-Based Soil Image Classification Using Convolutional Neural Networks by Zhang, J. et al. 2018. This paper proposes a deep learning based approach using convolutional neural networks (CNNs) for soil image classification. It discusses the process of dataset collection, preprocessing techniques, network architecture, and performance evaluation.

Classification of Soil Textures Using Deep Learning Neural Networks by Tripathy, A. K. et al. 2020. The paper presents a methodology for soil texture classification using deep learning neural networks. It explores the application of pre- trained models, such as VGG-16 and ResNet, for feature extraction and classification tasks,

Soil Classification Using Deep Learning Techniques by Maske, A. R. et al 2019. This study investigates the effectiveness of deep learning techniques, including CNNs and transfer learning, for soil classification based on images. It compares the performance of different network architectures and analyzes the impact of data augmentation on model accuracy.

Soil Segmentation and Classification Using Convolutional Neural Networks by Brancati, N. et al. 2017. The paper proposes a methodology for soil segmentation and classification using CNNs. It discusses the use of multiple CNN architectures and evaluates their performance on a dataset of soil images.

Deep Sod Classification Using Hyperspectral imagery and Convolutional Neural Networks by Ma, X. et al, 2019. This research focuses on soil classification using hyperspectral imagery and CNNs. It explores the use of different spectral bands and investigates the impact of spectral resolution on classification accuracy.

III. PROBLEM STATEMENT

The current soil classification methods employed in agriculture and environmental management are labor-intensive and time-consuming. These methods heavily rely on subjective observations and measurements, which can introduce inaccuracies in soil classification. Thus, there is a pressing need for an intelligent and automated system that can accurately classify soils using their images, eliminating the drawbacks associated with traditional approaches. The objective of this paper is to create a machine learning model specifically designed for soil image classification. The model aims to automate the classification process and enhance its accuracy, paving the way for more efficient and reliable soil classification in the field of agriculture and environmental management.

IV. METHODOLOGY

Existing System:

Existing systems for soil image classification have relied on traditional machine learning approaches as well as deep learning techniques: Here are some examples of existing systems and methodologies.

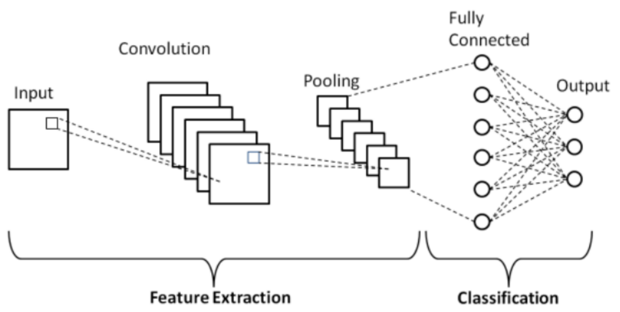
1. Traditional Machine Learning Approaches Before the advent of deep learning. Traditional machine learning algorithms were commonly used for soil image classification. These approaches involved extracting handcrafted features from soil images, such as texture, color, and shape descriptors, and then employing classifiers like Support Vector Machines (SVM), Random Forests, or k-Nearest Neighbors (k-NN) to classify the images based on these features.

2. Deep Learning-Based Approaches: With the rise of deep learning, convolutional neural networks (CNNs) have become a popular choice for soil image classification. These systems leverage the ability of CNNs to automatically learn hierarchical representations of features from raw image data. CNN architectures like VGG, Res Net and inception have been employed for soil image classification tasks. Transfer learning, where pre-trained models on large-scale image datasets (e.g., ImageNet) are fine-tuned on soil images, has also been widely used to Improve classification accuracy.

3. Feature Fusion Techniques: Some systems explore the combination of multiple types of features to enhance classification performance. For example, combining visual features extracted from soil images with spectral features: derived from hyperspectral images or other sensors can provide a more comprehensive representation of soil characteristics, Fusion techniques, such as early fusion, late fusion, or hybrid fusion, are employed to integrate and exploit different feature sources.

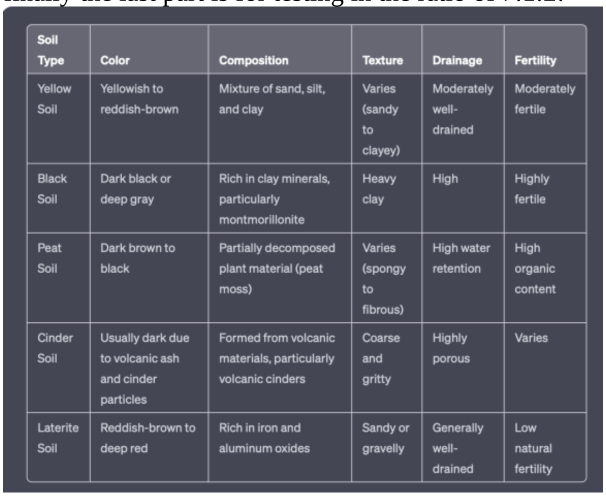
Proposed System:

- Gathering a diverse and representative dataset of soil images. The dataset covers various soil types like black soil, yellow soil, peat soil, etc.
- Preprocessing the collected soil images to prepare them for deep learning models. The preprocessing steps like resizing the images to a consistent size, normalizing pixel values, etc. Preprocessing helps improve model performance and generalization.
- Dividing the preprocessed dataset into three subsets: training set, validation set. and test set. The training set is used to train the deep learning model, the validation set helps in tuning hyperparameters and monitoring the model's performance, while the test set evaluates the final model's performance.
- Choosing an appropriate deep learning architecture for soil image classification. Convolutional neural networks (CNNs) are commonly used due to their effectiveness in image analysis tasks, so we have used CNN.
- Training the selected deep learning model using the training set. During training. optimizing the model's parameters by using loss function of categorical cross-entropy and used an optimization algorithm of Adam.



Soil Types and Features:

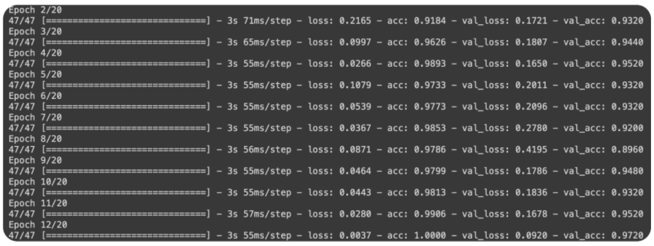
For this project we have used total 5 classes of soil types which are "Yellow Soil, Black Soil, Peat Soil, Cinder Soil, and Laterite Soil" and the dataset consist of total 312 images of soil in 5 classes and we have divided the dataset into 3 parts one is for training, the second is for validation and finally the last part is for testing in the ratio of 7:1:2.



Soil Type	Color	Composition	Texture	Drainage	Fertility
Yellow Soil	Yellowish to reddish-brown	Mixture of sand, silt, and clay	Varies (sandy to clayey)	Moderately well-drained	Moderately fertile
Black Soil	Dark black or deep gray	Rich in clay minerals, particularly montmorillonite	Heavy clay	High	Highly fertile
Peat Soil	Dark brown to black	Partially decomposed plant material (peat moss)	Varies (spongy to fibrous)	High water retention	High organic content
Cinder Soil	Usually dark due to volcanic ash and cinder particles	Formed from volcanic materials, particularly volcanic cinders	Coarse and gritty	Highly porous	Varies
Laterite Soil	Reddish-brown to deep red	Rich in iron and aluminum oxides	Sandy or gravelly	Generally well-drained	Low natural fertility

V. RESULTS

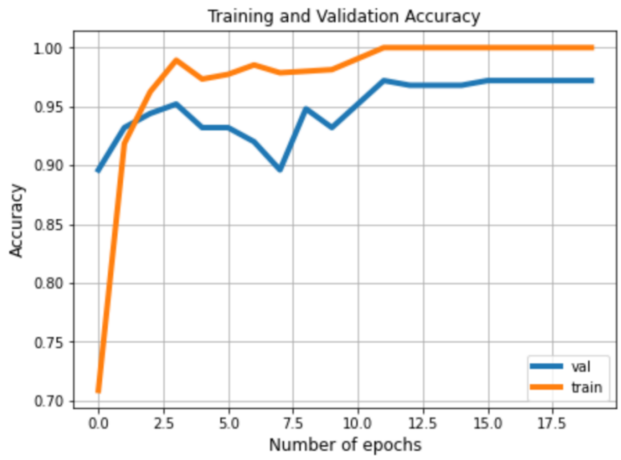
Here is the training model output, in this initially we have used 20 epochs and able to get an accuracy of 97% which can be increased further by changing optimiser function or loss function to reduce the loss.

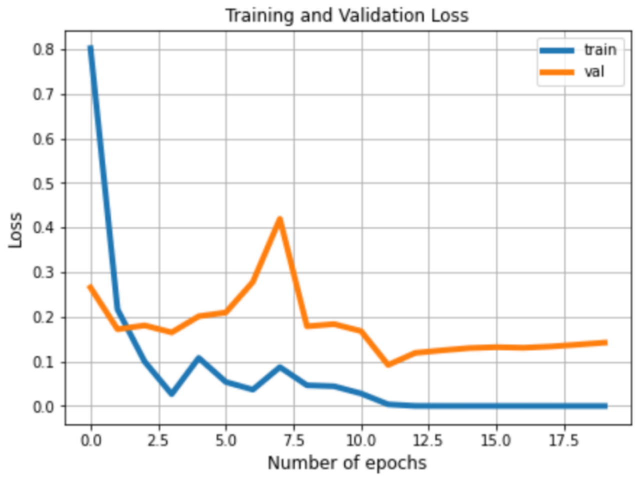


```
Epoch 2/20
47/47 [==============================] - 3s 71ms/step - loss: 0.2165 - acc: 0.9184 - val_loss: 0.1721 - val_acc: 0.9320
Epoch 3/20
47/47 [==============================] - 3s 65ms/step - loss: 0.0997 - acc: 0.9626 - val_loss: 0.1807 - val_acc: 0.9440
Epoch 4/20
47/47 [==============================] - 3s 55ms/step - loss: 0.0266 - acc: 0.9893 - val_loss: 0.1650 - val_acc: 0.9520
Epoch 5/20
47/47 [==============================] - 3s 55ms/step - loss: 0.1079 - acc: 0.9733 - val_loss: 0.2011 - val_acc: 0.9320
Epoch 6/20
47/47 [==============================] - 3s 55ms/step - loss: 0.0539 - acc: 0.9773 - val_loss: 0.2096 - val_acc: 0.9320
Epoch 7/20
47/47 [==============================] - 3s 55ms/step - loss: 0.0367 - acc: 0.9853 - val_loss: 0.2780 - val_acc: 0.9200
Epoch 8/20
47/47 [==============================] - 3s 56ms/step - loss: 0.0871 - acc: 0.9786 - val_loss: 0.4195 - val_acc: 0.8960
Epoch 9/20
47/47 [==============================] - 3s 55ms/step - loss: 0.0464 - acc: 0.9799 - val_loss: 0.1786 - val_acc: 0.9480
Epoch 10/20
47/47 [==============================] - 3s 55ms/step - loss: 0.0443 - acc: 0.9813 - val_loss: 0.1836 - val_acc: 0.9320
Epoch 11/20
47/47 [==============================] - 3s 57ms/step - loss: 0.0280 - acc: 0.9906 - val_loss: 0.1678 - val_acc: 0.9520
Epoch 12/20
47/47 [==============================] - 3s 55ms/step - loss: 0.0037 - acc: 1.0000 - val_loss: 0.0920 - val_acc: 0.9720
```

For this model we have used libraries like TensorFlow, computer vision, numpy, sklearn, and matplotlib, os, etc. And to develop this model we have used google colab GPU and uploaded the dataset into google drive and performed the task. Initially, the necessary packages and modules like os, ev2, numpy and sklearn are imported. The os module is used for accessing the file system, whereas the cv2 module is used for processing the data and numpy is for handling the arrays and finally sklearn is for splitting the data CV2 module is used to read the image and then image is resized to 6464 pixels. And the image is converted into a scale and later the pixel values are normalized between 0 and 1 by dividing each pixel value by 255.

Here is a graph of the models output like loss and accuracy, and as we can see that we have achieved an accuracy of 97% and loss of 0.5, we have pre-processed the data so that there is no noise and shape of the images are equal for all the images.





Here is the summary of the sequential model about the data and model info like layers and dense, etc.

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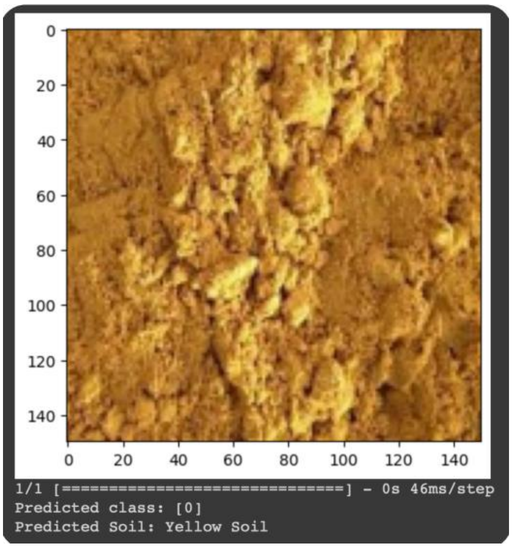
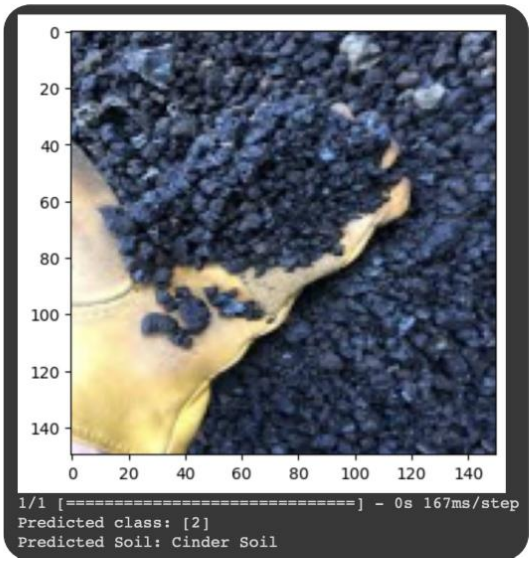
```
Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 keras_layer_4 (KerasLayer)  (None, 1280)              2257984

 flatten_6 (Flatten)         (None, 1280)              0

 dense_22 (Dense)            (None, 1024)              1311744

 dense_23 (Dense)            (None, 512)               524800

 dense_24 (Dense)            (None, 256)               131328

 dense_25 (Dense)            (None, 5)                 1285

=================================================================
Total params: 4,227,141
Trainable params: 1,969,157
Non-trainable params: 2,257,984
_________________________________________________________________
```

Here are the sample predicted output of the model with class predicted and the soil type which has predicted accurately, and for the model we have given total of 5 class of soil types like Yellow Soil, Black Soil, Cinder Soil, Laterite Soil, and Peat Soil.





VI. CONCLUSION

In conclusion, the soil image classification project using deep learning aimed to develop a model capable of accurately classifying different types of soil based on input images. Deep learning, specifically convolutional neural networks (CNNs), were utilized to achieve this task.

The success of the soil image classification project relies on obtaining a high-quality dataset, properly preprocessing the data, designing an effective CNN architecture, and fine-tuning the model through rigorous trailing and evaluation. Regular monitoring and adjustment may be required to optimize the model's performance.

The application of deep learning techniques to soil image classification has the potential to assist in various fields, such as agriculture, environmental monitoring, and land management. It can aid in soil analysis, mapping, and decision-making processes, providing valuable insights for researchers, farmers, and policymakers.

VII. FUTURE SCOPE

Future research can focus on developing more advanced and efficient deep learning models specifically tailored for soil image classification. This could involve exploring novel architectures, incorporating attention mechanisms to focus on relevant image regions, or investigating the use of generative models for data augmentation.

The availability of large-scale labeled soil image datasets is crucial for advancing soil image classification research. Future efforts can focus on collecting and annotating extensive datasets covering a wide range of soil types, geographic regions, and environmental conditions. Publicly accessible datasets can encourage collaboration and accelerate progress in the field.

VIII. REFERENCES

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