HybridTransferNet: soil image classification through comprehensive evaluation for crop suggestion

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ABSTRACT

Soil image classification is a critical task within the realms of agriculture and environmental applications. In recent years, the integration of deep learning has sparked significant interest in image-based soil classification. Transfer learning, a well-established technique in image classification, involves fine-tuning a pre-trained model on a specific dataset. However, conventional transfer learning methods typically focus solely on fine-tuning the final layer of the pre-trained model, which may not suffice to attain high performance on a new task. HybridTransferNet, a unique hybrid transfer learning approach designed for soil classification based on images is proposed in this paper. HybridTransferNet goes beyond the conventional approach by fine-tuning not only the final layer but also a select number of earlier layers in a pre-trained ResNet50 model. This extension results in substantially enhanced ability to classify when compared to standard transfer learning methods. Our evaluation of HybridTransferNet, conducted on a soil classification dataset, encompasses the reporting of various performance indicators, such as the F1 score, recall, accuracy, and precision. Our findings from experiments highlight HybridTransferNet's advantages over conventional transfer learning strategies, establishing it as a state-of-the-art solution in the domain of soil classification.

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1. INTRODUCTION

Soil image recognition models today involve numerous complexities, and training these models from the ground up demands substantial computational power and extensive data labeling efforts. To address these challenges, A machine learning technique called transfer learning (TL) has surfaced, which uses neural networks that have already been trained to transfer information to new tasks [1]. TL comprises using a single set of tasks to train a model and adapting it to another, facilitating swift performance when applied to related tasks. TL's main goal is to improve learning by optimizing the utilization of knowledge acquired from the source task. Evaluation of TL is based on the effectiveness of knowledge transfer, the time saved by utilizing pre-existing knowledge, with the ultimate performance achieved when compared to teaching from start, in the intended task [2]. TL serves as an effective approach for capitalizing on existing knowledge to enhance learning outcomes.

The classification of soil is a pivotal endeavor in agriculture and environmental monitoring, given the profound effects of soil characteristics on water retention, nutritional availability, and plant growth. The diversification in soil characteristics across agroecological zones contributes to the complexity of this task. This is particularly significant in countries such as India, where rural livelihoods are supported by agriculture, and it has a major economic role. Knowing the characteristics that are unique and constraints of different zones enables farmers to use resources as efficiently as possible, which in turn promotes increased agricultural output, security of food, and viable rural growth.

Image-based soil categorising has received a lot of interest lately because of developments in deep learning and imaging technologies [3], [4]. Deep learning models excel at extracting intricate features from soil images, enabling precise categorization into various classes. In image classification, transfer learning is a commonly used technique that usually entails optimising a previously trained model on a fresh dataset. However, traditional transfer learning methodologies frequently concentrate only on optimising the last layer of the trained model, which might not be enough to achieve excellent performance on a novel assignment.

A new hybrid transfer learning approach for image-based soil classification in this paper called HybridTransferNet is proposed. HybridTransferNet extends its fine-tuning beyond the final layer, encompassing a select number of earlier layers within a pre-trained ResNet50 model. This extension results in significantly enhanced categorization results in comparison to conventional transfer learning techniques. Our evaluation of HybridTransferNet on a soil classification dataset includes the reporting of multiple performance metrics, such as precision, accuracy, F1 score, and recall. The outcomes of experiments underscore the superiority of HybridTransferNet over conventional transfer learning techniques, establishing it as a modern and advanced approach in soil classification. Applications in agriculture and the environment stand to gain from the potential for improving soil categorization accuracy and efficiency provided by the proposed HybridTransferNet architecture.

Numerous research studies have delved into soil image classification, exploring diverse transfer learning approaches and contributing to the collective knowledge in this domain. In one notable investigation, Nguyen *et al.* [3] introduced an inventive classification methodology that amalgamated random forest (RF), multilayer perceptron (MLP), and support vector classification (SVC) models to accurately discern distinct soil classes. Their research was directed towards enhancing the precision and reliability of soil classification based on image data, thereby advancing the field of soil science applications.

Soil classification predicated on physical and chemical properties has been addressed using a spectrum of machine learning algorithms, including convolutional neural nets (CNN), naive bayes, and decision trees [5]-[7]. Furthermore, the application of machine learning in agriculture extends beyond soil classification, encompassing the prediction of crop yields, the detection of diseases and weeds, species identification, livestock management, and the implementation of intelligent irrigation and harvesting systems [8]-[10]. These machine learning algorithms have contributed to enhancements in productivity, product quality, operational efficiency, and the reduction of labor in various agricultural domains.

In the context of soil image classification, prior works have explored different facets and methodologies. One study conducted a comparative analysis of diverse techniques for selecting wrapper features in conjunction with classification techniques to recommend the most suitable crops for specific land conditions [7]. A comprehensive review underscored the potential advantages of leveraging machine learning for estimating agricultural productivity, identifying weeds and diseases, predicting soil parameters, and managing livestock [8]. The literature also referenced the utilization of pre-trained CNN models and transfer learning in the classification of hostel images [11]. Another study proposed an interfused machine learning approach that harnessed the Fusing Classifier Algorithm (FCA) and Interfused Machine Learning Algorithm (IMLA) to predict suitable crops based on geographical zones and agro-climatic parameters [12]. Furthermore, the use of transfer learning has been investigated in other fields, such as the categorization of auroral images. [13], malware image classification [14], ultrasound breast cancer image classification [15], smart city applications [16], and synthetic aperture radar analysis [17]. These explorations have yielded promising results in their respective domains.

While these prior works collectively advance the field of soil image classification and its associated applications, achieving a high level of accuracy in soil classification remains a formidable challenge, given the intricate pictures of soil's nature. Conventional methods for transfer learning are found to be constrained. In this work, a groundbreaking approach to soil image classification, known as HybridTransferNet is being proposed. This innovative methodology harnesses the power of transfer learning in a distinctive manner, offering a fresh perspective on tackling the inherent challenges of soil type classification from image data. By reimagining the application of transfer learning in the context of soil science, a novel solution that significantly advances the field of soil image classification is introduced. The following highlights the contribution of the research work:

- A novel methodology for soil image classification that leverages transfer learning in a unique way.
- Addressing the inherent challenges of classifying soil types from image data.

– Distinctively fine-tuning not only the last layer but also earlier layers of a previously trained ResNet50 model, yielding better results than conventional transfer learning techniques.
– Fine-tuning is necessary because it allows the model to adapt to the new task while preserving the knowledge gained from the initial training, which can lead to faster convergence and better performance on the specific soil classification task you want to accomplish.
– Demonstrating the effectiveness of HybridTransferNet by consistently achieving cutting-edge results in the categorization of soil, validated through comprehensive evaluation metrics.
– Highlighting the broader implications of accurate soil classification, including its potential to maximise the use of resources, increase agricultural output, guarantee food security, and encourage rural development that is sustainable.

2. METHOD

This manuscript introduces a soil categorization method employing a hybrid transfer learning approach. The process begins with the pre-processing of the soil image classification dataset, using methods for data augmentation to improve the model's capacity to generalize to newly acquired data. The pre-processed data is then split into three different sets: training, validation, and testing. The proposed HybridTransferNet model is then employed to predict soil types, including Alluvial, Red, Black, and Clay, on each of the testing, validation, and training datasets. To provide a visual representation of the workflow, Figure 1 illustrates the step-by-step process demonstrating the HybridTransferNet method for classifying soil images. A thorough examination is carried out to determine the efficacy of several transfer learning models, including the suggested HybridTransferNet model. A comprehensive evaluation of each model's ability is provided by the use of many measures, including precision, recall, accuracy, and the F1-score, to quantify performance.

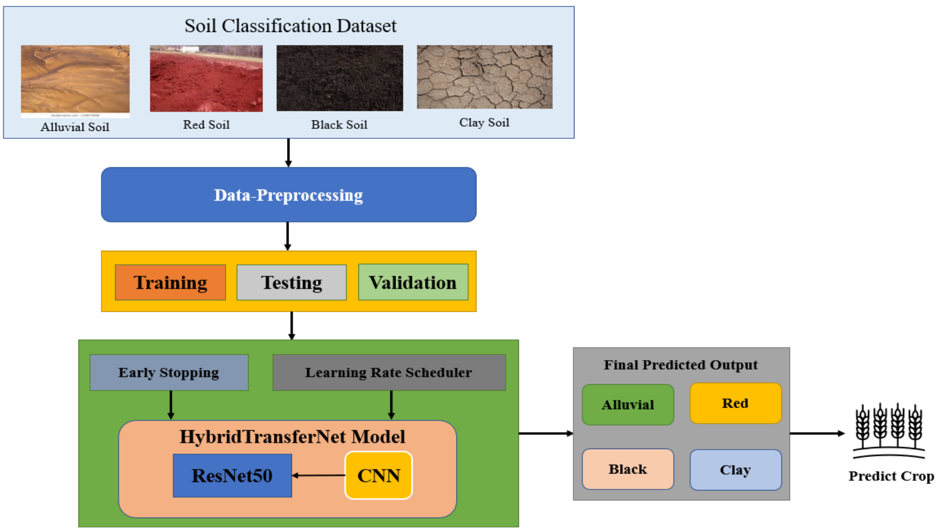

Figure 1. Work flow diagram of HybridTransferNet model for soil image classification

2.1. Dataset collection

In this study, the soil classification dataset was composed of a total of 720 images, each of which could be categorized into one of four distinct soil classes: Red, Black, Clay, and Alluvial Soils. These images were sourced from a variety of publicly available datasets [18], which were combined to form the dataset used for this research. To provide a visual representation of the dataset, a few images taken from soil image classification dataset are presented in Figure 1. Furthermore, Table 1 furnishes a comprehensive summary of the dataset, offering details on the distribution of images across the different soil classes, thereby providing an overview of the dataset's composition.

2.1.1. Data pre-processing

The images in the aforementioned collection varied in terms of resolution and size. All of the images were changed to the JPEG format in order to provide consistency and uniformity. Data augmentation techniques were used to further prepare the data for training. Specifically, the RandomResizedCrop() function was utilized to adjust the image size, ensuring that they all conform to a consistent size.

Table 1. The overview of the soil image classification set

Soil Type	Images
Alluvial	176
Black	212
Clay	145
Red	185

The dataset was then partitioned into three distinct sets such as: 1) Training set (70%), comprising much of the data (70%), was utilized for model training, 2) Testing set (20%): A subset of the data (20%) was reserved for testing, which is employed to evaluate the overall performance of the model, and 3) Validation set (10%). The validation set (10%) played a crucial role in hyperparameter tuning and monitoring the model's training progress. To further enhance the generalizability of the model, an augmentation of data technique known as RandomHorizontalFlip() was applied exclusively to the training set. This technique introduced variations in the form of horizontal flips, thereby augmenting the training data and improving the model's adaptability to different scenarios and orientations.

2.2. HybridTransferNet algorithm

The soil image classification task employed the HybridTransferNet algorithm, which encompasses a combination of transfer learning techniques. The approach involved a series of steps to achieve accurate classification results. By integrating pre-trained features and specialized tuning, the HybridTransferNet algorithm demonstrated its efficacy in handling soil image classification tasks effectively. The following steps were performed,

a. Import the dataset and divide it into three subsets: training, validation, and test sets.
b. Define data transformations for each dataset. These transformations may include resizing, normalization, data augmentation (e.g., random rotations or flips), and any other stages in preprocessing to get the data ready for model input.
c. Load the pre-trained ResNet50 model, which is trained beforehand on a sizable dataset (such as ImageNet) and contains learned features. Remove the last layer of the model, as it is specific to the original task it was trained on.
d. Freeze all layers in the pre-trained model except for the last one.
e. Define the loss function, commonly used for classification tasks, is cross-entropy. Choose an optimizer, such as Adam, and set its learning rate (e.g., 0.001).
f. Put in place a learning rate scheduler, such as ReduceLROnPlateau, that tracks the validation loss and, when the loss reaches a plateau, lowers the learning rate by a factor (such as 0.1).
g. While keeping an eye on the validation loss, train the model on the training set for a predetermined number of epochs (such as 50). To avoid overfitting, stop training if the validation loss does not become better after a certain number of epochs (such as 5).
h. Assess the performance of the top-performing model on the test set once it has been trained. Determine many performance parameters to measure the model's classification efficacy, including as precision, recall, accuracy, and F1 score.
i. Create plots of the training and validation accuracy curves, as well as the loss and validation curves.

2.3. Mathematical model

The underlying mathematical concept of the HybridTransferNet machine learning methodology is a holistic fusion of transfer learning principles. This algorithm capitalizes on the robustness of pre-trained features acquired from a source domain and meticulously fine-tunes them to accommodate the distinct characteristics of the target domain. This adaptation unfolds through a sequence of optimization steps, systematically adjusting the model's parameters to amplify its capacity to precisely classify soil images. The outcome is a sophisticated model architecture that masterfully amalgamates the strengths of transfer learning and domain adaptation, ultimately facilitating resilient and precise soil image classification. The following is a description of the HybridTransferNet machine learning model's mathematical model:

Let f be the HybridTransferNet model, Y be the ground truth label, and X be the input image. The HybridTransferNet model, denoted as f, is at the heart of our approach. It leverages a pre-trained ResNet50 architecture with a hybrid transfer learning strategy. Unlike conventional transfer learning methods that focus solely on fine-tuning the final layer of the trained model, HybridTransferNet goes further by fine-tuning both a few previous levels, followed by the final layer. This holistic approach allows the model to adapt more effectively to the unique features and complexities of soil images.

2.3.1. Forward pass

In the forward pass of the HybridTransferNet model, the predicted output for a given input image X is obtained. This predicted output, denoted as Y_hat, is a fundamental step in the classification process. It is calculated as shown in (1),

$$Y\_hat = f(X) \tag{1}$$

Here, f(X) signifies the application of HybridTransferNet model to the input image X. The model has been fine-tuned using proposed hybrid transfer learning strategy, which includes the fine-tuning of both earlier layers and the final ResNet50 architecture. The value of Y_hat represents the model's prediction for the class or category of the soil image X. This prediction is based on the features learned by the model during training, allowing it to make informed decisions regarding the soil's classification.

2.3.2. Loss computation

Computing the cross-entropy loss is a crucial step for training and evaluating the model's performance. This loss, denoted as L, quantifies the difference in the predicted labels (Y_hat) and the ground truth labels (Y) for a set of training examples. The cross-entropy loss is computed using the equation,

$$L = -1/M * \Sigma [Y * \log(Y\_hat) + (1 - Y) * \log (1 - Y\_hat)] \tag{2}$$

Where, M represents the total number of training examples in the dataset. Y signifies the term of ground truth associated with each training example. Y_hat denotes the predicted label generated by the HybridTransferNet model for each training example. log represents the natural logarithm. The loss L is a measure of how well the model's predictions align with the actual ground truth labels. By minimizing this loss during training, the model learns to make more accurate and informed predictions, ultimately improving its performance in soil image classification tasks.

2.3.3. Backward pass

The backward pass, often referred to as the "backpropagation" process, constitutes a pivotal stage in the training of neural networks, including the HybridTransferNet model. In the backward pass, the focus shifts to fine-tuning the internal parameters of the model in order to reduce the discrepancy between these forecasts and the actual ground truth labels. This reduction of the prediction error is essential for enhancing the model's performance.

a. Determine the loss's gradient in relation to the model's parameters:
   During the training phase of the HybridTransferNet model, the gradient of the loss (L) with respect to all model parameters, denoted as dL/dW, is computed. This gradient quantifies how changes in model parameters affect the loss function. The computation typically involves techniques like backpropagation, which efficiently calculates these gradients for each parameter.
b. Make use of an optimizer to update the model parameters (e.g., Adam):
   Following the computation of gradients, the model parameters are updated to minimize the loss and enhance the model's performance. This update is carried out using stochastic gradient descent (SGD) or Adam as an optimisation technique. The updated parameters are calculated as shown in (3).

$$W = W - alpha * dL/dW \tag{3}$$

Where: W represents the set of all model weights and biases. alpha (α) is the learning rate, which determines the step size for parameter updates. This backward pass, involving gradient computation and parameter updates, plays a crucial role in training the HybridTransferNet model to make more accurate predictions in soil image classification tasks.

2.3.4. Early stopping

Early stopping is a vital technique in the realm of training machine learning models, including the HybridTransferNet. Its purpose is to strike a balance between model optimization and preventing overfitting, a common challenge in deep learning. This technique is grounded in the idea that, during training, a model typically improves its performance on a training dataset while simultaneously risking a decline in its ability to generalize to unseen data.

a. Throughout training, keep an eye on the validation loss and preserve the best model according to that loss.
   Throughout the training process of the HybridTransferNet model, it is essential to continuously monitor the validation loss. The model has not observed this loss during training; instead, it is calculated on a different validation dataset. Monitoring the validation loss helps determine whether the model is overfitting,

underfitting, or effectively generalizing to new data. The primary objective is to minimize the validation loss. Additionally, it's common practice to save the parameters (weights and biases) of the model that achieves the lowest validation loss. This ensures that the best-performing model can be retaimed for later use.

b. Considering an inevitable number of epochs, stop training if the validation loss does not improve. (e.g., 5). To prevent overfitting and optimize training efficiency, an early stopping mechanism is often employed. This involves monitoring the validation loss over a fixed number of training epochs. If the validation loss does not show improvement for a specified number of consecutive epochs (e.g., 5), the training process is halted. Early stopping helps prevent the model from continuing to train when it has already reached its optimal performance on the validation dataset, reducing training time and potentially improving generalization to new, unseen data. These practices, monitoring validation loss and early stopping, contribute to effective training and ensure that the HybridTransferNet model achieves the best possible performance on soil image classification tasks while avoiding overfitting.

2.3.5. Performance evaluation

Once the training of the HybridTransferNet model is completed and the best model has been selected based on validation performance, it is crucial to assess its performance on an independent test set. This evaluation serves as a measure of the model's ability to generalize to new, unseen soil images. The best trained HybridTransferNet model is applied to the test set, which consists of soil images that were not used during training or validation. The model's predictions are compared to the ground truth labels for these test images. Various performance metrics are computed to quantify the model's effectiveness in soil image classification. These metrics typically include:

- Accuracy: Calculates the percentage of the test set's total number of properly identified images.
- Precision: Calculates the proportion of accurate positive predictions to all positive forecasts.
- Recall: Determines the proportion of genuine positive occurrences to all true positive forecasts.
- F1 Score: Represents the precision and recall harmonic mean, providing a balanced measure of model performance.

These performance metrics collectively offer insights into how well the HybridTransferNet model performs in classifying soil images, including its ability to correctly identify different soil classes and minimize false positives and false negatives.

2.3.6. Plotting

To gain a visual understanding of the HybridTransferNet model's performance during training, generate plots that depict the changes in key metrics over the training epochs. These plots are essential for assessing how well the model is learning and whether it is overfitting or underfitting. The training and validation loss curves provide insights into how the model's loss function changes during training. Typically, the training loss should decrease, while the validation loss may initially decrease but should stabilize or even increase if the model starts overfitting. The model's classification accuracy is demonstrated by the training and validation accuracy curves evolved over epochs.

3. RESULTS AND DISCUSSION

The results of the tests on soil image classification, involving a variety of convolutional neural network (CNN) architectures including visual geometry group (VGG) 16 [19], VGG 19 [20], residual network (ResNet) 18 [21], ResNet 50 [22], and DenseNet121 [23], in conjunction with different optimizers, showcase the effectiveness of these models in soil classification. Notably, ResNet18 and ResNet50 demonstrate a strong capacity to collect relevant characteristics for soil categorization by consistently achieving excellent accuracy scores across all optimizers. The experiments are conducted using Google CoLab.

Additionally, VGG16 and VGG19 display commendable performance, particularly when employed in tandem with the root mean square propagation (RMSProp) optimizer, signifying the efficacy of these architectures in extracting distinctive features from soil images. DenseNet121 also delivers robust performance across all optimizers, with RMSProp yielding the best accuracy.

Furthermore, our proposed HybridTransferNet architecture consistently demonstrates exceptional accuracy scores, as presented in Table 2, outperforming most other architectures across various optimizers. This underscores the efficacy and robustness of the HybridTransferNet approach in the task of soil image classification.

Model performance is largely dependent on the optimizer choice, which also affects the rate of convergence and overall correctness of the models. Notably, the RMSProp optimizer frequently outperforms other optimizers in terms of accuracy and regularly produces competitive results. This underscores the significance of incorporating adaptive learning rates and gradient normalization, which are instrumental in facilitating effective convergence and superior model performance.

In addition, the Adam optimizer performs well, especially when used with the HybridTransferNet architecture. This performance indicates the optimizer's effectiveness in optimizing convolutional neural network (CNN) models, showcasing its potential for achieving favorable results. Conversely, compared to RMSProp and Adamax, the stochastic gradient descent (SGD) optimizer shows comparatively lower accuracy ratings. These findings imply that, when employing the assessed designs, SGD might not be the best option for classifying soil. For a visual representation of these findings, please refer to Figure 2, which presents a comparison of accuracy levels achieved by different transfer learning models employing various optimizers in conjunction with the proposed HybridTransferNet model. Table 3 depicts the comparison of several methods with the suggested HybridTransferNet model for classifying soil images.

HybridTransferNet outperforms most previous architectures using various optimizers, constantly displaying outstanding accuracy ratings is presented. When compared to previous works in soil image classification, HybridTransferNet achieves exceptional accuracy. For instance, it surpasses the results obtained by Nguyen *et al.* [3], Vijayakumar and Balakrishnan [24], Barman and Choudhury [25], Srunitha and Padmavathi [26], Lu *et al.* [27], Odhiambo *et al.* [28], Bhattacharya and Solomatine [29], Zhao *et al.* [30], Mengistu and Alemayehu [31], Wu *et al.* [32], Yang *et al.* [33], Vibhute *et al.* [34], and other studies in this field.

Table 2. The accuracy attained for various transfer learning models for various optimizers is compared with the HybridTransferNet suggested model in the table

Name of the model	Adam	RMSProp	SGD	Adamax
Resnet18	96.83	96.3	94.18	95.24
Resnet50	97.35	97.35	94.18	95.24
VGG16	98.91	98.94	97.3	96
VGG19	96.83	98.34	90.48	93.12
DenseNet121	98.41	97.35	92	95.77
HybridTransferNet (proposed)	98.94	99.47	98.41	96.83

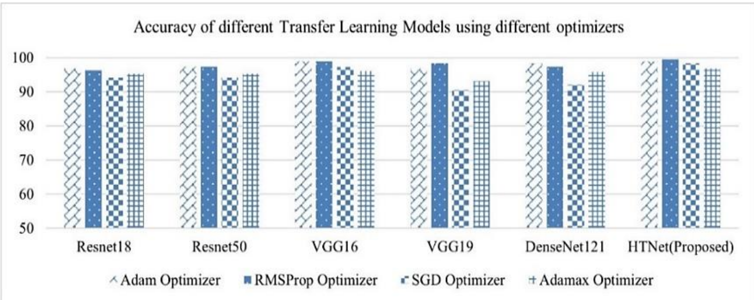

Figure 2. Comparison of accuracy results utilising several optimizers from various transfer learning models

Table 3. Comparison of the accuracy results from several works using the suggested HybridTransferNet model

Previous works	Models built	Accuracy achieved (%)
Nguyen *et al.* [3]	SVC, MLP, RF	SVC=98.4
Kumar and Balakrishnan [24]	ANN	95
Barman and Choudhury [25]	SVM	91.37, 95.72
Srunitha and Padmavathi [26]	SVM	95
Lu *et al.* [27]	CNN	AUC=91.47
Odhiambo *et al.* [28]	SVM-poly	94.3
Bhattacharya and Solomatine [29]	Decision Trees, ANN and SVM	89.34, 87 and 71.18
Zhao *et al.* [30]	ANN	88, 81
Mengistu and Alemayehu [31]	Back-Propagation Neural Network (BPNN)	89.7
Wu *et al.* [32]	Multi SVM with Polynomial Kernel	79.4 and 99.2
Yang *et al.* [33]	PLS-DA and Multi SVM with Polynomial Kernel	93.33 and 96.67
Vibhute *et al.* [34]	Multi SVM with Liner kernel	71.78
Proposed Work	HybridTransferNet	99.47

4. CONCLUSION

In this research, we provide a new hybrid transfer learning method for image-based soil classification in this work called HybridTransferNet. In HybridTransferNet, the last layer of a pre-trained ResNet50 model is combined with the fine-tuning of a few previous layers. This strategic fine-tuning results in notable enhancements in classification performance compared to conventional transfer learning methods.

To evaluate the effectiveness of HybridTransferNet, we conducted experiments using a dataset for soil classification and assessed many performance measures, including F1 score, accuracy, precision, and recall. Our empirical findings indicate that HybridTransferNet achieves a remarkable prediction accuracy of 99.47%. It notably surpasses the performance of traditional transfer learning models, including ResNet18, ResNet50, VGG16, VGG19, and DenseNet121, establishing itself as a state-of-the-art solution for soil classification tasks. The implications of this proposed methodology extend to the potential improvement of accuracy and efficiency in soil classification, with valuable applications in agriculture and environmental domains. Future research directions encompass the exploration of HybridTransferNet's applicability to other image-based classification tasks and the ongoing pursuit of methods to further enhance its performance and efficiency. In conclusion, one interesting approach to improving the precision and effectiveness of image-based soil categorization is HybridTransferNet.

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