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Review Article

Systematic Review of the Literature on Various Soil Classification Methods

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Abstract

Traditional methods for classifying soil have many challenges, such as being time-consuming, very expensive, intrusive, among others. By measuring precise soil properties including moisture, temperature, humidity, PH, and nutrient content/fertility, soil monitoring and Internet of Things (IoT) technology help improve agriculture by improving production. Then, with the help of the right data operations, this data is collected in cloud storage, allowing us to improve farming tactics and produce trend analyses. This, then, allows us to precisely utilize resources and steer our farming methods in prudent ways to optimize yield. In this research, we have reviewed many articles related to soil classifications and their various methods and techniques of classification.

Keywords: Soil Classification, Machine learning, Support Vector Machine (SVM).

INTRODUCTION

Although the world's population will continue to grow, it is predicted to reach a peak of roughly 9 billion people by the middle of this century. There is no easy way to feed 9 billion people sustainably, especially as more and more follow the consumption practices of developed nations and get better at it. It is necessary to pursue a variety of choices, including the ones we have covered here. We are hopeful about scientific and technological innovation in the food system, but not as an excuse to delay difficult decisions today. (Muir, Pretty, Robinson, Thomas, & Toulmin, 2015). The second Sustainable Development Goal (SDG) of the 2030 Agenda addresses the problems of hunger, food insecurity, and malnutrition in all its forms. 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. The situation is worsening in South America and most regions of Africa; likewise, the decreasing trend in undernourishment that characterized Asia until recently seems to be slowing down significantly. (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, energy consumption may cause climate change through the high emission of greenhouse gases. 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. Moreover, precision farming provides a way to automate Site Specification Management (SSM) using information technology, thereby making SSM practical in commercial agriculture. Precision agriculture includes all those agricultural production practices that use information technology either to tailor input use to achieve desired outcomes or to monitor those outcomes, such as variable rate application (VRA), yield monitoring, and remote sensing. (Jansirani, Karthick Raja, Hariprasanth, Sweetin Preethi, & Sorna Kumar, 2016). Today, machine learning is booming across the sector of knowledge. The use of machine learning in the agriculture sector would help farmers classify the soil since soil classification plays a vital role in cultivation. The machine learning provides an easier method, which is cheaper, less time-consuming, has good accuracy, and is more user-friendly compared with the conventional soil classification method, which is normally based on a table, chart, and graphs. This research is going to focus on soil classification based on machine learning.

RELATED WORKS

First, the literature of this research is going to look at the application of machine learning in precision agriculture. Firstly, before going deep, there is a need to actually understand machine learning and precision agriculture. To begin with, the computer is used to understand low-level information such as digital images (which give raw pixels) in the academic area. This is due to the fact that some computer vision problems, such as segmentation, detection, classification, and prediction, among others,There are several methods to overcome such issues. Moreover, the high-quality solution is among the ways of doing so and is called Convolutional Neural Network (CNN) (Martin Thoma 2017). The background idea of CNN came from machine learning. Machine learning has taken a new and dramatic twist recently, with the booming of artificial neural networks (ANN). ANN's biologically inspired computational models are able to far exceed the work of previous types of artificial intelligence in common machine learning tasks. 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. Finally, Precision Agriculture includes all those agricultural production practices that use information technology either to tailor input use to achieve desired outcomes or to monitor those outcomes, such as variable rate application (VRA), yield monitoring, and remote sensing (Jansirani et al., 2016).

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. However, there is a need for another study for 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). The use of ANN has been 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 assertiveness compatible with ordinary 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. However, it also serves as a useful tool for consultants and practicing 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 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 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. 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. based on Barman & Dev's (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. (Srivastava, P., Shukla, A., & Bansal, A., 2021) This paper also presents some databases created by the researchers according to the objective of the study. Databases are created under different environmental and illumination conditions, using different appliances such as digital cameras, digital camcorders, and smartphone cameras. Also, evaluation metrics are briefly discussed to lay out some graded measures for differentiation. The objective of this study is to process the soil images to generate a digital soil classification system for rural farmers at a low cost. Soil texture is the main factor to be considered before doing cultivation. 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 (N. Barkataki, S. Mazumdar, P. B. D. Singha, J. Kumari, B. Tiru, and U. Sarma)The proposed IoT system is composed of pH sensors, humidity and temperature sensors, soil moisture sensors, soil nutrient sensors (NPK) probes, and microcontroller/microprocessor equipped with Wi-Fi and cloud storage. When the sensors are implemented, they measure the corresponding characteristics and transmit time-stamped live data to the cloud server. These sensors work together to provide wholesome data to the analyst. For the recommending system, the SVM and Decision Tree algorithms are proposed to get the crop suitable for the given soil data and help enhance the growth using an optimized farming process. 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) was developed.	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 (ANN) and 5% over multiple linear regression (MLR) models.	The paper suggested the development of mobile agricultural apps with sophisticated functionalities in the future.
(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	Further, improvement in the mobile app developed can be made for the missing input properties affecting the soil classification.

		otherwise leads to erroneous soil Classification error.	
(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 fertility	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 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.	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.

(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.

Soil classification's purpose

The purpose of soil classification is to help farmers, gardeners, engineers, stormwater management experts, community planners, and many other professionals and hobbyists plan what to grow, what to build, and where to build. Soil classifications tell you a soil's texture and the ability of water to penetrate it.

Soil Mixture Types

Common names for soils in the soil classification system include clay, silt, loam, chalk, and peat. Most of these soils, however, are found in mixtures. Soil mixtures vary widely depending on where you live. Loamy soil typically has equal proportions of sand, silt, and clay.

A cubic foot of soil can weigh as much as 114 pounds, so it's pretty heavy. According to the U.S. Occupational Safety and Hazard Administration (OSHA), a cubic yard can actually weigh as much as a car, according to the U.S. OSHA says knowing the type and mixture of soil you're working with can help prevent a cave-in.

Soil for Planting

Knowing their fields' soil classification can help farmers decide what will grow best. Different soil types contain different amounts of acid. The soil's pH level indicates the level of acid in the soil. Some crops and plants grow better in more acidic soil, while others need soil that is less acidic or neutral. If you aren't sure what type of soil you have, you can take a handful of your soil in a bag to your county's extension office for testing. A soil test should also let you know if you have any contaminants in your soil. When deciding what to grow in your lawn, garden, or field, the type of soil will tell you if it is rich or poor in nutrients, if it drains quickly or slowly, and if it has peat, chalk, or loam. Sandy soil, for example, is easy to till and drains quickly, but has poor nutrients. Silty soil, on the other hand, drains more quickly but retains some moisture to feed plants.

Soil for Engineering

When building roads, planning new construction, or designing stormwater management systems, the purpose of soil classification becomes clear. Soils have been known to collapse over sinkholes, so soils are tested before construction to decide the best site for a new road. This helps to explain the importance of soil classification in civil engineering. Engineers and geologists describe the texture and grain size of soil using the Unified Soil Classification System, which is based on the "Twelve Orders of Soil Taxonomy." Those categories include gravel, sand, silt, clay, and organics. They are graded according to whether they are well-graded, poorly graded, high plasticity, or low plasticity. This system comes in handy to determine soil strength and uniformity.

Conclusion

In this paper, we have reviewed many papers related to soil classifications and also discussed the contributions, results obtained, and limitations of their research in the papers.

References

1. (FSIN), F. S. I. N. Global Report on Food Crises (2019).
2. Augusto, P., Morais, D. O., & Souza, D. M. De. (2019). Predicting Soil Texture Using Image Analysis Pedro. Microchemical Journal, #pagerange#. https://doi.org/10.1016/j.microc.2019.01.009
3. Barman, U., & Choudhury, R. D. (2019). E-. Information Processing in Agriculture. https://doi.org/10.1016/j.inpa.2019.08.001
4. Barman, U., & Dev, R. (2019). Soil texture classification using multi class support vector machine. Information Processing in Agriculture, (xxxx), 1–15. https://doi.org/10.1016/j.inpa.2019.08.001
5. Bittar, R. D. I. B., Martins, S., Alves, D. E. F., & Melo, F. R. D. E. (2018). ESTIMATION OF PHYSICAL AND CHEMICAL SOIL PROPERTIES BY ARTIFICIAL NEURAL NETWORKS 1, 2125, 704–712.
6. Dickens, C. (2014). University Building Energy Efficiency Lighting Retrofit. In Recent Researches in Urban Sustainability, Architecture and Structure (Pp. 47-52)., Morgan State University. Retrieved from htt://www.wseas.us/e-library/conferences/2013/Baltimore/SCARC/SCARC-08.pdf
7. Dutta, R. K. (2019). Development of Mobile App for the Soil Classification RESEARCH PAPERS, (March). https://doi.org/10.26634/jmt.6.1.14635
8. FAO, IFAD, UNICEF, W. and W. THE STATE OF FOOD SECURITY AND NUTRITION IN THE WORLD (2018).
9. Ghaderi, A., Shahri, A. A., & Larsson, S. (2019). An artificial neural network based model to predict spatial soil type distribution using piezocone penetration test data (CPTu), 4579–4588.
10. Jansirani, D., Karthick Raja, N., Hariprasanth, R. J., Sweetin Preethi, S., & Sorna Kumar, R. S. A. (2016). Synthesis of colloidal starched silver nanoparticles by sonochemical method and evaluation of its antibacterial activity. Journal of Chemical and Pharmaceutical Sciences, 9(1), 177–179. https://doi.org/10.1023/B

11. José, M., Pontes, C., Cortez, J., Kawakami, R., Galvão, H., Pasquini, C., … Emöke, B. (2009). Analytica Chimica Acta Classification of Brazilian soils by using LIBS and variable selection in the wavelet domain, 642, 12–18. https://doi.org/10.1016/j.aca.2009.03.001
12. Kumar, R., Dutta, R. K., & Dutta, K. (2016). Mobile App using ASTM System of Soil Classification Mobile App using ASTM System of Soil Classification, (January 2015).
13. Lu, Y., & Perez, D. (2018). Deep Learning with Synthetic Hyperspectral Images for Improved Soil Detection in Multispectral Imagery, (November). https://doi.org/10.1109/UEMCON.2018.8796838
14. Mahlia, T. M. I., Razak, H. A., & Nursahida, M. a. (2011). Life cycle cost analysis and payback period of lighting retrofit at the University of Malaya. Journal of Renewable and Sustainable Energy Reviews, 15(2), 1125–1132. https://doi.org/10.1016/j.rser.2010.10.014
15. Micheli, E., Ditzler, C., Mcbratney, A. B., Hempel, J., & Resources, N. (2010). Time for a Universal Soil Classification System, (January).
16. Mokarram, M., Mokarram, M. J., & Safarianejadian, B. (2017). Using Adaptive Neuro Fuzzy Inference System (ANFIS) for Prediction of Soil Fertility for Wheat Cultivation, 9(1), 37–44.
17. Muir, J. F., Pretty, J., Robinson, S., Thomas, S. M., & Toulmin, C. (2015). Food Security : The Challenge of, 327(February).
18. N. Barkataki, S. Mazumdar, P. B. D. Singha, J. Kumari, B. Tiru and U. Sarma. (2021). Classification of soil types from GPR B Scans using deep learning techniques, 2021 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT), 840-844, doi: 10.1109/RTEICT52294.2021.9573702.
19. Padmavathi, S., Viswavidyalayam, M., & Attribute, O. (2010). Soil Classification by Generating Fuzzy rules, 02(08), 2571–2576.
20. R. Reshma, V. Sathiyavathi, T. Sindhu, K. Selvakumar and L. SaiRamesh. (2020. IoT based Classification Techniques for Soil Content Analysis and Crop Yield Prediction, Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), 156-160, doi: 10.1109/I-SMAC49090.2020.9243600.
21. Shastry, K. A., & Sanjay, H. A. (2019). Cloud-Based Agricultural Framework for Soil Classification and Crop Yield Prediction as a Service. Springer Singapore. https://doi.org/10.1007/978-981-13-5953-8.
22. Srivastava, P., Shukla, A. & Bansal, A. (2021). A comprehensive review on soil classification using deep learning and computer vision techniques. Multimed Tools Appl 80, 14887–14914, https://doi.org/10.1007/s11042-021-10544-5.
23. Thakur, R. (2018). An Intelligent Model for Indian Soil Classification using various Machine Learning Techniques, 33–41.
24. https://www.hunker.com/12552019/purpose-of-soil-classification

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