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Machine Learning in Agricultural Soil Analysis: A Comprehensive Review on Classification and Fertility Prediction

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ABSTRACT

The role of soil classification in agriculture has become increasingly vital with technological progress. Traditional soil classification methods typically involve laborious tasks like manual sampling, visual assessments and basic lab tests. These approaches can be time-intensive, expensive and occasionally less precise, making them less ideal for contemporary agricultural demands, particularly with the need for enhanced productivity and precision. Technological advancements have introduced new methods such as remote sensing, machine learning and artificial intelligence, revolutionizing soil classification. These modern techniques enable rapid analysis of extensive land areas, enhancing both the accuracy and efficiency of soil classification. Accurate soil classification is crucial for selecting appropriate crops, determining fertilizer requirements and forecasting water usage, all of which contribute to improved yields and resource management. Technologies like remote sensing, soil sensors and GIS (Geographic Information Systems) facilitate efficient data collection and analysis, making precision agriculture more attainable. This data-driven strategy represents a significant advancement towards more sustainable and productive farming systems.

Keywords - Classification, Fertility, Machine learning, Deep learning, Soil

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I. Introduction

Agriculture serves as the principal occupation for a substantial majority of individuals in India [1], thereby constituting a pivotal sector within the nation's economy. The composition of soil, which consists of a mixture of clay, sand and silt particles in varying proportions, is instrumental in determining agricultural productivity. Soil texture, characterized by the relative proportion of these particles, exerts a significant influence on crop selection and the proliferation of weeds.

Agro-economy and related fields constitutes the largest source of livelihood in India, particularly within the extensive rural regions [16]. It acts as the pillar of the Indian economy and plays a major role in the national socio-economic progress. Beyond supporting millions of livelihoods, agriculture makes a substantial contribution to India's Gross Domestic Product (GDP). The GDP growth rate is a critical indicator of a nation's economic progress. An increase in GDP often signifies an improvement in the standard of living for the population. Economically advanced nations are generally regarded as favorable places to reside due to enhanced infrastructure, services and higher average incomes. In India, the GDP is driven by three primary sectors, each contributing uniquely to the national economy: 1 Agriculture sector 2. Manufacturing sector 3. Service sector. Soil is essential for supplying vital nutrients to crops and influencing their yield [17]. It constitutes the uppermost layer of the Earth's crust and is formed through the weathering of rock under the influence of climate, vegetation, relief and parent rock. The Indian Council for Agricultural Research (ICAR) has classified Indian soil into eight major groups: a) Alluvial soil b) Black soil c) Red soil d) Laterite soil e) Desert soil f) Mountain soil g) Saline and Alkaline soil and h) Peaty soil. Soil classification is essential to crop cultivation; however, many farmers lack the technical expertise to accurately identify soil types [18]. Soils are classified based on their inherent characteristics and external features, such as texture, color, land slope, and moisture content.

Machine learning and deep learning have emerged as powerful tools in the field of smart agriculture. The capacity of deep learning to manage large datasets and extract meaningful patterns renders it an invaluable resource in contemporary agricultural practices [19]. Soil classification involves exploring various methods to categorize soils, each playing a crucial role in enhancing agricultural practices and understanding soil properties. These methods are divided into traditional techniques and modern approaches such as machine learning and deep learning offer superior precision, computational efficiency and scalability for complex tasks [20]. The majority of research in this domain concentrates on the utilization of digital imaging, pattern recognition, and automated classification tools to tackle a range of challenges.

The purpose of this study is to systematically organize and present existing systems related to these topics in a coherent and beneficial manner.

II. Novel Methodologies and Techniques

This section examines the diverse research initiatives and efforts in agriculture that concentrate on soil classification, employing a variety of techniques and methodologies. **Padmapriya J [1]** explain soil classification which holds significant importance in the domains of agriculture, construction, environmental science and land management. The approach adopted in the identification of soil types is instrumental in comprehending soil factors including fertility, texture, and appropriateness for diverse applications. In contemporary research, ML and DL approaches are being widely adopted for soil classification owing to their capacity to process extensive datasets and intricate interrelations within the data. An advanced strategy employing a Multi-Stacking ensemble model in association with the Q-HOG (Quantized Histogram of Oriented Gradients) feature selection algorithm serves to augment both the precision and efficacy of soil classification endeavors. The Q-HOG is likely used as a feature extraction technique to detect patterns in the image data. The mathematical expression for HOG is as follows:

$$\mathrm{HOG}(x,y) = \sum_{i=1}^{N}[G_i(x,y))] \quad \text{------ (1)}$$

Where:

- $G_i(x,y)$ represents the gradient orientation and magnitude at the pixel (x,y) for the i-th bin in the histogram.
- N stands for the number of gradient bins.

The quantizations with respect to gradients are further refined by quantizing the orientation angles into bins. The feature set derived from Q-HOG will be used as input for both machine learning and deep learning.

Multi-Stacking Ensemble Model:

A multi-stacking ensemble is an advanced ensemble method where multiple individual models are trained and their predictions are combined to generate a final output. It includes two layers:

Base Learners: The base learners (Involving algorithms such as Naïve-Bayes, KNN, SVM, and Deep neural models such as RNN, LSTM, GRU, and VGG16) generate predictions.

Meta-Learner: A meta-model learns to combine these predictions to make the final decision.

The process can be expressed mathematically as:

$$f_{final}(X) = f_{meta}([f_1(X), f_2(X), \ldots, f_n(X)])\text{---(2)}$$

Where,

- fmeta is the meta-learner model.
- f1, f2,…,fn the predictions made by the base models (RNN, LSTM, GRU, Naïve-Bayes, KNN, SVM, VGG16).
- X represents the input feature vector (soil data and image features).

The final output, final(X) will be the soil classification.

Akshar Tripathi et al[2] the present the application of Deep Learning Multi-Layer Perceptron (DLMLP) neural networks in the domain of crop yield forecasting with particular emphasis on the significance of soil parameters, including moisture, soil salinity, and soil organic carbon (SOC). The methodological framework utilizes remotely sensed data sourced from Sentinel-1 and Sentinel-2 satellites in conjunction with field data, thereby underscoring the critical role of soil health in the accurate prediction of wheat crop yields.

SR Juhi Reshma et al[3] describe the soil fertility and the application of fertilizers are essential components of successful agricultural practices. The deployment of ML techniques, including SVM, Decision Trees, and Multi-Layer Perceptrons (MLP) can substantially enhance the prediction and analysis of soil nutrient levels. By employing these models, farmers are empowered to make better-informed choices about fertilizer application, thereby improving crop yields and promoting sustainable agricultural practices. It is also essential to formulate these machine learning algorithms in mathematical terms.The following is an explanation of the operational mechanisms of each algorithm.

a) Support Vector Machine (SVM)
A supervised SVM model handles classification and regression tasks; in this study, forecasting fertilizer quantity is done via Support Vector Regression. The equation for an SVR is,

$$f(x) = w^T + b \quad \text{------------ (3)}$$

Where:

- x is the feature vector (soil nutrients, crop type, etc.)
- w^T is the weight vector
- b is the bias term

The goal is to minimize the error between the predicted and actual fertilizer amounts while keeping the margin (the difference between the hyperplane and the support vectors) as large as possible.

b) Decision Tree (DT)
A decision tree takes the form of a tree diagram, with each branch node standing for one of the input features and each branch represents a decision rule based on that feature. The mathematical formulation of a decision tree involves recursive splitting of the data based on the best feature (one that minimizes the impurity or error).For regression, the tree is split based on minimizing the Mean Squared Error (MSE) is:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad \text{---------- (4)}$$

Where:

- y_i is the actual fertilizer amount
- $\hat{y}_i$ is the predicted fertilizer amount

c) Multilayer Perceptron (MLP)
A multilayer perceptron is a deep learning model with stacked layers of artificial neurons to perform transformations on the input data. All neurons in one layer are fully connected to those in the subsequent layer and their activations are computed using functions like sigmoid or ReLU. The formal representation of a single–hidden–layer MLP can be written as:

$$Y = f\,(W_2 \cdot f\,(W_1 \cdot X + b_1) + b_2) \text{----------(5)}$$

Where:

- X is the input feature vector (soil nutrient content, etc.)
- W1 and W2 are weight matrices
- b1 and b2 are bias terms
- f is the activation function (like ReLU or sigmoid)
- y is the predicted fertilizer amount

The network is trained by adjusting the weights using an optimization algorithm (e.g., gradient descent) to minimize the error, typically using Mean Squared Error (MSE).**Xueying Li, et al [4]** examines soil classification through the application of near-infrared spectroscopy technology, with a particular emphasis on adopting Convolutional Neural Networks and Support Vector Machines within a deep learning paradigm to classify soils. The research analyzed six distinct soil types originating from various land cover categories in Qingdao, China, namely orchards, woodlands, tea plantations, farmlands, bare land, and grasslands.**Liang Zhong et al [5]** illustrate the utilization of long-term vegetation phenology data from MODIS (MCD12Q2) to assess the spatial distribution patterns of soil organic carbon at a regional scale, with a focus on Anhui province, China. This work highlights how leveraging decades of vegetation phenology data alongside deep learning algorithms can boost the accuracy of SOC distribution models, informing both carbon inventory and landscape management decisions.**Pallavi Srivastav et al [6]** provide the significance of soil classification, particularly in light of the increasing global food demands driven by population growth. It underscores the limitations inherent in traditional soil classification methods, which are often time-consuming and labor-intensive, and emphasizes the necessity for more efficient computer-based solutions. Furthermore, the paper discusses the development of specialized databases by researchers, specifically designed for soil classification. These databases consider diverse environmental and illumination conditions and are compiled using various devices, including digital cameras, camcorders, and smart phones. By detailing evaluation metrics, the discussion offers a blueprint for comparing and gauging the efficacy of different soil classification approaches. In essence, this manuscript acts as an introductory guide for aspiring researchers in soil classification, presenting core concepts of traditional and state-of-the-art methods and highlighting emerging trends and prospective research paths. **K Anandan et al [7]** examine the utilization of deep learning techniques, specifically Convolutional Neural Networks (CNNs) for predicting soil properties through hyper spectral data. This approach exploits the ability of CNNs to autonomously extract features from the data, thereby potentially improving the accuracy of predictions for soil properties that are essential in agricultural production. **Muhammad Hammad Saleem et al [8]**, provides a comprehensive overview of how deep learning (DL) and machine learning (ML) have been applied to agricultural tasks through automation, particularly in agricultural robots. The key takeaway is the significant improvements that DL techniques, such as Convolutional Neural Networks, have made in achieving human-level accuracy in various agricultural applications. Below is a breakdown of the key points and their implications for the field. Key Applications in Agriculture Using ML and DL:

1. Plant Disease Detection and Classification:

i. RCNN (Region-based Convolutional Neural Network) has been highlighted as an advanced deep neural model that achieves a detection rate of 82.51% for plant diseases and pests.

ii. This significantly outperforms traditional ML models such as Multi-Layer Perceptron (MLP), which achieves only 64.9% and K-Nearest Neighbors (K-NN), which achieves 63.76%.

2. Crop/Weed Discrimination:

i. ResNet-18, a famous DL architecture is particularly effective for crop/weed discrimination. It achieved a higher area under the curve score of 94.84%.

ii. This performance far exceeds that of traditional ML techniques like Random Forest (RF), which scored 70.16% and Support Vector Machine, which scored 60.6%.

3. Land Cover Classification:

i. Fully Convolutional Networks (FCN) recorded an accuracy of 83.9% in land cover classification.

ii. In comparison, traditional ML methods like SVM (67.6%) and RF (65.6%) showed significantly.

Shinya Inazumi et al [9] explores the application of deep learning techniques for the classification of soil types with a particular emphasis on clay, sand and gravel. It illustrates the effective use of a neural network model to categorize these soil types based on image data. Below is a breakdown of the key findings and considerations discussed in the study:

1. High Recall for Sand

The model achieved a high recall rate of 1 for sand. This means that all sand images were correctly identified as sand. The model exhibited a pronounced sensitivity in detecting sand; however, it may face challenges in accurately distinguishing sand from other soil types, particularly when the images share similar characteristics.

2. High Matching Rate for Clay and Gravel

The model showed a high matching rate for clay and gravel. This indicates that the model can discriminate between clay and gravel effectively without much mixing of the two types of soil. This suggests that the features associated with clay and gravel are more distinct in the images, allowing for better classification.

3. Impact of Image Resolution on Accuracy

Image resolution is a critical factor influencing the model's performance. When the pixel count of the image is insufficient, the model encounters difficulties in feature detection, resulting in diminished accuracy. Conversely, an increase in pixel count enhances the model's ability to capture features, thereby improving accuracy. This highlights the importance of choosing the right image resolution for training the neural network, as having too few pixels can prevent the model from learning important details in the images.

D Yusnita et al [10] provide essential insights into sustainable agricultural practices within the Baebunta Sub-District by utilizing the USDA Soil Taxonomy system to classify soils, thereby evaluating their agricultural potential.· Analyzing the mineral content of the soil, which underscores the importance of enhanced management practices for soils with significant quartz presence. Recommending management practices, such as the addition of organic matter, to improve soil structure, minimize nutrient leaching and boost fertility, thus ensuring the long-term viability of paddy fields. By addressing soil degradation and improving soil management practices, it is possible to ensure that the soil in Baebunta Sub-District remains productive for agriculture, providing livelihoods for local farmers while protecting the environment.

M.C.Pegalajara et al [11] propose soil color is a significant indicator in soil science, offering critical insights into soil properties, including organic matter content, mineral composition, moisture levels, and drainage capacity are critical for understanding soil characteristics. The Munsell soil-color charts are widely employed for soil classification, offering a standardized system to correlate the color of a soil sample with a specific Munsell color notation. However, the visual assessment of soil color using these charts is subjective and susceptible to errors due to variability in human observation. To mitigate these issues, an advanced method incorporating Artificial Neural Networks and fuzzy logic can be employed to establish a more reliable and objective classification system. The Munsell soil colour system is based on three main components:

- **Hue (H)**: Refers to the colour family, such as red, yellow, green etc.
- **Value (V)**: Indicates the lightness or darkness of the colour, ranging from 0 (black) to 10 (white).
- **Chroma (C)**: Measures the intensity or purity of the colour, from 0 (grey) to high numbers for vivid colours.

To address these challenges, we propose an advanced system that integrates Artificial Neural

Networks (ANNs) and Fuzzy Logic to achieve more precise and objective Munsell soil color classifications. This methodology operates by calculating the Munsell color chips that most closely correspond to the actual color of the soil sample. The Munsell system categorizes colors into a series of charts comprising 238 standardized color chips, each corresponding to a distinct hue, value, and chroma. The color of a soil sample is typically assessed through visual comparison with these chips. Nevertheless, this method is inherently subjective and human error may arise due to variations in lighting conditions or individual perceptual differences.

Proposed Intelligent Methodology:

a. Artificial Neural Networks (ANNs) for Colour Prediction

ANNs can be trained to recognize and classify the Munsell colour based on input features derived from the soil sample. The main stages in applying ANNs for this task include:

I. Input Features:

i. The input features for the neural network can be extracted from digital images of the soil samples or by directly measuring the RGB (Red, Green, Blue) values of the soil sample using a colorimeter.

ii. The RGB values may be transformed into corresponding Munsell coordinates (hue, value and chroma).

II. Network Architecture:

i. To establish a model that captures the relationship between raw RGB values and their corresponding Munsell hue, value, and chroma, one can opt for the use of either a multilayer perceptron (MLP) or a convolutional neural network (CNN).

ii. The network is trained using a supervised learning approach, where the training dataset consists of soil colour samples with known Munsell colour notations.

III. Training Process:

i. The network learns to map the input RGB values to the Munsell colour space by minimizing a loss function, such as mean squared error (MSE) between the predicted and actual Munsell coordinates.

ii. The network can be trained using backpropagation to update the weights and biases.

IV. Output:

The artificial neural network (ANN) will output the predicted Munsell hue, value, and chroma coordinates for a specific soil sample, thereby facilitating a more accurate and objective evaluation of soil color.

b. Fuzzy Logic for Matching to Munsell Chart

Once the artificial neural network (ANN) forecasts the soil color in terms of hue, value, and chroma, fuzzy logic can be applied to ascertain the most similar Munsell color chip from the charts. This fuzzy logic system is adept at managing uncertainty and imprecision in the classification process by employing approximate reasoning instead of relying on exact matches.

I. Fuzzification:

i. The output from the ANN (predicted hue, value, and chroma) is fuzzified, meaning it is represented as a range of possible values with degrees of membership in each fuzzy set. For example, a hue value of 5 might belong to both the red and orange fuzzy sets, but with different degrees of membership.

II. Membership Functions:

i. For each color component—hue, value, and chroma—the model establish membership functions to evaluate the extent of similarity between the predicted value and the corresponding Munsell chart value.

ii**.** The predicted soil sample's hue can be evaluated against the hues on the Munsell chart using fuzzy sets representing various hues (e.g., red, yellow), with the same approach applied to value and chroma.

III. Defuzzification:

The final output is defuzzified to provide a single Munsell notation that represents the most likely match for the soil sample. This is achieved by computing the centroid of the membership functions, yielding the precise Munsell hue, value, and chroma that best match the nearest Munsell chip.

Yue Yuet et al[12] introduces an innovative methodology for soil classification utilizing a Liquid Crystal Tunable Filter (LCTF)-based system in conjunction with a three-dimensional Convolutional Neural Network (3D-CNN). The integration of compressive sensing, Principal Component Analysis (PCA), and 3D-CNN provides a solid framework for precise and efficient soil classification, effectively addressing the limitations encountered by traditional methods. This approach enhances soil feature analysis, thereby facilitating more reliable soil classification for both agricultural and environmental applications. **Qiangqiang Yuan et al[13]** study presents a groundbreaking method for soil analysis and categorization by combining computer vision with sensor network technologies. The approach utilizes a Gravity Analog Soil Moisture Sensor attached to an Arduino-UNO board, along with image processing techniques, to identify and analyze various soil types. The research concentrates on soils from the Amhara region and Addis Ababa city in Ethiopia.

Abrham Debasu Mengistu et al[14] illustrates the application of multiple machine learning procedures for the classification of soil texture classes based on terrain parameters within a mountainous watershed. The objective was to classify soil textures—namely clay, loam, and sand—in the core areas of the Three Gorges of the Yangtze River in southwest China, utilizing machine learning methodologies. The purpose is to examine the performance of different algorithms, including Support Vector Machines, Artificial Neural Networks and Classification Trees (CT) in classifying soil types. The findings indicate that SVMs, particularly those employing a polynomial function, demonstrate high reliability for soil texture classification based on terrain parameters. The results underscore the potential of machine learning to offer valuable insights in soil and water conservation engineering, especially in complex landscapes such as mountainous watersheds. **Pramudyana Agus Harlianto et al[15]** This study conducts a comparative analysis of four machine learning algorithms—Support Vector Machine (SVM), Neural Network, Decision Tree, and Naïve Bayes—in the context of classifying soil types using empirical data. The mathematical frameworks underlying each algorithm are examined, ranging from the optimization problem inherent in SVM to the probability-based decision-making process with a linear kernel in Naïve Bayes, thereby elucidating the distinct methodologies each model employs for the classification task. The findings indicate that the SVM algorithm demonstrates superior performance, achieving an accuracy rate of 82.35%. Table1: gives summarization of various methods.

III. CONCLUSION

The evolution of digital cameras and smart phones has introduced several challenges in image processing, particularly concerning images captured by these devices. Soil detection and classification have emerged as active research domains, significantly contributing to the development of various applications that aid farmers in identifying distinct soil types and estimating productivity, accompanied by expert recommendations. This paper endeavors to present a comprehensive survey of several machine learning methodologies, employed in soil classification. The selected studies encompass a broad spectrum of issues, reflecting the diversity of approaches within this field. Despite the availability of numerous techniques for soil classification, there remains substantial potential to develop methods that are computationally efficient, robust, and demonstrate high detection and recognition rates.

Table1: Summarization of different methods

Sl.No	References	Methodology	Dataset	Future Scope/Limitation	Efficiency and Recognition
1	Padmapriya J,et al (2023)	1)feature selection algorithm Q-HOG 2)K-Nearest Neighbour (KNN) for categorization 3)SVM for binary classification	Soil dataset is taken from exploration site vriddhachalam	The proposed research focuses on employing deep learning architectures to identify weeds based on soil type	Accuracy:98.96 % Precisios:96.14% Recall a:99.65%
2	Akshar Tripathi et al (2022)	DLMLP model	Synthetic Aperture Radar (SAR) data from the Sentinel-1 satellite and optical data from the Sentinel-2 satellite of the European Space Agency (ESA)	Synthetic Aperture Radar (SAR) datasets with longer wavelengths, such as those in the L-band and S-band, are increasingly utilized for evaluating soil health parameters	The DLMLP test R^2 : 42.2% MAE:37.97% RMSE : 38.61%

3	S R Juhi Reshma et al (2022)	Support vector machine (SVM), Decision Tree (DT), and Multilayer Perceptron (MLP)	Not specified	The implementation of MLP with a hybrid activation function can significantly enhance model performance by integrating the advantages of various activation functions	Accuracy :94%
4	Xueying Li, et al(2021)	Visible near-infrared spectroscopy technology, convolutional neural network	Six distinct soil types, namely orchards, woodlands, tea plantations, farmlands, bare land, and grasslands, are present in Qingdao, China	To investigate a novel approach for the rapid, nondestructive and precise classification of land cover	Accuracy : 95%
5	Lin Yang et al (2021)	Convolutional neural network (CNN)	A total of 733 samples were collected in the years 2011, 2015, and 2016, originating from three distinct projects, each employing different sampling strategies	The metrics of land surface phenology, which reflect the long-term characteristics of vegetation growth may prove to be effective or even superior	Accuracy :5.57% RMSE : 31.29%
6	K Anandan et al (2021)	1)DL model is used to predict the soil properties from hyper spectral data 2)CNN is used for building the neural network model	LUCAS dataset is used	Incorporating additional soil properties into the analysis could substantially enhance the precision and effectiveness of agricultural methodologies	RMSE : 5.68%.
7	Emmanuel Kwabena Gyasi et al (2023)	A convolutional neural network (CNN) model called Soil-MobiNet to classify soils	The model has the Vellore Institute of Technology Soil (VITSoil) dataset, which comprises 4,864 soil images distributed across nine categories	Future research can focus on increasing the soil classes	validation accuracy: 98.47% testing accuracy of:93%
8	Abrham Debasu Mengistu et al (2018)	Classification and characterization is performed	Total dataset of 540 images 70% was used to build training and the remaining 30% of	The study can be further explored and analyzed through various machine learning techniques, examining the physical	Accurac:89.7%

		through BPNN	the total was used for testing data	and chemical characteristics in relation to imaging technology	
9	Pramudyana Agus Harlianto et al (2017)	Machine learning algorithm such as neural network, decision tree, naïve bayes, and SVM used	Soil dataset is taken from the real data	(SVM)represent robust machine learning algorithms that can be utilized to enhance the precision of weed detection and soil analysis in agricultural contexts	Accuracy:82.35%.
10	Sk Al Zaminur Rahman et al(2018)	Weighted k-Nearest Neighbor (k-NN), Bagged Trees and Gaussian kernel based Support Vector Machines (SVM) are used for soil classification	n soil datasets of six upazillas of Khulna region	Support Vector Machines (SVM) are indeed powerful and widely used machine learning algorithms, especially in applications like weed detection and soil analysis in agriculture	Accuracy:92.93%

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