Investigating Efficiency of Soil Classification System using Neural Network Models

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***Abstract*—Soil is a vital requirement for agricultural activities providing numerous functionalities restoring both abiotic and biotic materials. There are different types of soils, and each type of soil possesses distinctive characteristics and unique harvesting properties that impact agricultural development in various ways. Generally, farmers in the olden days used to analyse soil by looking at it visually while some prefer laboratory tests which are time-consuming and costly. Testing of soil is done to analyse the features and characteristics of the soil type, which results in selecting a suitable crop. This in turn results in increased food productivity which is very beneficial to farmers. Hence, to recognize the soil type an automatic soil identification model is proposed by implementing Deep Learning Techniques. It is used to classify the soil for crop recommendation by analysing accurate soil type. Different Convolution Neural Networks have been applied in the proposed model. They are VGG16, VGG19, InceptionV3 and ResNet50.Among all those techniques it is analysed that better results were obtained with ResNet50 having an accuracy of about 87% performing Multi-classification that is Black soil, Laterite Soil, Yellow Soil, Cinder soil & Peat soil.**

Keywords—Agricultural; convolution neural network; soil classification deep learning; VGG16; VGG19; InceptionV3; multi-classification; ResNet50

I. Introduction

Soil stands as a vital agricultural resource, housing a plethora of nutrients essential for crop cultivation. Each region possesses its unique soil composition, giving rise to diverse soil types worldwide. Serving as Earth's outer layer, soil encompasses various minerals, organic matter, living organisms, and water. Acting as a bridge between the planet's internal layers and its surface, soil plays a pivotal role in facilitating plant growth. The availability of nutrients and water in the soil determines the growth of a plant, making it a crucial factor for analysis. In the current era, effective plant management holds paramount importance to ensure human sustainability. The global population have been steadily increasing, thus there is a growing need to enhance food, fabric, and medicine production. Consequently, improving the agricultural sector becomes imperative, as it stands as a primary source capable of meeting these escalating demands.

The growth of different types of crops is influenced by diverse factors such as the availability of nutrients, water, and oxygen in the soil, balancing both environmental and physical conditions to achieve a good yield. Among all these resources the current work concentrates on the different classifications of soil to identify the specific category of soil which ultimately determines a selective crop. Each region is determined with different types of soils like black soil, peaty soil, alluvial soil, red soil, desert soil, forested soil, laterite soil, and many more. For soil classification various Deep Learning techniques are implemented as they are categorized based on the considered soil images. To classify soil types, a variety of features such as hue, saturation, texture, colour, intensity, and other relevant characteristics are extracted and utilized.

Deep learning is an architecture comprising a large number of layers that enables the transformation of raw data into meaningful features. This process is often referred to as feature engineering in the context of deep learning models. Various types of CNNs are used for classification. Some of the existing models are implemented using both Machine Learning and Deep Learning Techniques [1]. The author implements a model using K-NN Classifier and SVM Classifier on different types of soil image datasets [2] [9] [14]. The author implements a model using an SVM classifier. The research in [3] [13] proposed a technique designed using an SVM classifier and ResNet50, CNN while the author in [4][17], employs a range of neural network models, including CNNs, DBNs, LSTMs, Multilayer Perceptron, and Autoencoders. These architectures serve various purposes such as image processing and feature extraction within the study. The study in [5] [16] proposed a technique implementing an, Network Model (CNN), SVM classifier and StoolNet. The research in [15] [6], the author implemented a Network Model based on Convolutional Neural Networks (CNN). This model was designed to filter images using five different types of masks: spot, wave, level, ripple, and edge. These masks are utilized as filtering techniques in image processing, helping to extract specific features or enhance certain characteristics in the images. The application of these masks within a CNN framework suggests that the study focuses on leveraging convolutional operations to analyses and process images for a particular purpose, such as texture analysis or pattern recognition [10]. A model has been proposed by the author that combines Naive Bayes and Artificial Neural Network (ANN) techniques. This hybrid approach is utilized to analyze physical parameters like water content and dry density, as well as soil parameters such as internal friction angle, cohesion. Simultaneously in [6] the study employs a Gabor Filter for edge detection, followed by Std, skew, Mean, and kurtosis and other sinusoidal measures to retrieve images. The classification task involves using the CNN algorithm for land and soil images. Additionally, a Visual Transformer for image classification is introduced, showcasing superior accuracy compared to CNN, SVM, ResNet-50 and subsequent machine learning models as stated in study [3].

Therefore, in this paper, a model developed is determined using VGG16, InceptionV3, VGG19 and ResNet50associated with Transfer Learning resulting in better and more accurate soil classification. The main objective of this model is to do multi-classification that is yellow soil, Laterite Soil, Cinder soil, Black Soil and Peat soil. The general workflow of the proposed model is explained and continued with the Literature Survey in Section II and Section III provides a diagrammatic approach for the developed model. Section IV covers the experimental evaluation. Section V presents the conclusion of the proposed paper.

II. Literature Survey

Rahman Zaminur proposed a system that utilized the K-NN Classifier, a machine learning algorithm, for classifying soil texture. The research recommended Support Vector Machine as the most effective classifier. The approach involved Bootstrap resampling and a stacked decision tree ensemble classifier. The study encompassed nine different soil types and also explored alternative algorithms such as Artificial Neural Network and GAtree [1].

Navya and Vijay E V proposed a system the image classification process, employing diverse methods including, Sub-pixel Classification, Artificial Neural Network Classification and Maximum Likelihood Classification. They opted for SVM due to its versatility and suitability for comparison purposes. The research utilized a range of pre-processing methods to identify patterns, leading to improved classification analysis [2].

Jagetia Aaryan underscored the significance of precise soil classification, substantiated by multiple parameters such as void ratio, moisture content, liquid limit, clay content, specific gravity and plasticity. Employing the Visual Transformer, an advanced technique for image classification, resulted in impressive accuracy rates of 98.13% during training and 93.62% during testing [3].

Prabhavathi V's research is cantered on Utilizing deep learning algorithms to classify soil, particularly highlighting an inventive deep learning model. The investigation delves into a range of deep learning algorithms, encompassing CNNs, DBNs, LSTM, Autoencoders and Multilayer Perceptron CNNs, in particular, exhibit remarkable accuracy when it comes to Identifying soil through the analysis of hyperspectral bands derived from satellite data and categorizing aggregates using stereo-pair images [4].

Srivastava Pallavi research proposal investigates soil classification techniques through computer vision and the utilization of image processing. colour and soil texture are determined employing methods such as the Munsell colour chart, elutriation, pipette, decantation, The model incorporates StoolNet, which attains a remarkable 100% accuracy in classifying burozem soil and yellow soil [5].

Aparna Yerrolla examines the International Soil Reference and Information Centre dataset, which includes various soil images belonging to different classes. Feature extraction is performed using the Gabor filter to capture attributes like entropy, standard error, and mean. The analysis places significant importance on soil colour extraction. Texture characteristics are extracted using the Laws mask method, involving filtering images with five different mask types: edge, ripple, level, wave and spot. The application of Convolutional Neural Networks (CNNs) with three-layered hidden layers enables the algorithm to effectively classify land images and soil, distinguishing between categories such as Clayey peat, Silty sand, Clay, Humus clay, Peat, Sandy clay and Clayey sand [6].

Barkataki Nairit introduced a deep CNN model designed for automatic soil classification through non-invasive techniques such as ground penetrating radar (GPR). A fabricated dataset was created through the use of gpr-Max for both training and validation. Through a 5-fold cross-validation, the model demonstrated exceptional performance, achieving an impressive accuracy rate of 97% in classifying seven distinct soil types based on ground penetrating radar (GPR) B-Scan images [7].

Khullar Vikas puts forward an effective soil classification system by leveraging deep learning techniques. The study incorporates a diverse set of algorithms, including Random Forest, KNN, Ada-Boost, SVV Machine, Quadratic Discriminant Analysis, Logistic Regression, Decision Tree, Extra Trees, Gaussian Naïve Bayes, and Histogram Gradient Boosting. Additionally, the use of VGG16 and InceptionResNetV2 deep networks for soil classification enhances the categorization process, yielding robust and dependable results that outperform prior state-of-the-art methodologies [8].

Greema S Raj describes a survey done on soil classification using different techniques. Decision tree predictions are made using a binary tree model, known for its speed and accuracy. Naïve Bayes classifiers utilize the Bayes theorem for predicting unrelated features within a class. Parameter estimation is performed using maximum likelihood or Bayesian methods. SVM is a heuristic algorithm employed for supervised learning, determining the optimal hyperplane to separate two classes [9].

Ladan Samadi's research focuses on soil classification using machine learning algorithms, namely ANN and Naïve Bayes. Neural networks are effective in establishing relationships between input variables and target parameters. The Unified Soil Classification System (USCS) is employed for soil classification based on and particle size analysis Atterberg limits. Naïve Bayes and ANN algorithms are utilized for classification, considering particle size analysis and Atterberg limits. The objective is to develop an Artificial Neural Network model that predicts soil classification based on soil conditions and collected data on soil mechanics parameters [10].

Rakesh Kr Dwivedi's Deep learning process, using K-means clustering, aids farmers in classifying soil based on its texture, clay, silt, sand concentrations, and pH value. Soil image classification utilizing machine learning involves three steps: image segmentation, feature extraction, and classification [11].

Abhinav Pandey utilizes a deep CNN methodology for satellite image classification, concentrating on the classification of soil types using chemical and physical properties as criteria. Using the DGX-2, the trained deep CNN achieves an average accuracy of 0.67 and a maximum accuracy of 0.80 in five runs when utilizing images with vegetation removed. However, accuracy decreases to 0.41 due to vegetation fluctuation over time. The desert soil class shows the highest confidence, while the black soil class exhibits the lowest. The average classification accuracy during testing is 0.72, indicating the effectiveness of the model in classifying different soil types from satellite images [12].

The existing methods were implemented mostly on one type of soil from various soil images, based on their respective parameters. This research works aims to classify different types of soil like black soil, yellow soil, laterite, cinder and peat soil with more efficient CNN models.

III. Proposed Model

The suggested model uses the input photos to determine the type of soil. Several varieties of convolution neural networks, which are a part of deep learning techniques, are used in this instance to automatically classify data. Several unseen layers are stacked upon each another in a specific order to create CNN, feed-forward neural network which is multi-layered, which extracts features that are displayed as patterns. The pre-processed input data is then sent through many CNN types, such as ResNet50, InceptionV3, VGG16, and VGG19, to further aid in the classification of the picture of soil under consideration. Fig. 1 illustrates the suggested model's workflow.

The collection of images in the dataset is divided into four categories: images of black soil, yellow soil, peat soil, cinder soil, and laterite soil. It is gathered from offline and internet sources. When putting them into the model, they are mainly divided into Train and Test data images and are pre-processed utilizing techniques for image transformation. Pre-processing procedures, which involve the implementation of Data Augmentation Techniques, are executed in this context. During data augmentation, specific circumstances are applied, such as rotating the image at a ninety-degree angle and modifying it horizontally and vertically. This is done in order to capture more photographs and view it from various perspectives. Images are resized simultaneously to change their aspect ratio and size to a standard 220x220x3 format.

Every image has a specific label applied to it and is mapped for additional classification. As a consequence, pre-processed train and test image data are obtained. Thus, the acquired trained dataset is used to train the model, and the test dataset is used to assess the model.

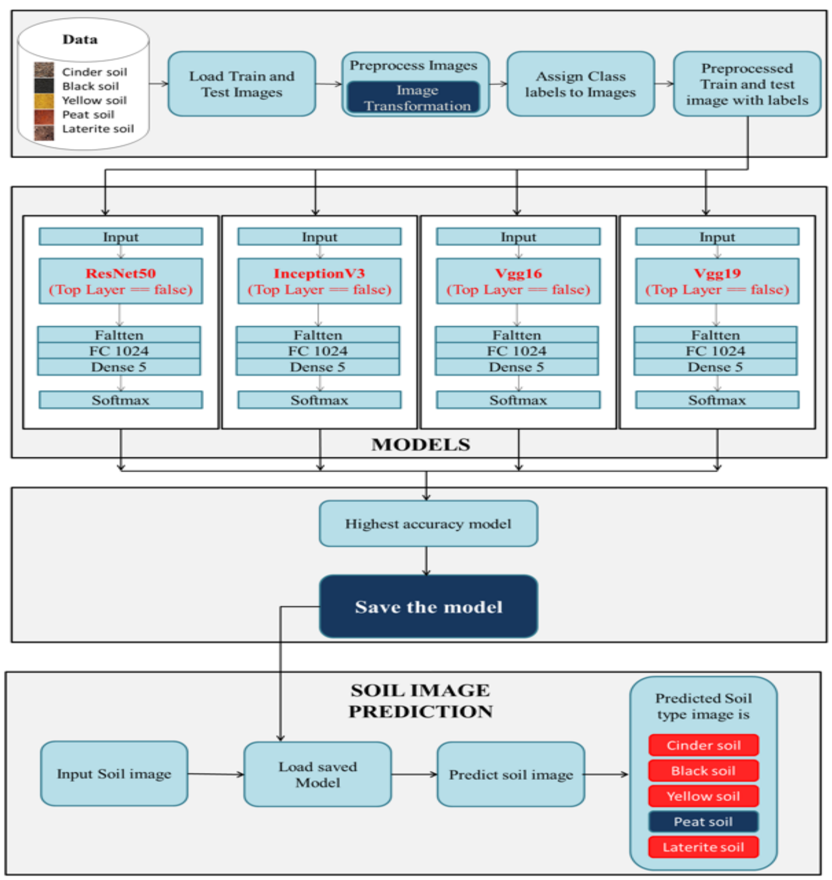

Fig. 1. Workflow of the proposed model.

The acquired data undergoes processing through several CNNs, namely Inception V3, ResNet50, VGG16, and VGG19. Each neural network's individual layer operates on the input data, extracting distinct patterns crucial for classifying the particular soil type under examination. CNNs stand out as highly efficient architectures for image recognition and classification owing to their pattern recognition capability, significantly aiding in the prediction and classification of input image data and yielding the highest achievable accuracy. Standard CNNs typically comprise three fundamental types of layers, often referred to as "building blocks": convolutional, pooling, and fully connected layers. The initial two layers, convolution and pooling, primarily focus on feature extraction, while the third, the fully connected layer, translates these identified features into the final output, such as a classification. Within a CNN, which functions as a sequence of mathematical operations, the convolution layer plays a pivotal role, providing a specialized version of linear operations. Digital images are represented as an array of integers or a two-dimensional (2D) grid capturing pixel values. A kernel, serving as an optimizable feature extractor, is applied at each position across the image, allowing for the extraction of essential features.

We use Transfer learning technique to Connect base model with fine-tuned model Fully Connected Layers. Subsequently, layer freezing is carried out employing the trained data images for the model's first run. When knowledge is taken from an established model and applied to a newly proposed model, transfer learning plays a significant role. Every item listed above The Transfer Learning Mechanism is the foundation upon which CNNs operate. The epochs, learning rate, optimizer and batch size are among the many parameters that are changed for each Convolutional Neural Networks, to classify the photos of dirt, save the model and run it.

Plots of loss percentages and accuracy have been made in accordance with the outcomes of the designed model. One indicator used to assess the model's performance in an understandable manner is accuracy. A metric called loss indicates how well the model performs following each optimization step. In order to anticipate the provided input soil input, we must load the saved model weights concurrently with the input picture path of the testing image, and then predict the input image using the loaded model. Class label assigned determines the index of output, which is based on the index of the maximum element within an array along a specified axis.

Algorithm: Implementation of Model:

Input: Images of different kinds of soil

Output: Prediction of image (Peat, Yellow, Laterite, Black and Cinder Soil images)

Step 1.Importing all training and testing images corresponding to soil categories into the dataset.

Step 2. Preprocessing the Images.

- Enhancing all training and testing images through the application of data augmentation techniques.

Step 3.Associating class labels with their respective images by creating a mapping.

Step 4.Generating the pre-processed dataset after performing all necessary transformations, including data augmentation, and mapping class labels with their corresponding images.

Step 5.Utilizing ResNet50, InceptionV3, Vgg16, and Vgg19 models as the base models for further analysis or processing.

Step 6.Integrating a fine-tuned model into Vgg16, InceptionV3, ResNet50, and Vgg19 by customizing the top layers. Steps

- Configuring the model with specific parameters such as epochs, batch size and learning rate to train and optimize the neural network.
- Incorporating a flattened and fully connected layer into the base model architecture.
- Appending a dense layer with five units (for the number of classification classes) and applying the “SoftMax” activation function to the model.

Step 7. Implementing transfer learning by connecting the base model with fine-tuned fully connected layers to leverage the pre-trained features and optimize the model for the specific classification task.

Step 8. Freezing the layers to maintain their pre-trained weights and prevent them from being updated during the initial execution of the model.

Step 9. Training the model by fitting the training data images to it.

Step 10. Saving the model weights after training for future use or further analysis.

Step 11. Plotting accuracy and loss percentages to visualize the performance of the designed model during training and evaluation phases.

Step 12. The classification of images has been successfully completed using the trained model.

1) VGG16: The utilization of Very Deep Convolutional Networks in Large-Scale Image Recognition showcases the impact of network depth on accuracy within extensive image identification scenarios. The primary focus is a comprehensive analysis of networks with incrementally deeper layers, employing an architecture using (3x3) convolution filters which is relatively small. This study reveals that increasing the depth to a range of 16–19 layers significantly enhance performance compared to current configurations. Our team participated in the 2014 ImageNet Challenge, leveraging these discoveries, leading to our team securing top two places in the localization and classification tracks, respectively. This success underscored the adaptability of our representations across diverse datasets, consistently yielding state-of-the-art results. To encourage continued exploration of deep visual representations in computer vision, our two most impactful ConvNet models available for research purposes.

2) VGG19: The depth of convolutional networks affects their accuracy in large-scale image identification contexts. It employs an architecture with (3x3) convolution filters, just like VGG19, and shows that going deeper to 16–19 weight layers can yield a discernible improvement over the current configuration. When using this VGG19, we have more hidden layers, which yields the best outcomes.

3) InceptionV3: Convolutional networks are the foundation of most state-of-the-art computer vision systems for various workloads. Since its debut in 2014, very deep convolutional networks have made considerable progress in a number of benchmarks. We investigate strategies for scaling up networks that leverage factorized convolutions and aggressive regularization to make the most efficient use of the extra processing. While it's often true that larger model sizes and increased computational resources lead to improved performance in various tasks, provided there is a sufficient amount of labelled data for training, we are exploring methods to efficiently scale up neural networks. This involves applying strong regularization techniques and optimizing convolutions through appropriate factorization, ensuring that the additional computation is used as efficiently as possible, these methods are compared to the state of the art using ILSVRC 2012 automation challenge validation set and find notable improvements: For single frame evaluation, a network with less than 25 million parameters and a computational cost of 5 billion multiply-adds per inference produced errors of 21.2% top-1 and 5.6% top-5. Using an ensemble of four models with multi-crop assessment, we report a 17.3% top-1 error and a 3.5% top-5 error on the validation set and 3.6% error on the test set.

4) ResNet50: Deep residual networks have emerged as a category of highly extensive architectures, demonstrating exceptional accuracy and attractive convergence behaviours. The analysis delves into the propagation formulations fundamental to the residual building blocks, suggesting that both forward and backward signals can be seamlessly transmitted from one block to any other block, specifically when utilizing identity mappings as skip connections followed by activation after addition. Numerous ablation experiments confirm the significance of these identity mappings, which, in turn, serve as the inspiration behind our introduction of a novel residual unit. This new unit not only enhances generalization but also streamlines the training process.

Deep residual networks represent a class of highly extensive architectures known for their exceptional accuracy and favourable convergence behaviours. This analysis explores the propagation formulations within the residual building blocks, particularly when employing identity mappings as skip connections along with post-addition activation. It indicates the direct transferability of both forward and backward signals between various blocks. Numerous ablation experiments further affirm the significance of these identity mappings. As a result, this serves as the driving force behind our proposal for a novel residual unit, aiming to streamline training processes and enhance generalization.

IV. Experimental Analysis

In this paper, the system has been tested with 4 deep-learning keras API models using different optimization techniques with 203 soil images of five categories: Laterite Soil, Peat Soil, Black Soil, Yellow Soil and Cinder Soil.

There are 47 tests done where nine images for each category all the images in the dataset are divided into eight batches. Each image has its own 30 iterations along with various features optimizers that belong to Adam and SGD. There are 156 training images of are done for each model.

For the VGG16 and VGG19 systems recorded mean accuracies are 100% & 100% and loss error rates are 0.0032 & 0.0019, for InceptionV3 system recorded a mean of 87% and the mean loss value is 0.4747.

By using the SGD optimizer technique with the ResNet50 System recorded highest accuracy is 100% and the loss error rate is 0.0013 using the Adam optimizer technique with the ResNet50. From all the above models ResNet50 with the Adam optimizer system is a bit higher than the remaining models.

To compute accuracy, we utilize the confusion matrix, which consists of four categories: True Positives, True Negatives, False Positives, and False Negatives. This matrix enables the calculation of various valuable metrics.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

TABLE I. Measuring Accuracy using the Presented Techniques

Models	VGG16	VGG19	Inception V3	ResNet50
Validation Accuracy	1.0000	1.0000	0.8750	1.0000
Validation Loss	0.0032	0.0019	0.4747	0.0013
Training Accuracy	0.8871	0.9355	0.5645	0.8750
Training Loss	0.9862	0.5171	1.0490	0.9059

The graphs below illustrate the accuracy and loss metrics obtained from different models, including VGG16, InceptionV3, VGG19 and ResNet50.

As illustrated from Fig. 2, the accuracy values ranging from 0.0 to 1.0 is represented on X-axis and the number of epochs (100) executed in the model is represented on Y axis. Throughout the study, 100 epochs were conducted, and the optimal accuracy was achieved at 26 epochs, accompanied by a loss rate of 0.0032. The blue line on the graph corresponds to the training data, while the orange line represents the validation data. It is important to note that 20% of the images were randomly selected from each class for testing purposes, ensuring a representative evaluation of the model’s performance.

As illustrated from Fig. 3, the accuracy values ranging from 0 to 70 is represented on X-axis and the number of epochs (100) executed in the model is represented on Y axis. The graph illustrates the loss corresponding to the accuracy of the VGG16 model. The optimal result was achieved at 26 epochs with a minimal loss rate of 0.0032. The blue line in the graph represents the training data, and the orange line represents the validation data. It's important to note that 20% of the images were randomly selected from each class for testing purposes, ensuring a representative evaluation of the model's accuracy and loss.

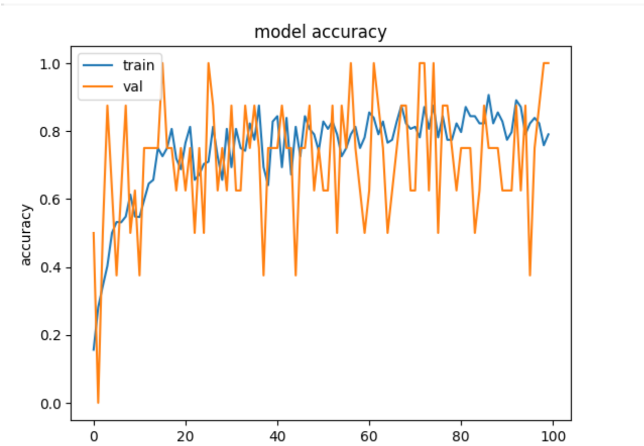

Fig. 2. Accuracy of VGG16.

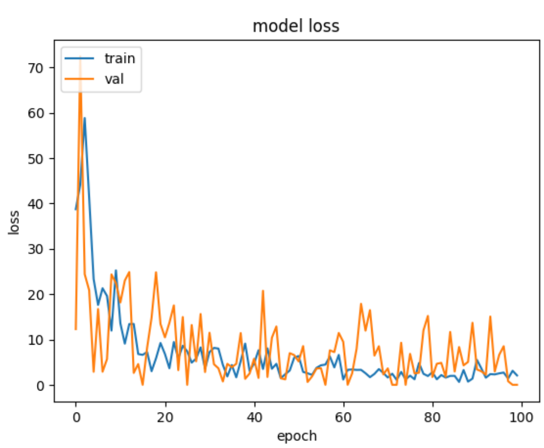

Fig. 3. Loss of VGG16.

As illustrated from Fig. 4, the accuracy values ranging from 0.3 to 1.0 is represented on X-axis and the number of epochs (100) executed in the model is represented on Y axis. In the course of this study, 100 epochs were conducted, and the highest accuracy was achieved at 58 epochs, with a minimal loss rate of 0.0019. The blue line on the graph corresponds to the training data, while the orange line represents the validation data. It's worth noting that 20% of the images were randomly selected from each class for testing purposes, ensuring a representative evaluation of the model's performance.

The blue line is representative of the training data, while the orange line signifies the validation data. Notably, for testing, 20% of images were randomly selected from each class.

As illustrated from Fig. 5, the accuracy values ranging from 0 to 60 is represented on X-axis and the number of epochs (100) executed in the model is represented on Y axis. The graph illustrates the loss corresponding to the accuracy of the VGG16 model. The lowest loss rate was achieved at 58 epochs, with a value of 0.0019. The blue line in the graph represents the training data, while the orange line represents the validation data. It's important to note that 20% of the images were randomly selected from each class for testing, ensuring a reliable evaluation of the model's accuracy and loss.

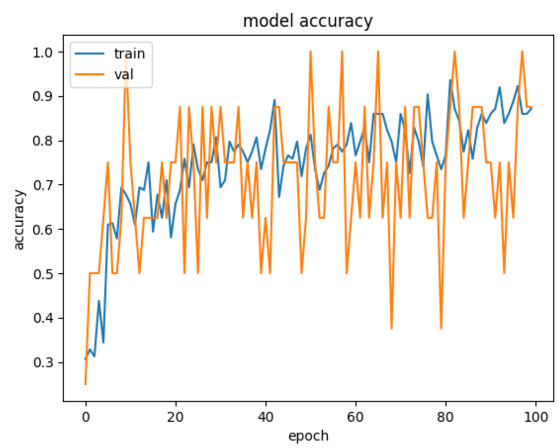

Fig. 4. Accuracy of VGG19.

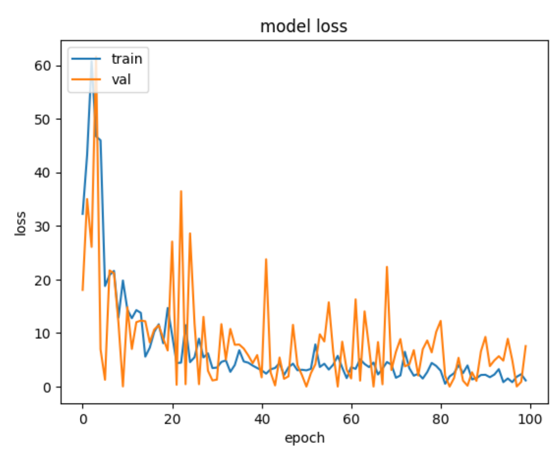

Fig. 5. Loss of VGG19.

As illustrated from Fig. 6, the accuracy values ranging from 0.0 to 0.8 is represented on X-axis and the number of epochs (100) executed in the model is represented on Y axis. During the study, the model was trained for 100 epochs, and the highest accuracy, 87%, was achieved at 52 epochs with a corresponding loss rate of 0.4747. The blue line on the graph represents the training data, while the orange line represents the validation data. It's important to note that for testing purposes, 20% of the images were randomly selected from each class, ensuring a representative evaluation of the model's performance.

The blue line corresponds to the training set, while the orange line represents the validation set. Notably, for testing purposes, 20% of images were randomly selected from each class.

As illustrated from Fig. 7, the accuracy values ranging from 0 to 80 is represented on X-axis and the number of epochs (100) executed in the model is represented on Y axis. The graph illustrates the loss corresponding to the accuracy of the VGG16 model. The lowest loss rate was achieved at 52 epochs, with a value of 0.4747. The blue line on the graph corresponds to the training data, while the orange line represents the validation data. It's important to note that for testing purposes, 20% of the images were randomly selected from each class, ensuring a representative evaluation of the model's accuracy and loss.

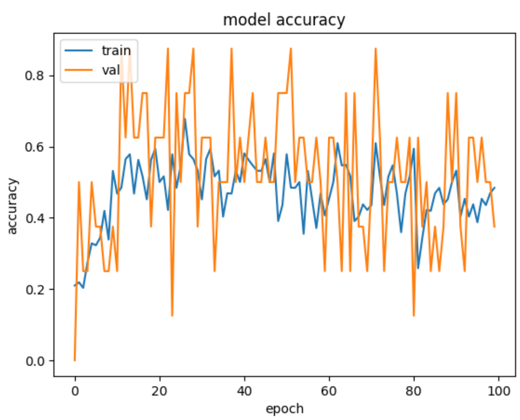

Fig. 6. Accuracy of inceptionV3.

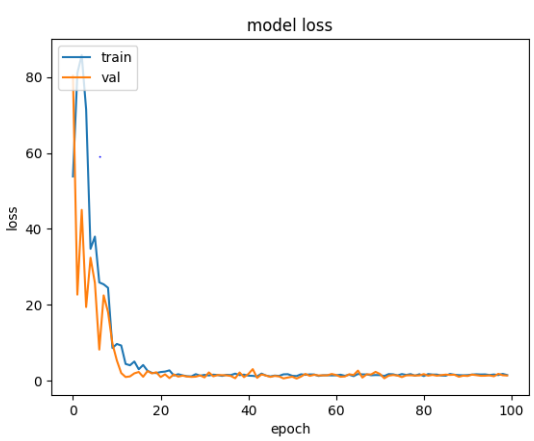

Fig. 7. Loss of inceptionV3.

As illustrated from Fig. 8, the accuracy values ranging from 0.4 to 1.0 is represented on X-axis and the number of epochs (100) executed in the model is represented on Y axis. Throughout the study, the model had been trained for 100 epochs, and the highest accuracy, achieved at 22 epochs, was recorded at 0.0013 loss rate. The blue line on the graph corresponds to the training data, while the orange line represents the validation data. It's important to note that 20% of the images were randomly selected from each class for testing purposes, ensuring a representative evaluation of the model's performance.

The training data is represented by the blue line, while the validation data is indicated by the orange line. Notably, 20% of images from each class were randomly chosen for testing.

As illustrated from Fig. 9, the accuracy values ranging from 0 to 40 is represented on X-axis and the number of epochs (100) executed in the model is represented on Y axis. The graph illustrates the loss corresponding to the accuracy of the VGG16 model. The lowest loss rate was achieved at 22 epochs, with a value of 0.0013. The blue line in the graph illustrates the training data, while the validation data is depicted by the orange line. It's important to note that for testing purposes, 20% of the images were randomly selected from each class, ensuring a representative evaluation of the model's accuracy and loss.

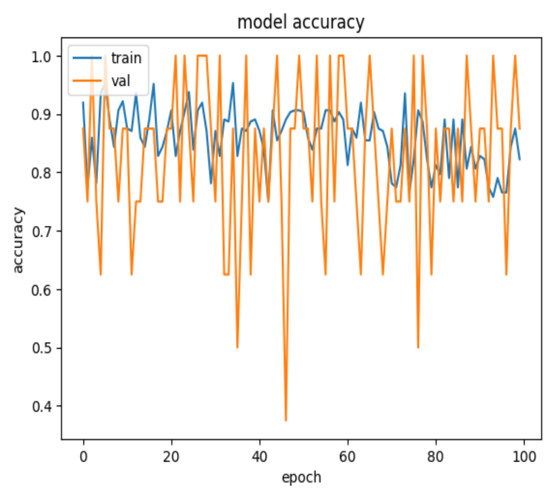

Fig. 8. Accuracy of ResNet50.

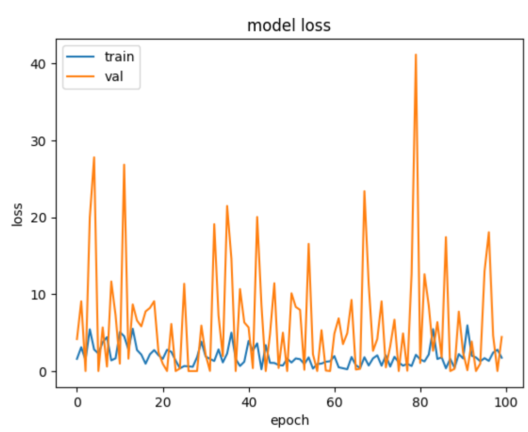

Fig. 9. Loss of ResNet50.

Out of the listed models, namely InceptionV3,VGG16, ResNet50 and VGG19 the ResNet50 model stands out, exhibiting the highest accuracy with minimal loss. Furthermore, in addition to accuracy and loss metrics, the output includes Soil Image and the subsequent soil classification as described below.

Fig. 10 shows the output of the model which is name of the soil here the classification of soil type is Yellow Soil, list of values in array and the image which is given as input to the model with height 220 and width 220.. Out of the listed models such as VGG16, VGG19, InceptionV3, ResNet50 , the ResNet50 got highest accuracy with less loss. So model taken ResNet50 for execution and identified as Yellow Image.

```
1/1 [==============================] - 1s 1s/step
Yellow Soil
array([[6.0063771e-34, 7.9120314e-18, 4.5903152e-30, 1.6081034e-23,
        1.0000000e+00]], dtype=float32)
```

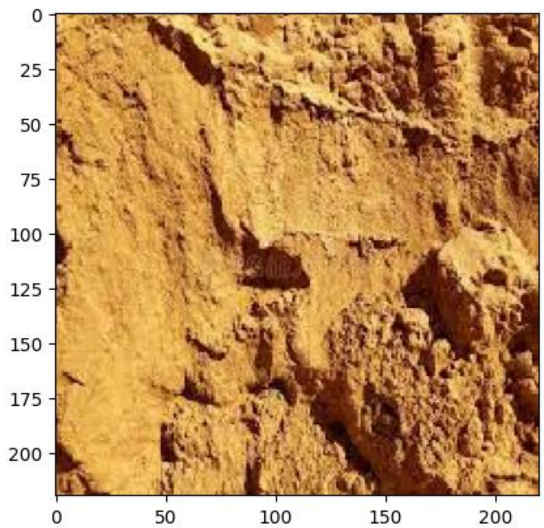

Fig. 10. Soil classification.

ResNet50 achieves high accuracy and minimal loss due to its 50-layer architecture utilizing a bottleneck design for building blocks. The bottleneck residual block incorporates 1×1 convolutions, called a "bottleneck," reducing parameters and matrix multiplications. This design enables faster training of each layer. Unlike the traditional two-layer approach, ResNet50 employs a stack of three layers, contributing to its superior performance.

V. Conclusion

Soil classification holds significant importance as it aids in the analysis of soil nutrients and minerals. This analysis enables precise crop management, leading to enhanced productivity and meeting the growing food demands. Deep Learning Techniques are employed to address challenges encountered in the manual soil classification process. This project emphasizes the utilization of Deep Learning and Image Processing for classifying soils, focusing on key soil characteristics such as particle size, texture and color. These techniques aim in replacing the traditional manual soil inspection methods. The proposed model incorporates four different Convolutional Neural Networks (CNNs) – ResNet50, VGG16, VGG19, and InceptionV3 – for multi-class classification, categorizing soils into Yellow, Peat, Cinder, Laterite and Black Soils respectively. Among these neural networks, ResNet50 outperformed the others, achieving a minimal error rate of 0.13% and a flawless accuracy of 100%. Although the model was tested with a limited dataset, expanding the dataset could potentially improve accuracy further. Additionally, incorporating pH values into the dataset and integrating crop recommendations could enhance the model's capabilities in extracting soil nutrients and minerals. This model can be enhanced by using large dataset, to get nutrients and minerals from soil by adding pH values to the dataset and also for crop recommendation.

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