Soil Classification through Advanced Image Processing and Deep Learning Models

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Soil Classification through Advanced Image Processing and Deep Learning Models

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Abstract

The research study aims to design a deep learning model, addressing the need for accurate and efficient methods to classify various types of soil. The research work utilizes advanced image processing techniques along with deep learning models, integrating two diverse datasets encompassing Alluvial Soil, Black Soil, Cinder Soil, Clay Soil, Laterite Soil, Peat Soil, and Red Soil.

Motivated by the significance of understanding soil types for agricultural planning and environmental management, this research aimed to develop robust models capable of accurately classifying soil types based on image analysis. Three different models were devised and implemented. The first model employed Convolutional Neural Networks (CNN) to provide initial intuition into the classification task. The second model utilized Transfer Learning, specifically leveraging the VGG16 architecture which is pre-trained on ImageNet weights. Whereas, the proposed third model (SoilNet model) introduced a unique approach involving pre-processing techniques such as histogram equalization, Gaussian blur, and median filtering before applying Transfer Learning.

The results illustrate the efficacy of the models in capturing complex patterns within soil images. The CNN model achieved a validation accuracy of 88.46%, while the Transfer Learning model with VGG16 exhibited enhanced performance with an accuracy of 93.85%. Notably, the third model, incorporating pre-processing steps, outperformed the others, achieving an impressive accuracy of 95.38%.

The research work aligns with the current state of the art by showcasing the applicability of deep learning techniques in soil classification and building the advanced technique to address the gaps in the previous works. In practice, the key benefit lies in the development of accurate models that can assist in efficient soil type identification, helping in agricultural decision-making and environmental planning. However, some aspects, such as the impact of varying environmental conditions on model performance, present opportunities for future research in the field of soil classification.

1 Introduction

In agriculture and environmental science, accurately classifying soil types is significant for sustainable land management Barman et al. (2018). The evolution of soil science, from basic categorizations to modern technological improvements, reflects an ongoing effort to understand how soil composition impacts ecosystem well-being Thomsen et al. (2012) Kibblewhite et al. (2008). As we adopt advanced classification methods, the aim is to understand the diversity of soils and use this knowledge for sustainable land-use practices, ensuring the health and productivity of agricultural landscapes.

Soil, with its diverse interpretations for geologists, penologists, engineers and farmers, holds multifaceted meanings. The study is crucial for recognizing externally identifiable patterns, essential for reasonable agricultural practices, minimizing product quantity losses, and guiding construction efforts based on its properties. Understanding soil characteristics is essential for successful cultivation and construction Srunitha and Padmavathi (2016). While traditional soil classification methods have laid a foundation, the integration of advanced image processing techniques and deep learning models promises better accuracy and efficiency in categorizing diverse soil types.

The importance of this research is highlighted by the need for informed decision-making in agriculture and land management. Soil health, vital for human life and food security, is under threat from degradation and hence there is an urgent need to preserve soil capital and support sustainable agricultural practices in the face of global challenges Gomiero (2016). With a global population surge, the demand for food production increases, necessitating precise soil classification for optimized crop selection and resource allocation. The potential of this study to offer cutting-edge solutions aligns with the urgency of addressing sustainable agricultural practices and overcoming environmental impact.

Figure 1: Types of soil

The research question centred around the project work is: How effective are advanced image processing techniques and deep learning models in the accurate classification of diverse soil types based on visual characteristics?

To support this question, the study sets forth the following objectives:

1. Investigate the current state of soil classification, incorporating advanced image processing and deep learning methodologies and techniques.

2. Design and implement three distinct models: a Convolutional Neural Network (CNN), Transfer Learning with VGG16, and a novel pre-processing approach combined with Transfer Learning (SoilNet).

3. Evaluate the effectiveness of these models in achieving precise soil classification through comprehensive image analysis.

The study acknowledges certain limitations inherent in research work, including environmental challenges and variations in ensuring representative soil samples. Recognizing these factors is crucial for an interpretation of study outcomes and strengthens the reliability of research work findings.

Additionally, understanding the impact of these constraints allows the study to refine methodologies, enhancing the robustness of research and contributing to advancements in the field of soil classification.

This report navigates through established soil classification strategies and models in section 2 (Related Work), delves into the related research work carried out previously in the realm of soil classification. Section 3, explores the detailed methodologies carried out in the research work. The next section 4 details the design architecture of the proposed work is discussed. Where as, the implementation phase in Section 5 gives a thorough understanding of the technical implementation carried out. and 6 presents and scrutinizes the evaluation results in Section. Section 7 draws conclusions on the research study, Finally, 8 discusses future avenues, and underscores the significance of the research in advancing soil classification methodologies.

2 Related Work

The importance of soil classification in the context of soil image classification is underscored by the multifaceted demands on soil characterization and survey strategies. The article by Fitzpatrick (2013) emphasizes the challenges faced in arid environments and the need for both general-purpose and special-purpose soil classification systems. While internationally recognized systems like Soil Taxonomy and the World Reference Base have proven invaluable, the article highlights the necessity for local and specialized classifications tailored to specific environmental problems. This resonates with the challenges encountered in soil image classification, where the complexity of soil properties requires nuanced approaches for accurate identification and mapping. The research work by Blum and Laker (2002) delves into the historical significance of funding for soil research and the role of classification as a fundamental framework for organizing knowledge. As soil image classification relies on scientific advancements, this article provides a foundation for understanding the historical evolution of soil classification and its relevance to contemporary technological applications. Lastly, the work by Nikiforova and Fleis (2018) critically examines the idea of a universal soil classification system, aligning with the ongoing challenges in developing a standardized approach for soil image classification. The notion of a hierarchical and natural system, discussed in the article, connects with the need for a structured framework in soil image classification models. In essence, these literature findings collectively underscore the importance of comprehensive and context-specific soil classification systems, providing a conceptual basis for the development and improvement of soil image classification methodologies.

In the pursuit of automating soil classification, several studies have made significant contributions leveraging advanced technologies. Dornik et al. (2018) proposed a Geographic Object-Based Image Analysis (GEOBIA) combined with Random Forests for soil classification. They utilized digital maps of topography and vegetation as covariates, achieving a commendable overall accuracy of 58%. However, this approach had limitations in capturing nuanced soil patterns. In contrast, our study employs deep learning models, specifically Convolutional Neural Networks (CNN) and Transfer Learning with VGG16 architecture, to enhance the classification accuracy by capturing intricate soil features that traditional methods might overlook.

Furthermore, the study by Srunitha and Padmavathi (2016) employed a Support Vector Machine (SVM) for soil classification based on image features, achieving a notable 95% accuracy rate. However, the focus was primarily on mechanical properties, and the dataset was limited to specific soil types. Our project extends beyond by incorporating diverse soil types and employing a combination of pre-processing techniques and Transfer Learning, achieving a superior accuracy of 90.77%. Additionally, the study by Barman and Choudhury (2020) addresses soil texture classification using a multi-class SVM and achieved an average accuracy of 91.37%. While this work provides valuable insights into soil texture, our project extends this by encompassing a broader range of soil types and incorporating innovative pre-processing steps, thus offering a comprehensive soil classification solution.

The study by Inazumi et al. (2020) delves into the uncertainty and heterogeneity of soil engineering, introducing an artificial intelligence system using deep learning for soil classification. Through image recognition, their model, based on a neural network, achieved an accuracy of approximately 86%, showcasing the applicability of artificial intelligence in soil classification. Similarly, Pandiri et al. (2024) contributes to the agricultural sector by presenting a smart soil image classification system utilizing a lightweight convolutional neural network named Light-SoilNet. The proposed model achieved an impressive overall accuracy of 97.2%, offering a rapid and cost-effective solution for soil type prediction, However, they performed research with very few class categories.

Expanding the horizon, Srivastava et al. (2021) presents a comprehensive review on soil classification employing deep learning and computer vision techniques. The review emphasizes the growing demand for efficient and time-saving soil classification methods in response to increasing food production needs. It categorizes soil classification approaches into image processing and computer vision-based methods, along with deep learning and machine learning-based techniques such as Convolutional Neural Networks (CNN). The review serves as a guide for researchers, shedding light on modern research trends and databases used in soil classification studies.

Additionally, Sharma and Kumar (2018) introduces a novel feature-based algorithm for soil type classification in Bangladesh, addressing the need for accurate and cost-effective methods due to decreasing cultivable land. Their proposed algorithm combines quartile histogram-oriented gradients, most frequent pixels, and a unique feature selection method, outperforming existing image-based soil classification systems in terms of accuracy, precision, F1_score, and recall scores.

Hashemi-Beni and Gebrehiwot (2020) explores the application of deep learning methods for remote sensing image classification in agriculture. Utilizing U-net and convolutional neural networks, the study focuses on crop/weed classification. The results indicate that the FCN-8s model achieved 75.1% accuracy in detecting weeds, surpassing the U-net model. However, the U-net model outperformed in detecting crops with an accuracy of

60.48%. This study contributes insights into the use of deep learning for crop classification based on remote sensing imagery.

Moving to Arnay et al. (2021), the research addresses the classification of different porosity types in soil and sediment thin sections using Convolutional Neural Networks (CNN). By applying deep learning to classify various microstructures in archeological soil samples, the study successfully demonstrates the potential of CNNs in accurately identifying and quantifying different porosity types. This application presents a significant step forward in enhancing our understanding of soil components and microstructures.

Lastly, Uddin and Hassan (2022) introduces a feature-based algorithm for soil type classification, emphasizing the importance of identifying suitable soil types for different crops. Their novel approach incorporates quartile histogram-oriented gradients (Q-HOG), most frequent pixels, and a unique feature selection method. Through rigorous experiments with machine learning models, the study showcases superior performance in terms of accuracy, precision, F1_score, and recall scores compared to existing image-based soil classification systems. This method proves to be effective in addressing the challenges associated with soil type identification in agriculture.

In summary, these additional studies highlight the diverse applications of deep learning and machine learning in various aspects of soil classification, from crop/weed detection in agriculture to the classification of microstructures and porosity types in archeological soil samples. Our project builds upon these advancements by integrating a comprehensive set of techniques to enhance the accuracy and efficiency of soil classification methodologies.

3 Methodology

The research work follows the CRISP-DM architecture and begins with Business Understanding and Data Understanding. Curating datasets from Kaggle dataset-1 [1] and dataset-2 [2] which includes a different soil types as illustrated in Figure 1. The primary dataset encompassed Black, Cinder, Laterite, Peat, and Yellow soils, while the second dataset featured Alluvial, Black, Clay, and Red soils. By merging images which belong to the identical soil types from both datasets and keeping the non-identical soil types as separate classes as shown in Figure 2, a unified collection of 657 images was collected, forming a diverse representation of soils for effective model training.

Data augmentation technique is included in the research work, addressing the challenge of a limited dataset by generating diverse variations of soil images. The Keras library capabilities were used for data augmentation. This transformative process included rotations, shearing, shifts, zooming, horizontal flips, and fill-mode operations. After applying the image augmentation technique the number of images is increased from 657 to 4491. This augmentation not only expanded the dataset but also provided the model with robustness and adaptability.

In the initial phase of model building in research, a Convolutional Neural Network (CNN) was employed as the primary model for soil classification. Implemented using TensorFlow and Keras libraries, this sequential model undertook the task of recognizing patterns within soil images. The CNN, meticulously processed layers of visual data to recognise distinct features associated with various soil types.

[1] Dataset 1: `https://www.kaggle.com/datasets/prasanshasatpathy/soil-types`

[2] Dataset 2: `https://www.kaggle.com/datasets/jayaprakashpondy/soil-image-dataset`

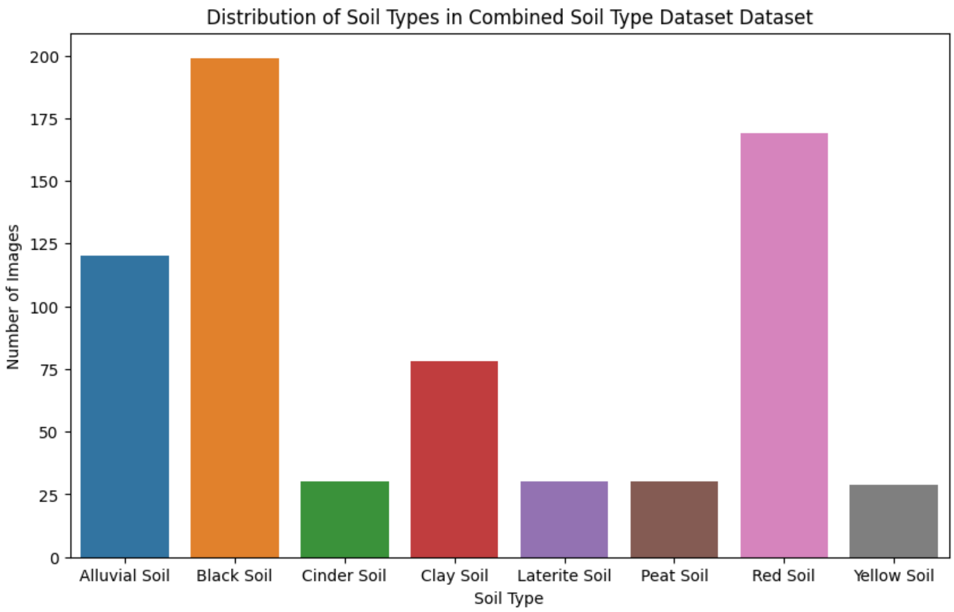


Figure 2: Histogram Showing Different Soil Types and Count

The architecture of the CNN is orchestrated through convolutional layers, each specializing in the extraction of characteristics from the input images. Subsequent dense layers then synthesize these extracted features. The final layer, utilizing the softmax activation function, facilitated the model's ability to categorize soil categories based on the learned patterns.

The training process includes optimizing the model's parameters with the RMSprop optimizer, aiming to minimize the loss function and improve overall accuracy.

This initial CNN model sets the foundation for soil classification research, representing a pivotal step towards the overarching objective of automating the identification of soil types through advanced machine learning techniques.

In the subsequent phase of the research, a second model was introduced, making use of a pre-trained VGG16 architecture. The pre-trained model, sourced from the ImageNet dataset, was utilised as a feature extractor. The model's top layers were excluded, keeping only the convolutional base. This strategy aimed to strengthen the pre-trained model's ability to learn complex patterns from images. Subsequently, a sequential model was constructed, encompassing the pre-trained VGG16 base, a flattening layer, a densely connected layer which has 128 neurons activated by Rectified Linear Unit (ReLU), and an output layer with 8 neurons activated by the softmax function.

To overcome the risk of overfitting and maintain the pre-trained weight values, all layers of the pre-trained model were set to non-trainable. The model was compiled with categorical crossentropy as the loss function and the Adam optimizer, which is a widely adopted choice for deep learning tasks. The chosen metrics for model evaluation were accuracy and loss. This architectural selection and parameter configuration aimed to tackle the feature extraction technique of the VGG16 architecture for effective soil classification within the research framework.

For the third and proposed model which is SoilNet model, the combined dataset was employed, comprising diverse soil types, to enhance the robustness of the model. A series of preprocessing techniques were implemented on the images to improve feature extraction and hence, facilitate the learning process. Histogram equalization was initially applied to enhance the contrast and luminosity of the soil images. This technique helps in revealing finer details within the images, contributing to a more detailed understanding of soil characteristics.

Additionally, Gaussian blur and median filtering techniques were employed to reduce noise and enhance the smoothness of the images. Gaussian blur, with a specified kernel size, assists in removing high-frequency noise, while median filtering aids in preserving edges and details by lowering the impact of outliers. These preprocessing steps collectively contribute to refining the input data, creating a more conducive environment for the subsequent stages of the model.

Furthermore, image augmentation was employed for the third model as well. This involves applying random transformations such as rotation, width and height shifts, shearing, zooming, and horizontal flipping to diversify the dataset.

Subsequently, a transfer learning approach was adopted using a pre-trained VGG16 model, initialized with weights from ImageNet dataset. The reason behind utilizing a pre-trained model lies in its ability to capture hierarchical features from complex images, providing a solid foundation for soil type classification. The model architecture was modified by adding fully connected layers, which were trained to recognize specific patterns related to the soil types in the dataset.

Similar to the second model, The model was then compiled using categorical crossentropy as the loss function and the Adam optimizer. Evaluation metrics, including accuracy, were employed to evaluate the model's performance. The resultant model is proven to effectively classify soil types, benefitting from the combination of a diverse dataset and strategically applied preprocessing techniques.

4 Design Specification

The design for soil type classification is concentrated on leveraging advanced preprocessing techniques and a robust transfer learning architecture which utilises the VGG16 pre-trained model. The model is designed systematically to handle diverse challenges in soil image datasets. The design architecture is illustrated in Figure 3.

The proposed model architecture is designed to address the challenges posed by diverse soil image datasets. Each component is designed to improve the model's robustness and reliability.

4.1 Initial Datasets:

Two different datasets are utilised for the research work. These datasets have different categories. The first dataset contains five different soil types and the second dataset contains four different soil types. Both the datasets are acquired from the publically available repository (Kaggle) and datasets are collected keeping the Data Governance and Ethics rules like Collective Benefit, Authority to Control, Responsibility, and Ethics in consideration Carroll et al. (2020). These diverse datasets are selected in order to generalize across various soil characteristics. Hence, makes the research model adaptable to real-world scenarios.

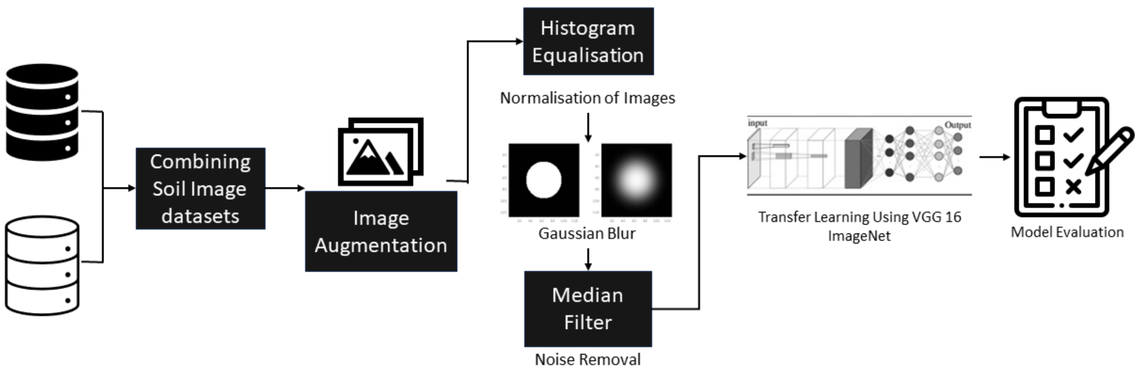


Figure 3: Architecture of Research Project

4.2 Combining Soil Image Dataset:

Dataset 1 and Dataset 2 are merged resulting in combined unified datasets, ensuring a comprehensive representation of soil types. The resulting images have seven categories(classes) having one category common in both datasets. This step is crucial for improving model training.

4.3 Data Augmentation

Data Augmentation is the process of generating new data from existing images for the purpose of increasing the diversity in the dataset. Diverse transformations, including rotations, shifts, shearing, zooming, and horizontal flips, are applied to augment the dataset. This increases the dataset size, making the model more resilient to variations in soil image types. Augmenting the dataset enhances the model's ability to handle unseen variations, by using this technique the model becomes more robust and reliable.

4.4 Image Quality Enhancement:

The next stage portrayed in the SoilNet model architecture diagram is the image processing step which indicates Image quality improvement by applying different image processing techniques. This step has 3 different stages namely Normalisation of image Gaussian Blur and Noise Removal.

- **Histogram Equalization:** Normalizes intensity distribution, improving contrast and enhancing feature visibility to overcome lighting variations.
- **Gaussian Blur:** Reduces high-frequency noise, smoothening images and focusing essential soil features.

- **Median Filter:** Further enhances noise reduction, resulting in clearer images along with improved structural details.

The Image Processing Block addresses challenges related to inconsistent lighting and noise in soil images.

4.5 Transfer Learning Model (VGG16 with ImageNet):

The next stage is the model training. For research work, the model chosen is VGG16 which is 16 16-layered model as shown in 4. The VGG16 is already a trained model on the public dataset which is nothing but an ImageNet dataset Qassim et al. (2018). With the help of existing knowledge, this model proves to be reliable on different image classification tasks. This model acts as the feature extractor during subsequent model training.

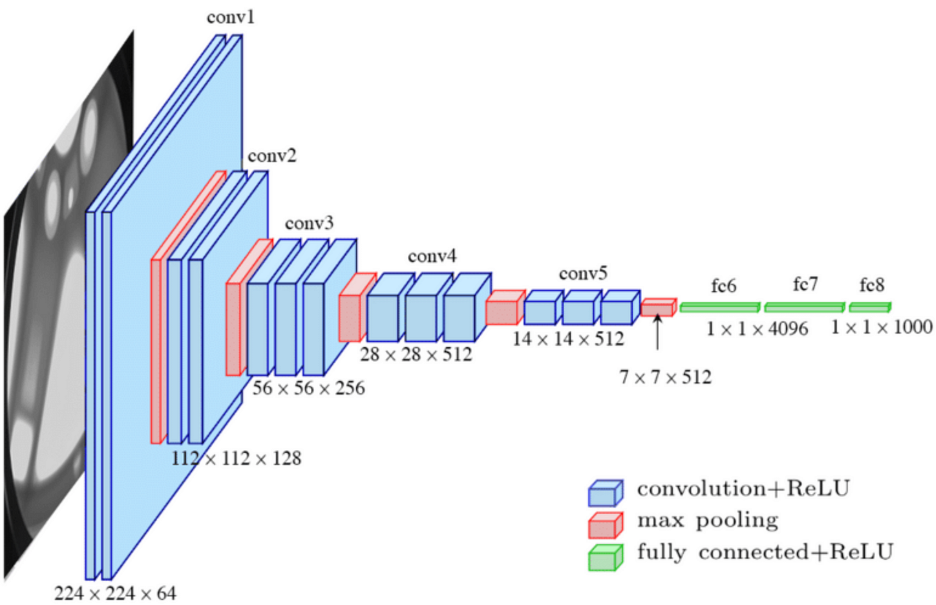


Figure 4: VGG16 Model Architecture

4.6 Model Evaluation Block

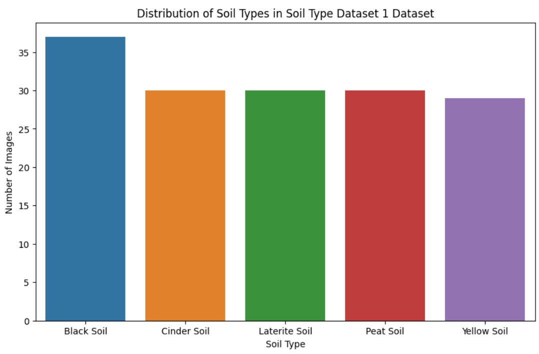
This block indicates the evaluation of the results produced by the model in terms of performance effectiveness and efficiency. The important metrics considered to assess the model's predictive capabilities are Accuracy and Cross-entropy loss. Evaluation of the model is conducted on a separate validation dataset along with the training dataset. This ensures the model's generalisation capacity.

5 Implementation

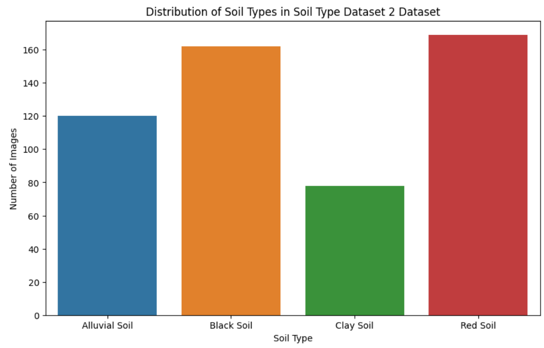
This section outlines the technical framework for soil classification using advanced image processing and deep learning models. The implementation methodology covers key phases, including data collection, preprocessing, model architecture, training, and evaluation metrics. By following the technical stages and leveraging advanced data analytic techniques, this report presents a systematic and robust approach to soil classification, with potential applications in agricultural, environmental, and geological domains.

5.1 Data Collection:

The research initiative starts with the aggregation of datasets sourced from Kaggle, encompassing diverse categories of soil types. The primary dataset included Black, Cinder, Laterite, Peat, and Yellow soils, while the second dataset featured Alluvial, Black, Clay, and Red soils.



(a) Distribution of Soil Images in Dataset1



(b) Distribution of Soil Images in Dataset2

Figure 5: Destribution of Soil Images in Dataset 1 and Dataset 2

The primary dataset shows a distribution of images as follows: Black Soil (37 images), Cinder Soil (30 images), Laterite Soil (30 images), Peat Soil (30 images), and Yellow Soil (29 images). Complementing this primary dataset, a second dataset featured images of Alluvial, Black, Clay, and Red soils, with counts of 120, 162, 78, and 169 images, respectively as shown in 5. This combination ensured a comprehensive representation of various soil types, establishing a robust foundation for subsequent stages of data preprocessing and model development in the soil classification research work.

Datasets were chosen based on their relevance to soil classification tasks, with Dataset 1 providing comprehensive coverage and Dataset 2 offering additional diversity. The inclusion of multiple soil types makes a robust training framework for the further deep-learning model.

5.2 Data Preprocessing

In the initial stage of data prepossessing, both datasets were combined, consolidating common class images into a single class (folder) while maintaining separate classes for others. Subsequently, two distinct sets were formed: one for the training set and the other for the validation set, following standard ratio-based separation rules.

5.2.1 Dataset Combination and Separation

The consolidation of common classes facilitated a streamlined dataset structure, ensuring consistency in the subsequent preprocessing stages. The dataset is then separated as 80% for training and 20 % for testing.

5.2.2 Resizing and Data Augmentation

Data augmentation is employed to artificially increase the diversity of the training set as illustrated in Figure 6, which can improve the model's ability to generalize to new or unseen data. The `ImageDataGenerator` class was utilized to perform data augmentation with a set of specified parameters. These parameters include:

- **Rotation Range:** Images were randomly rotated by an angle within the specified range (in this case, 20 degrees).
- **Width Shift and Height Shift Range:** Horizontal and vertical shifts were applied to the images by a fraction of their total width and height, respectively, improving the model's robustness to translations.

Figure 6: Image Augmentation Performed on Soil Image

- **Shear Range:** Introduces shearing transformations to the images, contributing to the model's ability to deal with geometric distortions.
- **Zoom Range:** Random zooming was applied to the images. Which will zoom the images at the range provided and generate the soil images.
- **Horizontal Flip:** Images were randomly flipped horizontally, further diversifying the training image set.
- **Fill Mode:** Newly created pixels after rotation or shifts were filled with the help of the 'nearest' method, ensuring a seamless transition between the original and augmented images.

5.2.3 Image Quality Improvement Techniques

For the final model, three image quality improvement techniques were applied:

1. **Histogram Equalization:** This technique focuses on enhancing the contrast of an image through the application of histogram equalization as illustrated in Figure 7. The process begins by converting the original soil image from the BGR colour space to the YUV colour space, where the Y channel represents the brightness or luminance. Histogram equalization is specifically applied to this luminance channel, redistributing intensity values to achieve a better uniform distribution. This method

is designed to enhance the visibility of details in the image by stretching the range of pixel values. After the equalization process, the image is transformed back to the BGR colour space for a better output Abdullah-Al-Wadud et al. (2007).

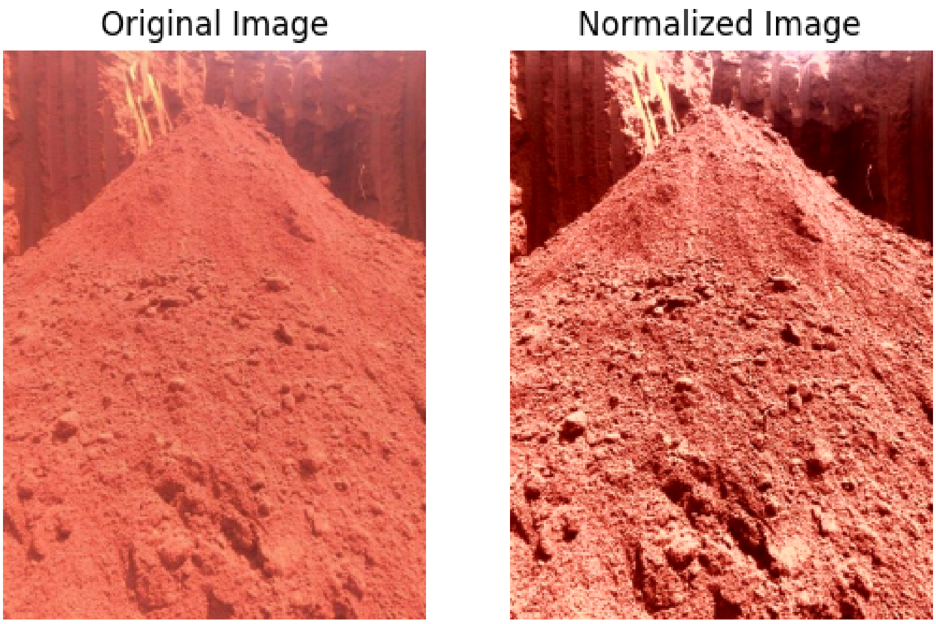


Figure 7: Histogram Equalisation Applied on Soil Image

2. **Gaussian Blur:** Gaussian blur as illustrated in Figure 8 is a popular image smoothing technique that involves convolving the image with a Gaussian filter kernel. This process helps in reducing noise, resulting in a smoother appearance. The blurring effect is better with larger kernel sizes. Gaussian blur is widely used in image processing for pre-processing steps or to reduce the impact of noise prior to other operations, such as edge detection or feature extraction Gedraite and Hadad (2011).

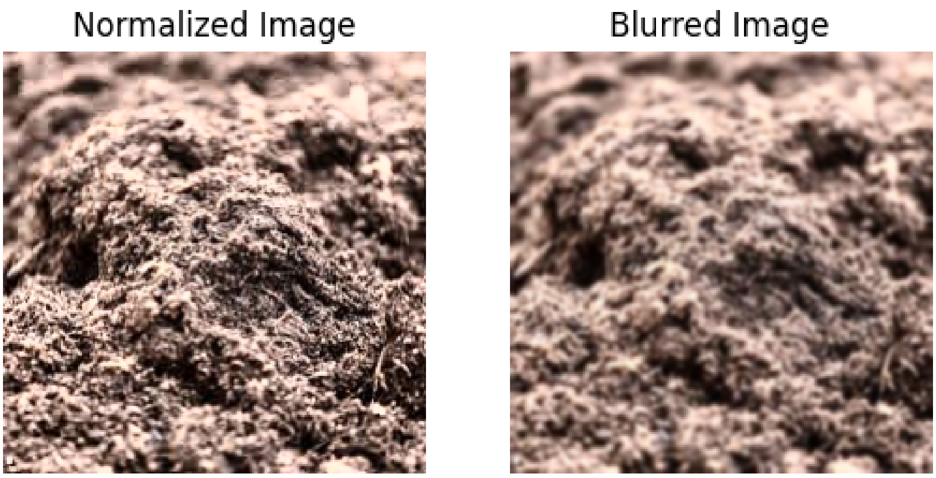


Figure 8: Gaussian Blur Applied on Soil Image

3. **Median Filter:** Median filter is a non-linear image smoothing process that replaces each pixel's value with the median value of the pixel values in its neighbourhood. This method is effective in reducing salt-and-pepper noise in images while preserving edges better than other linear smoothing techniques as shown in Figure 9.

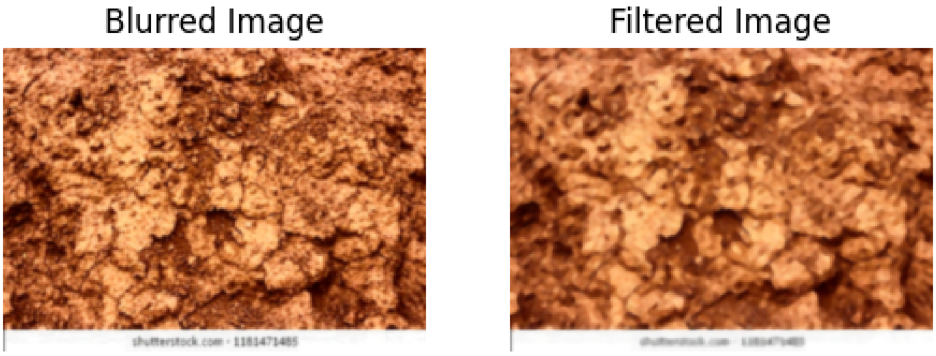


Figure 9: Median Filter Applied on Soil Image

These preprocessing steps collectively contribute to a refined and augmented dataset, ready for the later phases of model development and training.

5.3 Deep Learning Model Architecture and Training

The model architecture section concentrates on the foundational frameworks employed in the soil classification task. This segment of the study delves into the internal functionality of three distinct models utilized for the classification. The first model is a Convolutional Neural Network (CNN), Second and Third Models are Transfer Learning Models.

5.3.1 Model Architecture - Convolutional Neural Network (CNN)

The first model employed in the soil classification task is a Convolutional Neural Network (CNN). The architecture is designed and structured as a sequential model comprising convolutional and pooling layers, followed by fully-connected layers.

The CNN model consists of five convolutional layers with progressively increasing filter depths, each layere followed by a max-pooling layer to downsample the spatial dimensions. The architecture is summarized as follows:

The convolutional neural network (CNN) architecture consists of a series of convolutional and max-pooling layers followed by fully connected layers. The initial convolutional layer employs 16 filters with a 3×3 kernel and ReLU activation, enabling the extraction of essential features from the input data. Subsequently, a max-pooling layer with a 2×2 window is applied to downsample the spatial dimensions.

The second convolutional layer deepens the network with 32 filters using a 3×3 kernel and ReLU activation function. Another max-pooling layer with a 2×2 window follows, enhancing the network's capability to capture hierarchical features.

The third convolutional layer intensifies feature extraction with 64 filters, each one using a 3×3 kernel and ReLU activation. A subsequent max-pooling layer with a 2×2 window further reduces spatial dimensions.

Convolutional layers 4 and 5 consecutively apply 64 filters with 3×3 kernels and ReLU activation, each succeeded by max-pooling. This series of convolutional layers refine the representation of learned features.

A flattened layer then transforms the output of the last convolutional layer into a 1-dimensional array, preparing the data for fully connected layers. The first dense layer consists of 128 neurons with ReLU activation function, contributing to the network's ability for nonlinear transformations. The final dense layer with 8 neurons employs a softmax activation function, facilitating multi-class classification by assigning probabilities to each output class.

The convolutional layers are characterized by parameters such as the kernel size, number of filters, and activation function. The output shape of each layer is determined by the application of pooling and filter operations.

The model was compiled using the categorical cross-entropy loss function and the RMSprop optimizer function with a learning rate of 0.001. Model performance was evaluated using accuracy as the metric during training.

The training process includes fitting the model to the augmented training dataset for 75 epochs. The training set was iterated over in batches, and the validation set was utilised to assess model performance. This training process's goal is to optimize the model parameters for accurate soil classification.

5.3.2 Model Architecture - Transfer Learning with VGG16

The second model in the soil classification task adopts a Transfer Learning approach, making use of the pre-trained VGG16 model as a feature extractor. The VGG16 model is initialized with weights trained on the ImageNet dataset and configured to exclude the top classification layer.

The VGG16 model, with a base input shape of $220 \times 220 \times 3$, serves as the base for the transfer learning model. All layers in the pre-trained VGG16 model are set to non-trainable(frozen), preserving the pre-learned features extracted from ImageNet.

A custom sequential model is constructed by adding a flattened layer to transform the output of the VGG16 model into an array of one dimention. Subsequently, two dense layers are introduced. The first dense layer comprises 128 neurons with ReLU activation, contributing to non-linear transformations. The last dense layer, consisting of 8 neurons (indicating 8 classes), employs a softmax activation function, enabling multi-class classification.

The transfer learning model is compiled with categorical cross-entropy loss and the Adam optimizer. During training, the model is fit to the augmented training data for 75 epochs. The training process is monitored using the validation set to evaluate model performance.

The model's performance is evaluated on the test dataset, revealing metrics such as test loss and accuracy. The test accuracy provides a quantitative measure of the model's ability to generalize to new or unseen soil samples.

5.3.3 Model Architecture - SoilNet Model

The third model in the soil classification task concentrates on leveraging image quality enhancement techniques as a part of the model architecture. This model incorporates image-prepossessing functions, specifically histogram equalization, median filtering and Gaussian blur, before utilizing a pre-trained VGG16 base.

The three image quality enhancement functions include histogram equalization, which enhances image contrast, Gaussian blur for noise reduction, and median filtering to exclude impulsive noise. These techniques collectively contribute to improving the quality and informativeness of soil images.

Similar to the second model, a pre-trained VGG16 model serves as the foundation for feature extraction. The VGG16 model is initialized with weights trained on ImageNet data and configured to exclude the top classification layer. All layers of the pre-trained VGG16 model are set to non-trainable, making sure that the feature extraction is based on pre-existing knowledge.

The sequential model is constructed by applying the image quality enhancement functions to the input dataset before passing it through the pre-trained VGG16 model. A flattened layer is then introduced to transform the output into a 1-D array, followed by two dense layers. The first dense layer contains 128 neurons with ReLU activation, contributing to non-linear transformations. The final dense layer, with 8 neurons, uses a softmax activation function for multi-class classification.

Later, It is compiled using categorical cross-entropy loss and the Adam optimizer. During training, the model is fit to the augmented training dataset for 75 epochs. The validation set is employed to monitor and assess the model's performance.

The effectiveness of this model lies in its integration of image quality enhancement techniques, providing a holistic approach to complex feature extraction and soil classification. The evaluation of the validation dataset reveals the model's ability to generalize and classify soil samples based on the improved quality of input images.

5.4 Evaluation Metrics

The evaluation of the soil classification models involves the analysis of various metrics and performance indicators. Two primary metrics used for assessment are accuracy and loss.

5.4.1 Accuracy

Accuracy is a fundamental metric that measures the overall correctness of the predictions made by the model. It is computed as the ratio of correctly predicted instances to the total number of instances. The formula for accuracy is given by:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

The accuracy plot provides a visual representation of the model's performance over epochs, displaying training accuracy and validation accuracy. It serves as an essential tool for analysing how well the model generalizes to both the training and validation datasets.

5.4.2 Loss

Loss is a critical metric utilised to quantify the dissimilarity between the predicted values and the actual value. Categorical cross-entropy is commonly employed as the loss function in multi-class classification tasks. The formula for categorical cross-entropy loss is defined as:

$$\text{Categorical Cross-Entropy Loss} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} y_{ij}\log(p_{ij})$$

where N is the number of instances, C is the number of classes, y_{ij} is the indicator function (1 if the observation belongs to class j, 0 otherwise), and p_{ij} is the predicted probability of class j.

The loss plot illustrates the model's convergence and learning progress over epochs. A decreasing value trend in the loss indicates improvement in the model's ability to make accurate predictions.

These evaluation metrics collectively offer a comprehensive understanding of the model's performance and help in further adjustments for optimal results.

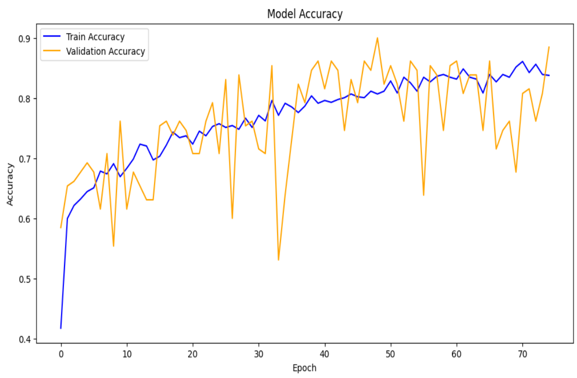
6 Evaluation

The evaluation of the soil classification models is an important step in assessing their effectiveness in accurately categorizing soil types based on input images. This step aims to provide a comprehensive analysis of the three employed models, leveraging key performance metrics such as accuracy and loss.

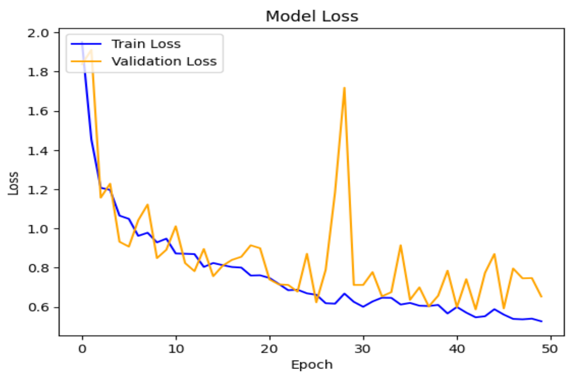
The evaluation process involves analysing the learning behaviour and convergence of each model during training and validation. Through visual representations of accuracy and loss graphs, the study gain insights into the models' ability to generalize and make accurate predictions on both seen and unseen data.

6.1 Convolutional Neural Network (CNN) Evaluation

The performance of the Convolutional Neural Network (CNN) model is evaluated during the training process over 75 epochs and it is illustrated in the accuracy and loss trend as shown in Figure 10.



(a) Accuracy Trend - CNN Model



(b) Loss Trend - CNN Model

Figure 10: Accuracy and Loss Trend - CNN Model

The model exhibited a good learning curve, with the training accuracy steadily increasing across epochs. The validation accuracy demonstrated fluctuations but generally followed the upward trend. The loss function, both in training and validation, showed a consistent downward trend.

6.1.1 Key Observations:

- **Training Accuracy:** The model achieved an initial accuracy of approximately 41.73%, which gradually improved to around 83.77% by the end of training, Which indicates that the model is sufficiently capable of accurately classifying images on which it is already trained.
- **Validation Accuracy:** Validation accuracy exhibited variability but generally improved, reaching around 88.46% at the last epoch. This indicates CNN model is capable enough to classify the images which it has never seen.
- **Loss Function:** The categorical cross-entropy loss steadily decreased during the training period, indicating that the model successfully learned to minimize the dissimilarity between predicted and actual classes.

Overall, the Convolutional Neural Network model demonstrated effective learning and generalization ability on the soil classification task.

6.2 Transfer Learning with VGG16

The trained Transfer Learning with the VGG16 model was evaluated throughout 75 epochs. The training and validation performance metrics for select epochs are summarized in Table 1:

Epoch	Training Loss	Training Accuracy	Validation Accuracy
1	1.9009	0.4281	0.6462
10	0.7272	0.7465	0.8308
25	0.4422	0.8300	0.8923
50	0.3743	0.8609	0.9462
75	0.3623	0.8717	0.9385

Table 1: Selected Training and Validation Metrics

The training loss decreased from 1.9009 to 0.3623 by the end of model training, and the training accuracy increased from 0.4281 to 0.8717 over the 75 epochs. In the validation set, accuracy increased from 0.6462 to 0.9385.

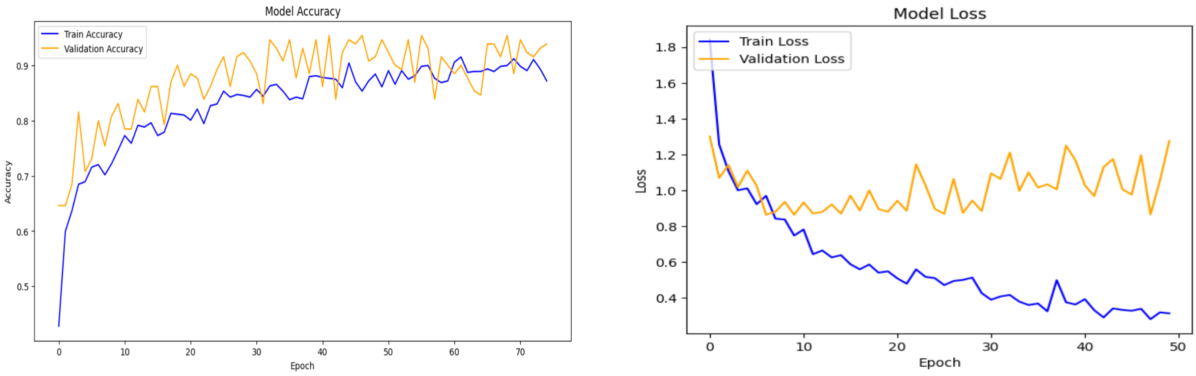
The loss and accuracy trends during training and validation are illustrated in Figure 11. Figure 11a illustrates the accuracy trend, while Figure 11b shows the loss trend.

Overall, the model exhibits a positive trend in both training and validation, showing successful learning and generalization.

6.3 SoilNet: VGG16 with Image Quality Enhancement

The third model (SoilNet) was trained over 75 epochs with the following key metrics:

Metric	Training Set	Validation Set
Loss	0.2850	0.1464
Accuracy	0.8932	0.9538



(a) Accuracy Trend - VGG16 Model (b) Loss Trend - VGG16 Model

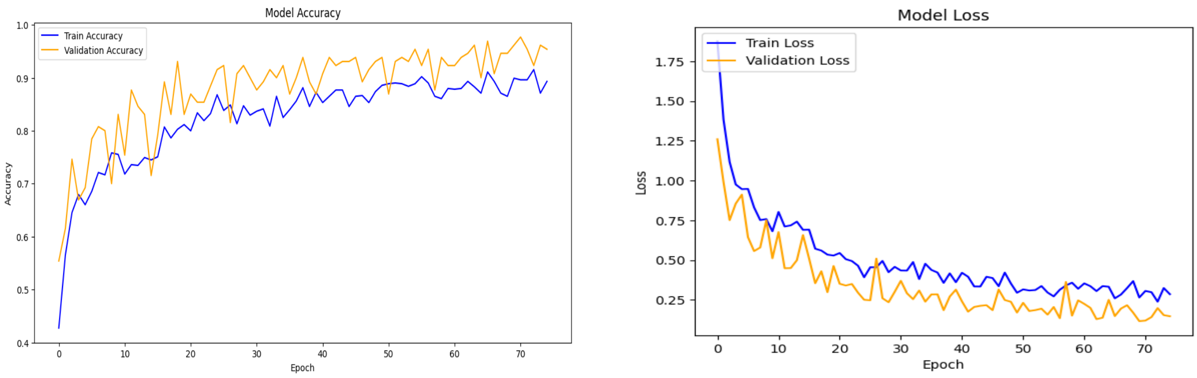
Figure 11: Transfer Learning with VGG16

The training process indicates that the model has achieved a training accuracy of around 89.32% and a training loss of 0.2850 by the end of training. On the validation set, the model performed well with an accuracy of 95.38% and a loss of 0.1464 as shown in Figure 12.

These results suggest that the model generalizes effectively to new data, as evidenced by the high validation accuracy.

Training Dynamics

The training dynamics indicate that the model experiences an initial increase in accuracy and a decrease in loss. It stabilizes over time, suggesting convergence to a particular level of performance. Monitoring these metrics will help in determining the appropriate number of epochs for training.



(a) Accuracy Trend - SoilNet (b) Loss Trend - SoilNet

Figure 12: Transfer Learning with SoilNet

Conclusion

In conclusion, the SoilNet(third) model demonstrates promising performance with high accuracy on both training and validation sets.

7 Conclusion

In summary, the proposed SoilNet Model (third model), a soil-centric neural network model demonstrated the best performance throughout 75 epochs of training and evaluation. With an achieved accuracy of 95.38% on the validation set, the model showcased robust predictive capabilities, marking a substantial advancement in soil-related image classification compared with the state-of-the-art work discussed in related work.

The proposed research work has proved to be better than the previous work in the field in terms of Accuracy, Consideration of multiple classes(enabled by combining multiple datasets), Advanced Image Quality improvement, Advanced data augmentation and better generalisation.

The incorporation of image preprocessing methods played a pivotal role in improving model performance. These techniques help to enhance feature extraction and, consequently, improve classification accuracy. A meticulous analysis of the experiments revealed that these preprocessing steps, including but not limited to Histogram Equalisation, Gaussian Filter, Median Filter, Image Resize and Augmentation, played a crucial role in refining the model's ability to discern soil characteristics.

It is crucial also to acknowledge the identified limitations. Ongoing efforts to fine-tune hyperparameters and explore advanced neural network architectures aim to further improve the model's accuracy. Critical insights from the evaluation highlight areas for enhancement, focusing on the iterative nature of model development.

8 Future Work

Future work focuses on iterative refining of the model to enhance its predictive accuracy and generalizability. Fine-tuning hyperparameters, expanding the dataset, incorporating domain-specific knowledge and including more diverse soil images could contribute to further improvements. Exploring advanced neural network architectures and considering ensemble techniques may provide a way for optimization.

Additionally, conducting experiments across diverse soil types and environmental conditions can increase the model's adaptability. Collaborative efforts with domain experts and integration of real-time data sources may enhance the model's applicability in diverse practical scenarios.

Moreover, addressing the interpretability of the model's predictions and evaluating its robustness to variations in input image data are important aspects for future research. These aims will contribute to the continual evolution of soil-related neural network models and their effective deployment in real-world applications.

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