BENEFITS AND DRAWBACKS OF DIFFERENT SOIL TYPES

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ABSTRACT
Traditional methods for classifying soil have several drawbacks, including the fact that they take a long time, are expensive, and are intrusive, to name a few. Soil monitoring and Internet of Things (IoT) technology assist enhance agriculture by increasing production by precisely tracking soil parameters like moisture, temperature, humidity, PH, and nutrient content and fertility. The data is then collected in cloud storage with the aid of the appropriate data operations, enabling us to enhance agricultural strategies and generate trend analyses. This allows us to precisely allocate resources and manage our farming operations in order to enhance yield. We have read a large number of articles in this study that discuss different classification systems and strategies for soils.

Keywords: *Sandy Soil, Clay Soil, Loamy Soil, Soil Classification, Machine learning.*

I. INTRODUCTION

Even though it will continue to increase, it is anticipated that by the middle of this century, there will be a high of about 9 billion people on the planet. 9 billion people cannot be fed sustainably in an easy way, especially as more and more people adopt the consumption habits of wealthy countries and become more adept at it. It is essential to pursue a range of options, such as the ones we have discussed here. We are excited about scientific and technological advancement in the food system, though not as an excuse to put off today's difficult decisions. (2015) Muir, Pretty, Robinson, Thomas, and Toulmin The 2030 Agenda's second Sustainable Development Goal (SDG) focuses on the issues of hunger, food insecurity, and malnutrition in all of its manifestations. It is now projected that the total number of people affected by undernourishment or chronic food poverty in the world has risen from about 804 million in 2016 to almost 821 million in 2017. South America and the majority of Africa are experiencing a worsening of the situation, and the previously reducing trend in Asia's undernourishment appears to be drastically slowing down. (FAO, IFAD, & UNICEF, 2018). The study complements the evidence released by the World 2018 State of Food Security and Nutrition, finding 821 million undernourished individuals. The latest report provides the worldwide level of chronic food insecurity. The Global Study on Food Crises explicitly focuses on the most extreme forms of acute food insecurity in the most urgent food crises in the world. ((FSIN), 2019). Sustainable development is the face of the world today. International communities are looking forward to sustainable energy (renewable energy), agriculture, and so on. For instance, the significant emissions of greenhouse gases associated with energy use may contribute to climate change. For these reasons, many organizations and governments set policies through creating ways of generating clean energy, potential energy savings ways, and reducing greenhouse gas emissions. (Mahlia, Razak, & Nursahida, 2011). Renewable energy can also be generated through the use of precision agriculture. Sustainable agriculture is defined as the one that, over the long term, enhances environmental quality, provides for basic human food and fiber needs, strengthens the resource base on which agriculture depends, is economically viable, and improves the quality of life for farmers and society as a whole. Additionally, precision farming offers a way to use information technology to automate Site Specification Management (SSM), making SSM applicable in commercial agriculture. Precision agriculture encompasses any agricultural production techniques that make use of information technology, such as variable rate application (VRA), yield monitoring, and remote sensing, to either adapt input use to achieve desired results or to monitor those outcomes. (Jansirani, Karthick Raja, Hariprasanth, Sweetin Preethi, & Sorna Kumar, 2016). Today, machine learning is booming across the sector of knowledge. Farmers could classify the soil with the use of machine learning since farming depends heavily on the categorization of the soil. In comparison to the traditional soil classification method, which is typically based on a table, chart, and graphs, machine learning offers an easier method that is less expensive, time-consuming, accurate, and user-friendly. This study will concentrate on soil classification using machine learning.

II. RELATED WORKS

The literature for this study will first examine the use of machine learning in precision agriculture. First, it's important to grasp machine learning and precision agriculture before diving in. In the academic field, the computer is initially utilized to comprehend basic data like digital photographs (which provide raw pixels). This is because there are numerous ways to solve some computer vision problems, including segmentation, detection, classification, and prediction, among others. Convolutional Neural Network (CNN) is one of the methods for doing this, and it is a high-quality solution (Martin Thoma, 2017). The background idea of CNN came from machine learning. Artificial neural network growth has recently given machine learning a fresh and dramatic twist (ANN). In common machine learning tasks, ANN's computational models with biological inspiration are capable of doing significantly better than earlier forms of artificial intelligence. For example, the most impressive form of ANN is the Convolutional Neural Network, known as CNN. The main objectives of CNN are to solve difficult image-driven recognition tasks and then precise, yet simple architecture provides an easy way of getting originated with ANN (Keiron & Ryean 2015). Moreover, the research by Thakur (2018) indicated that among the Machine Learning Techniques like Support Vector Machine, Artificial Neural Network, and K-Nearest Neighbors' Algorithm (k-NN), It has been observed that SVM is the most developed classifier for the soil in which it can work efficiently with a high level of accuracy. Last but not least, precision agriculture encompasses all agricultural production techniques that employ information technology, such as variable rate application (VRA), yield monitoring, and remote sensing, to either adapt input use to achieve desired results or to monitor those outcomes (Jansirani et al., 2016).

2.1 Ongoing Challenges in Soil Classification Based on Machine Learning

Barman and Dev (2019)The paper shows that the Support Vector Machine classifier can be used to classify soil images using the linear kernel. Yet further investigation is required to better understand the fine loamy sand. Another paper indicates the contribution of the cloud-based agricultural framework to soil classification based on hybrid support vector machine (M-SVM), and for wheat yield prediction, a customized artificial neural network (M-ANN) was developed. The paper suggested the development of mobile agricultural apps with sophisticated functionalities in the future. Shastry and Sanjay (2019) (Bittar, Martins, Alves, & Melo, 2018). It has been demonstrated that using ANN is a promising method for estimating soil physical and chemical parameters from a smaller number of soil samples, potentially saving money on laboratory analysis. The ANNs were trained, chosen, and utilized to assess all soil qualities based on their assertiveness in the mapping of criteria that were taken into consideration. By utilizing Student's t-Test, the mean errors of conventional kriging estimations were compared to those of ANNs and then to the original values. The outcomes showed that the ANN exhibited aggressiveness consistent with standard kriging. A mobile application has been demonstrated and developed for soil classification, and the results show that the mobile app is useful for correctly classifying a large number of soils and reducing. (Kumar, Dutta, & Dutta, 2016). The paper explains that an Android-based mobile app can classify soil. The application is not simply useful for teaching purposes in class. But it's also a helpful tool for consultants and working engineers. At present, the mobile app does not handle cases of missing data, resulting in either incomplete data collection procedures or erroneous instruments, as a part of future work (Dutta, 2019). The classification predicted using the conventional method was 100% accurate when using the computer vision approach used to recognize soil textures based on soil photographs. The new method is low-cost, environment-friendly, non-destructive, and faster than the standard method. The paper highlighted that the prediction of soil texture could be made by using image analysis (Augusto, Morais, & Souza, 2019). The paper by Bittar et al. (2018) gives room for estimation of physical and chemical soil properties by artificial neural networks1. When compared to the values obtained using conventional kriging, the soil attributes estimated by ANN, which in the geostatistical study shown spatial dependence, did not exhibit any appreciable changes. The application of ANN has proven to be a viable method for estimating soil physical and chemical parameters from fewer soil samples, potentially saving money on laboratory analysis. based on Soil Texture Classification Using Multi-Class Support Vector Machine by Barman & Dev (2019). For all of the soil samples, the suggested approach provides an average accuracy of 91.37%; this result is quite similar to that of the United States Department of Agriculture's soil categorization. (Bansal, A., Shukla, A., & Srivastava, P., 2021) In accordance with the study's goal, the researchers also present various databases in this publication. Databases are made using many tools, including digital cameras, digital camcorders, and smartphone cameras, under a variety of lighting and environmental circumstances. Also included in order to lay up some graded measurements for differentiation are evaluation metrics. This work aims to analyses soil photographs to create a low-cost digital soil classification system for farmers in rural areas. The primary aspect to take into account before cultivating is the texture of the soil. It affects the crop selection and regulates the water transmission property. The conventional hydrometer method determines the percentages of sand, silt, and clay present in a soil sample. This method is very costly and time-consuming (R. Reshma, V. Sathiyavathi, T. Sindhu, K. Selvakumar & L. SaiRamesh 2020). 2021 (S. Mazumdar, J. Kumari, B. Tiru, U. Sarma, N. Barkataki, P. B. D. Singha, and S. A microcontroller/microprocessor with Wi-Fi and cloud storage, pH sensors, humidity and temperature sensors, soil moisture sensors, soil nutrient sensors (NPK) probes, and other components make up the proposed Internet of Things system. When the sensors are used, they measure the associated properties and send time-stamped real-time data to the cloud server. These sensors combine to give the analyst accurate data. The SVM and Decision Tree algorithms are suggested for the recommendation system to get the crop suitable for the provided soil data and aid increase the growth employing an optimum farming procedure. Table 1 below shows a summary review of similar research conducted showing the author's information, contribution, the result obtained and limitations.

The table below summarizes the similar literature reviewed while conducting this research.

Table 1: Research Gap

Author / Year of publication	Contributions	Results Obtained	Limitations
(Barman & Dev, 2019)	The paper shows that the Support Vector Machine classifier can be used to classify the soil images using the linear kernel	The result from the method (multi-class support vector machine) provides an average of 91.37% accuracy for the soil samples, and the result is nearly the same with the United States Department of Agriculture soil classification.	However, there is a need for another study for the fine loamy sand, loamy sand and silty clay to have a good classification.
(Shastry & Sanjay, 2019)	This paper indicates the contribution of the cloud-based agricultural framework to soil classification base on hybrid support vector machine (M-SVM), and for wheat yield prediction, customized artificial neural network (M-ANN)	In this paper, the performance improvements in the range of 2–43%, 4–35%, and 1–11% were observed for M-SVM with respect to k-Nearest Neighbour (k-NN), Naïve Bayes (NB), and standard SVM classifiers, respectively. M-ANN performed with an improvement of 2% over the standard artificial neural network	The paper suggested the development of mobile agricultural apps with sophisticated functionalities in the future.

	was developed.	(ANN) and 5% over multiple linear regression (MLR) models.	
(Bittar, Martins, Alves, & Melo, 2018)	The use of ANN has shown to be a promising technique to estimate soil physical and chemical properties from a reduced number of soil samples, which may represent a reduction in costs with laboratory analysis.	The ANNs were trained and selected based on their assertiveness in the mapping of considered standards, and then used to estimate all soil properties. The mean errors of ordinary kriging estimates were compared to those of ANNs and then compared to the original values using Student's t-Test. The results indicated that the ANN had an assertiveness compatible by comparing with ordinary kriging.	Further researches are needed to improve the network and to increase the amount of data for training. The values of soil properties estimated by ANN are promising for spatial variability studies.
(Kumar, Dutta, & Dutta, 2016)	A mobile application has been demonstrated and developed for the soil classification in this paper.	The results show that the mobile app is useful for correctly classifying a large number of soils and reducing the tedious work of referring graphs, tables and flow charts manually which otherwise leads to erroneous soil classification error.	Further, improvement in the mobile app developed can be made for the missing input properties affecting the soil classification.
(Dutta, 2019)	The paper contributes that An Android-based mobile app can classify soil.	The application is not simply useful for teaching purposes in class. However, it also provides a helpful utility to the consultants and the practicing engineers.	At present, the mobile app does not handle the cases for missing data, resulting in either due to the incomplete data collection procedures or erroneous instruments, as a part of future work.
(Lu & Perez, 2018)	Deep Learning with Synthetic Hyperspectral Images for Improved Soil Detection in Multispectral Imagery	The paper presents a 4 layers deep convolutional neural network (CNN) model for soil detection by using the combination of 80 synthetic hyperspectral bands and its original 8 multispectral bands which are collected by the WorldView-2 satellite. This significant improvement indicates that by using the pan-sharpened synthetic hyperspectral bands, the performance of the CNN model for soil detection has been greatly improved, the synthetic hyperspectral bands with the increased spatial resolution is an excellent alternative in enhancing the performance of object detection and classification in remote sensing applications.	For future work, would investigate furtherly if there is a subset of the synthetic hyperspectral bands which highly correlated to the soil class and more efficient in detecting the soil category by using non-linear dimension reduction methods such as principal component analysis or deep autoencoder, by deducting the dimensions of the bands, it will highly likely accelerate the model training and expedite the convergence, and potentially improve the detection accuracy and increase the robustness of the CNN model.
(Augusto, Morais, & Souza, 2019)	The paper highlighted that the Prediction of Soil Texture could be made by Using Image Analysis	The computer vision approach adopted for the recognition of soil textures based on soil images matched 100% of the classification predicted according to the standard method. The new way is low-cost, environment-friendly, non-destructive, and faster than the standard method.	As a consequence, it opens the possibility of employing cell phone for image acquisition and instant record of information on the field.
(Mokarram, Mokarram, & Safarianejadian, 2017)	Using an Adaptive Neuro-Fuzzy Inference System (ANFIS) for Prediction of Soil Fertility for Wheat Cultivation. The paper developed a fuzzy logic model using the Sugeno fuzzy inference system to soil	The results show that the model with the error of 1.6543e0.5 and -1.5941e0.5 for train and checked respectively had the most accuracy for the prediction of fertility. So ANFIS is an efficient method for the prediction of soil fertility. The advantage of this model than the other models is definition	Using ANFIS for prediction of soil parameters that their Measurement requires a lot of time and money is very good. In the method, the input and output data category multiple classes that for each class obtains only one law.

	fertility	membership function according to train data (soil fertility) automatically. In fact, definition membership function using ANFIS model and due to the reduction expert opinion causes that the error the probability of being zero.	
(José et al., 2009)	Analytical methodology for soil classification based on the use of laser-induced breakdown spectroscopy (LIBS) and chemometric techniques.	Soil classification based on the use of LIBS data and chemometrics methods. The methodology was validated in a case study involving three Brazilian soil types (Argissolo, Latossolo, and Nitossolo). Better discrimination of the soil types was attained by employing a subset of selected spectral variables for LDA, as compared to the use of full-spectrum SIMCA modelling. More specifically, the best results were obtained with SPA–LDA, which achieved an average classification rate of 90% in the validation set and 72% in cross-validation.	Future works could investigate the combination of LIBS with other techniques, such as VIS–NIR spectroscopy, for the purpose of improving the classification outcome.
(Padmavathi, Viswavidyalayam, & Attribute, 2010)	Soil Classification by Generating Fuzzy rules	In the First approach, convert the training data into an initial set of fuzzy rules, and then we merged those initially generated fuzzy rules sequentially one after the other in order to reduce the number of fuzzy rules. Then finally testing datum can be taken to test the generated fuzzy rules. In the second approach, we have modified the first program in such a way that it accepts input attributes and generates the final rule that also states the type of texture class. The second approach is more effective than the first approach.	Further Modification has to be done to the same program which could accept input attributes and generates a fuzzy rule that specifies the type of the texture class also.
(Barman & Dev, 2019)	Soil Texture Classification Using Multi-Class Support Vector Machine.	The proposed method gives an average of 91.37 % accuracy for all the soil samples, and the result is nearly the same as the United State Department of Agriculture soil classification.	The texture of the soil is determined with the traditional hydrometer method and USDA triangle, which is a very time and labor consuming process.
(Bittar et al., 2018)	The paper gives room for estimation of physical and chemical soil properties by artificial neural networks1.	The soil properties estimated by ANN, which in the geostatistical analysis presented spatial dependence, showed no significant differences in relation to the values determined by ordinary kriging. The use of ANN has proved to be a promising technique to estimate soil physical and chemical properties from a reduced number of soil samples, which may represent a reduction in costs with laboratory analysis.	Further studies are needed to improve the network and to increase the amount of data for training. The values of soil properties estimated by ANN are promising for spatial variability studies.

III. BENEFITS AND DRAWBACKS OF VARIOUS SOIL TYPES

A. Sandy soils

To the touch, they feel airy and textured. Large-particle sand soils dry out rapidly, are frequently deficient in nutrients, and are acidic. Both liquid fertilizer and water have a propensity to leak from the soil and end up in waterways before the plant can use them.

Advantages of Sandy Soils:

1. Warms up quickly in the spring

Disadvantages of Sandy Soils

1. Dries out quickly in the summer
2. Nutrients and water often leech away especially with rainfall.
3. Often acidic

Managing Sandy Soil: Apply less water and less fertilizer, but more frequently, to sandy soils to get the best results. You can also add organic matter to your soil to boost the soil's capacity to retain nutrients. Compost, fertilizers high in carbon, and substances containing a lot of soil microbes can all be added to boost organic matter.

B. Clay soils

They are the heaviest soil varieties and frequently regarded as the most difficult to work with. In the spring, they frequently take longer to warm up because they retain water. Clay soils can present significant dangers for soil compaction and cracking. In the end, this prevents plant roots from penetrating dense clay layers in addition to looking unsightly. But clay soils are nutrient-rich, unlike sandy soils. Nutrients store significantly longer in clay soils and are less likely to leach away.

Advantages of Clay Soils

- Clay soils hold onto nutrients so the plant has the food it needs
- Great for growing things that need a lot of water

Disadvantages of Clay Soils

- Holds onto water, slow to drain
- Slow to warm in the spring
- Compacts easily
- Tends to be alkaline

Managing Clay Soil

One of the hardest soil types to manage is clay, but with the correct management methods, you can raise your soil's overall quality. Aerating your soil each fall will lessen soil compaction, which is good for lawn. Utilizing items high in soil microorganisms will aid in the breakdown of nutrients in your soil and the development of roots that can more readily penetrate dense clay layers. Compost and other materials rich in soil microorganisms can be added to your soil to improve the organic matter in your garden beds and agricultural crops. Additionally, avoid compaction by not working in moist soil. Finally, think about utilizing a cover crop in the cool season.

C. More fertile than sandy soils, silty soil

This is the transitional soil type between clay and sand. Silty soils are more likely to create a crust than other soil types. Silty soils have a floury texture when dry, but are easily formed into balls in your hand when wet.

Advantages of Silty Soils

- Fertile soils that hold onto nutrients better than sandy soils
- Better water holding capacity than sandy soils
- Easier to work with than clay soils

Disadvantages of Silty Soils

- Water filtration can be poor
- Has a greater tendency to form a crust
- Can become compact and hard

Managing Silty Soil

To lower the risk of compaction, avoid working in moist silty soils. Utilize compost and items that are rich in soil microbes to increase the organic matter in the soil.

D. Sand, clay, and silt are all present in loamy soils, which are said to be the most fertile form of soil.

Sand lessens compaction and enhances drainage, while clay and silt particles enhance moisture retention. Neither do loamy soils become wet in the winter nor do they dry out in the summer.

Advantages of Loamy Soils

- Drought resistant due to water-holding capacity

- Faster to warm up in the spring, compared to clay
- Can hold nutrients, making soils fertile
- Good infiltration of air and water

Disadvantages of Loamy Soils

- Depending on how your soil was formed, some loamy soils can contain stones that may affect harvesting of some crops.

Managing Your Loamy Soil

Even though loamy soils are best for growing crops, flowers, or turfgrass, all soils must be managed to preserve or enhance soil health. The secret to fostering a healthy soil environment is adding goods rich in soil microorganisms.

IV. CONCLUSION

In this essay, we analyzed a number of studies on soil classifications and talked about the contributions, findings, and research constraints of those papers.

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