

AI Based Crop Recommendation Systems Using Environmental and Soil Factors

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Abstract: A crop recommendation system based on soil nutrients and data on soil conditions, specifically nutrient levels (nitrogen, phosphorus, potassium, and soil pH), are used to advise farmers on suitable crops. This technology often uses machine learning algorithms to analyze the data and recommend crops that would likely thrive in the particular soil conditions. Predicting the nutrients in the soil helps farmers choose crops that maximize yield and efficiency while minimizing resource waste. Deep learning models, such as DenseNet, ResNet 50, VGG 19, and Long Short-Term Memory networks for classification and decision making, are trained on datasets that relate soil nutrient levels to crop compatibility. Based on the study of the soil data, the algorithm recommends a list of suitable crops. With time, the system can incorporate farmer feedback to provide better recommendations. The Crop Recommendation System (CRS) describes a system that suggests crops based on environmental factors and farmer input. Choosing crops that are suitable with the soil might lead to higher yields. By recommending appropriate crops, the system can help maximize the usage of fertilizer and water. Promoting the use of crops that are suited to the soil's nutrients can lead to more environmentally friendly farming practices. The potential of machine learning models to enhance precision farming and expand their application in agriculture is highlighted in this study. Maximization, crop management and resource allocation is the main focus of this work.

Keywords: Crop recommendation; deep learning models: DenseNet, ResNet 50, VGG 19, and Long Short-Term Memory networks; environmental factors.

Introduction

Food is a highly sought-after human essential. Agriculture is the primary industry and the primary source of food. Soil is the main agricultural resource that has the essential nutrients required for plant growth. Over time, new equipment has replaced outdated farming methods, and modern technology have improved agriculture. It is critical to regulate how much fertilizer should be administered to each crop. Without soil testing, it is very challenging to ensure that the crop is receiving the right amount of fertilizer and to maximize yield. The time-consuming process of laboratory soil sample analysis involves collecting soil samples, getting them ready for analysis, doing physical or chemical analysis, interpreting the findings, and then suggesting fertilizer for crops. A soil nutrient prediction system that predicts

nitrogen, phosphorus, and potassium (NPK) levels and recommends which crop to plant is developed in this work. Precision agriculture, which focuses on crop monitoring, fertilization, irrigation systems, and yield prediction, has made considerable strides in the agricultural industry in recent years [6]. Choosing the appropriate crop based on local soil and climate conditions is another way to increase productivity [7].

The development of crop recommendation systems that consider location-specific factors would be beneficial to farmers, as the study discussed in this article aims to develop a recommendation system that provides the best produce based on regionally specific topography and climate parameters [10]. In this paper, we used the graph convolution neural networks model [11] to develop a crop recommendation system that is dependent on terrain and environmental elements. Therefore, farmers need to have the tools necessary to choose the crop that is most appropriate for the specific soil and weather conditions of the area [8]. Applications such as crop suggestion, crop disease diagnostics, fertilizer management, and others have been developed in underdeveloped countries as a result of applying machine learning to agricultural planning goals [9].

Literature Survey

This study reveals a straightforward yield forecasting technique made for farmers' convenience. A smartphone app that acts as a communication tool to inform farmers about the various factors influencing agricultural productivity is the recommended solution. Agricultural production is estimated using a range of machine learning approaches, including SVM, ANN, RF, MLR, and KNN. The random forest method was the most accurate, with a 95% accuracy rate [21].

This study presents Agro DSS, a unique system that connects agricultural systems with cutting-edge decision support. Among the tools are decomposition, time series grouping, predictive modeling, accuracy assessment, and structural change detection. Users can utilize them to forecast simulated scenarios and comprehend domain relationships or interconnections [22].

To develop a crop recommendation system based on soil characteristics, the researchers combined ensemble models with majoritarian voting methods including naive Bayes and K-nearest neighbor. This approach aims to choose crops as precisely and effectively as feasible. These algorithms analyze agricultural productivity under particular weather conditions using statistical data, including state/district crops, agricultural production, and environmental characteristics, to provide categorization images [25]. This article examines cloud-based agricultural recommendation engines driven by AI-driven precision agriculture and machine learning to help farmers grow crops based on data. Extreme gradient boosting, decision trees, random forests, KNN, and support vector machines (SVM) are tested to find the best prediction machine learning (ML) method for a cloud-based recommendation platform. The creation and widespread usage of open-source, free precision agricultural technology has contributed to the production and acceptance of high-quality crops [26]. In this post, we introduce Agro Consultant, an intelligent system that helps Indian farmers choose crops based on the planting season, farm location, soil properties, and weather conditions including climate and precipitation. The results showed that the

Multi-Label Classification (MLC) model surpasses the existing models in terms of prediction when compared to KNN and random forest [23]. This study presents a highly accurate and efficient method of crop recommendations based on site-specific factors utilizing a majority voting ensemble model that uses trees at random, CHAID, K-nearest neighbor, and naive Bayes. This approach helps farmers to select the best variety.

Methodology

By creating a recommendation system based on machine learning and image editing, our research aims to solve the problem of choosing the finest crops. KNN, XGBoost, random forest, and other neural network-based photo augmentation methods were investigated in this study, and it was discovered that XGBoost outperformed the others. The accuracy of the developed model is adequate [27]. The goal of this review is to provide a thorough overview of the most recent research using deep convolutional neural networks (CNNs) for plant phenotyping applications.

Applications of different CNN designs for monitoring plant growth, detecting plant stress, and evaluating postharvest quality are specifically examined. Finally, a number of suggestions are made for more study on the use of CNN architecture in plant phenotyping [28]. This study shown that combinations of soil amendments, conditioners, and residue management can reduce soil salinity and significantly increase crop output, in addition to optimizing irrigation and drainage management for each unique situation. These findings demonstrate that the higher yields needed to sustain and boost agricultural output can also be achieved through conservation agriculture [29].

This article covered four topics: (1) the effects of conventional and unconventional cropping practices on soil health in agro-systems; (2) the evolution of the plant-microbe soil complex and the biochemical mechanisms that sustain soil health under agricultural stress; (3) the evolution of the notion of soil quality and health in agro-systems over the past few decades and the primary indicators currently used to assess soil health; and (4) problems in agro-ecosystems that affect soil health [30].

Results and Discussion

While there may be many advantages to using artificial intelligence in soil health management, there are also some drawbacks. They are:

Data Quantity and Quality: To properly assess and forecast soil health, AI models need a sizable volume of high-quality data. It might be difficult to gather thorough and precise soil data, particularly in isolated or poorly researched areas.

Model Interpretability: Deep learning neural networks and other AI models can be intricate and challenging to understand. Gaining the trust of users and stakeholders may depend on your ability to comprehend how the AI determines the health of the soil.

Integration with Conventional Practices: It can be difficult to incorporate AI technologies with current processes and soil management techniques. For adoption to be effective, AI recommendations must be in line with local customs and expertise.

Cost: Putting AI solutions into practice for managing soil health can be expensive, particularly when it comes to data collection, model development, and field deployment. For small-scale farmers or agricultural organizations with limited resources, cost may be an obstacle.

Concerns about Privacy, Data Ownership, and Ethics: When applying AI to soil health management, there may be ethical and regulatory issues. To prevent legal problems, it is crucial to make sure that all applicable rules and regulations are followed.

In order to overcome these obstacles, farmers, researchers, technology developers, legislators, and other stakeholders frequently need to work together to create customized AI solutions that take into account the larger social, economic, and environmental context while addressing particular soil health management requirements.

Table 1 denotes the limitations involved in estimating the soil parameters by conventional laboratory analysis. Table 2 depicts the estimation of soil parameters using AI related methods.

Table 1. Comparison with limitations for soil parameters testing

Reference	Technique	Strength	Limitations
Plant, et.al. [9]- 1989	CALEX	Prepares scheduling guidelines for crop management	Time consuming
Gholami, et.al. [10]-2017	ANN (Artificial Neural Network)	To estimate soil erosion, high calculation speed, high accuracy	Plots required to monitor rill erosion
Zhao, et.al. [11]- 2007	ANN	High-resolution soil texture maps generated using coarse resolution soil texture map	Low accuracy
Mosaffaei, et.al. [12]-2020	ANN	Predict degradation in national park management plan	Adaptation challenge with new data.
Shao, et.al. [13]-2021	BP-ANN (Back Propagation-Artificial Neural Network)	Classify and evaluate soil quality, where soil nutrients contaminated with heavy metal contamination in the arid area	Expensive
Dahmardeh, et.al. [14]-2017	ANN, ANFIS (Adaptive Neuro-fuzzy Inference System)	The effects of tillage type, temperature, sodium are evaluated based on type of intercropping to carbon-nitrogen ratio	Measures only two chemical properties
Pellegrini, et.al. [15]-2021	ANN	Predict Soil microbial-biomass from soil physical and chemical properties	Only a few cases were studied.
Jalal, et.al. [16]-2021	ANN, ANFIS,	Prediction models developed	Internet dependent

	GEP (Gene Expression Programming)	to evaluate swell pressure and unconfined compression strength of expansive soils	
Kim, et.al. [17]-2008	ANN	Estimates soil erosion, NH ₄ -N concentrations and dissolved P of runoff	Not accurate for higher erosion values
Arsoy, et.al. [18]- 2013	ANN	Soil water content determination based on dielectric permittivity measurement	Time consuming
Liu, et.al. [19]- 2015	SVM (Support Vector Machine)	Classification and assessment of urban soil quality	sensitive to outliers
Guan, et.al. [20]- 2011	SVM	Soil salinity prediction for irrigation water management in irrigation districts	Prior Knowledge of EC value required
Mustafa, et.al. [21]- 2018	SVM	Geospatial prediction of soil erosion	High Complexity
Wijitdechakul, et.al. [22]-2016	UAV (Unmanned Aerial Vehicle)	Interpret the plant health conditions for user.	Expensive
Pluer, et.al. [23]- 2020	UAV	To test field scale variation in soil characteristics	High Complexity
Krenz, et.al. [24]- 2019	UAV	To identify the degradation status of soils	Tussocks or exposed shrub roots cannot be detected
Falco, et.al. [25]- 2018	UAV	To estimate sprout density and plant vigor throughout the growing season	High Complexity
Rosa, et.al. [26]- 1999	ImpelERO	To evaluate soil erosion	Time consuming
Kaufmann, et.al. [27]-2009	Fuzzy logic expert system	To evaluate the plant productivity of restored soils	Internet dependent.
Ahsanuzzaman, et.al. [28]-2004	Expert system	To evaluate groundwater pollution from application of manure to soil	Internet-based.

Table 2. Comparison of the results for soil testing using AI methods

REFERENCES	DATA INPUT	ALGORITHM	FEATURES	CHARACTERISTICS	OPTIMAL RESULTS
Fernandes, et.al. [29]- 2019	8556 Samples	ANN	Estimates soil organic	Soil Organic matter	R ² =0.76, RMSE=1.98g

			matter content from soil chemical attributes		Kg-1
Mirzaee, et.al. [30]-2016	100 soil samples	ANNSK (Artificial Neural Network Simple Kriging)	To predict soil organic matter content	Soil Organic matter	R2=0.633, RMSE=0.271
Somaratne, et.al. [31]- 2005	240 soil samples	ANN, MLR (Multivariate Linear Regression)	to predict SOC contents across different land use patterns	Soil Organic matter	1. ANN: Ci(R2=0.92), Ce(R2=0.83) 2. MLR: Ci(R2=0.73), Ce(R2=0.82)
Bouasria, et.al. [32]- 2020	369 soil samples	DT (Decision Tree), K-NN (K-Nearest Neighbour), ANN	To predict soil organic matter content	Soil Organic matter	ANN:(MS image: R2=0.6553, PAN image: R2=0.6985)
Huang, et.al. [33]- 2020	102 soil samples	BPNN, SVR (Support Vector Regression) , PLSR (Partial Least Square Regression)	To predict soil organic matter concentration	Soil Organic matter	1. BPNN:(R2=0.880, RMSE=2.679) 2. SVR:(R2=0.895, RMSE=2.531) 3. PLSR:(R2=0.808, RMSE=3.393)
Swetha, et.al. [34]- 2020	90 soil samples	RF (Random Forest), CNN (Convolutional Neural Network)	Smart phone application for predicting soil texture	Soil Texture	Clay (R2=0.97-0.98), Sand (R2=0.96-0.98), Silt (R2=0.62-0.75) 4.
Zhao, et.al. [35]- 2009	450 sampling points	ANN	To predict soil texture based on soil attributes obtained	Soil Texture	LM:(RMSE-Clay: 7.9, Sand:16.6), RP:(RMSE-Clay: 8.5, Sand:14.9)

			from existing coarse resolution soil maps		
Penghui, et.al. [36]-2020	Various types of variables	ANFIS-GOA, ANFIS-SSA, ANFIS-GWO, ANFIS-PSO, ANFIS-GA, ANFIS-DA	To predict soil temperature	Soil Temperature	ANFIS-mSG was found to be efficient
Sattari, et.al. [37]- 2020	3995 Records	DT-GBT (Decision Tree- Gradient Boosted Tree)	To predict the soil temperature at	Soil Temperature	Soil Temperature
Behmanesh, et.al. [38]-2017	Soil temperature dataset (1997-2008)	GEP, ANN, MLR	To estimate the soil temperature at different depths	Soil Temperature	ANN performed efficiently
John, et.al. [39]-2020	60 soil samples	ANN, SVM, RF, MLR	Estimation of soil organic content and soil nutrient indicators	Soil Organic Content Nutrient	RF:R2=0.68, SVM:R2=0.36, ANN:R2=0.36, MLR:R2=0.17
Pathumthusabana, et.al. [40]-2021	1700 soil sample images	CNN, Lenet, AlexNet, Vgg16	classification of SOC and soil macronutrients	Soil Organic Content, Soil Macronutrients	Accuracy: Lenet:77.4%, AlexNet:85.31%, Vgg16:87.38%
Rajamanickam, et.al. [41]-2021	1000 Samples	DT, KNN, SVM	Predicts soil fertility based on macro and micro nutrients status	Soil Fertility	MSE (DT:0.01, KNN:0.6897, SVM_linear:0.6552 SVM_rbf:0.559
Zhang, et.al. [42]- 2021	Various types of variables	DT, RF	Predicts soil fertility	Soil Fertility	RF and DT are the most accurate

					methods
Hassan-Esfahani, et.al. [43]-2015	Various types of variables	ANN, UAV	Estimates surface soil moisture	Soil Moisture	RMSE:2.0, MAE:1.3, R2:0.77
Gill, et.al. [44]-2006	Various types of variables	SVM, ANN	Predicts soil moisture	Soil Moisture	SVM performed efficiently
Prakash, et.al. [45]-2020	Various types of variables	MLR, SVM, RNN (Recurrent Neural Network)	Predicts Soil Moisture	Soil Moisture	MLR performed efficiently
Sarmadian, et.al. [46]-2008	125 soil samples	MLR, ANN	Predicts soil parameters	Soil Properties	ANN performed efficiently
Kurnaz, et.al. [47]- 2015	Various types of variables	ANN	Predicts compression and recompression index of soil	Soil Properties	Compression index(R2=0.8973), Recompression Index(R2=0.3600)
Mohanty, et.al. [48]-2015	721 soil samples	ANN	Evaluates Pedotransfer function of Field Capacity and Permanent Wilting Point	Soil Properties	ANN indicated unbiased and higher predictability

Conclusion

Recent studies show that agriculture is the most significant sector of the Indian economy, employing over 60% of the labor force and contributing more than 17% of GDP. Farming needs to be transformed by fast soil testing and crop disease detection using machine learning algorithms and artificial intelligence techniques on real-time datasets in order to regularly determine soil fertility and crop health status. The use of artificial intelligence has revolutionized soil management techniques. AI predicts nutrient levels, maps soil changes, applies precision fertilization and irrigation, detects early plant disease symptoms, directs targeted treatments, predicts the dangers of soil erosion, evaluates soil qualities, and sends out autonomous robots for control measures through algorithms for machine learning. AI will make smart agriculture the standard as we look to the future.

Intelligent, more efficient and sustainable agriculture will be made possible by the development and uptake of artificial intelligence (AI) technologies. This will be crucial in addressing the issue of food security, promoting rural revitalization, and protecting the environment.

References

1. Chen, Q., Li, L., Chong, C. and Wang, X., 2022. AI-enhanced soil management and smart farming. *Soil Use and Management*, 38(1), pp.7-13.
2. Bannerjee, G., Sarkar, U., Das, S. and Ghosh, I., 2018. Artificial intelligence in agriculture: A literature survey. *International Journal of Scientific Research in computer Science applications and Management Studies*, 7(3), pp.1-6.
3. <https://tracegenomics.com/>
4. Home | Natural Resources Conservation Service ([usda.gov](https://www.usda.gov))
5. Miner, G.L., Delgado, J.A., Ippolito, J.A. and Stewart, C.E., 2020. Soil health management practices and crop productivity. *Agricultural & Environmental Letters*, 5(1), p.e20023.
6. Lal, R., 2016. Soil health and carbon management. *Food and energy security*, 5(4), pp.212-222.
7. Kumar, A., Sharma, H. and Kumar, S., 2022. AI-Based Soil Fertility Management Review: Challenges And Opportunities. *Journal of Survey in Fisheries Sciences*, pp.283-288.
8. Zhang, X., Yang, P. and Lu, B., 2024. Artificial intelligence in soil management: The new frontier of smart agriculture. *Advances in Resources Research*, 4(2), pp.231-251.
9. Plant, R.E., 1989. An artificial intelligence-based method for scheduling crop management actions. *Agricultural systems*, 31(1), pp.127-155.
10. Gholami, V., Booi, M.J., Tehrani, E.N. and Hadian, M.A., 2018. Spatial soil erosion estimation using an artificial neural network (ANN) and field plot data. *Catena*, 163, pp.210-218.
11. Zhao, Z., Chow, T.L., Rees, H.W., Yang, Q., Xing, Z. and Meng, F.R., 2009. Predict soil texture distributions using an artificial neural network model. *Computers and electronics in agriculture*, 65(1), pp.36-48.
12. Mosaffaei, Z., Jahani, A., Chahouki, M.A.Z., Goshtasb, H., Etemad, V. and Saffariha, M., 2020. Soil texture and plant degradation predictive model (STPDPM) in national parks using artificial neural network (ANN). *Modeling Earth Systems and Environment*, 6(2), pp.715-729.
13. Shao, W., Guan, Q., Tan, Z., Luo, H., Li, H., Sun, Y. and Ma, Y., 2021. Application of BP-ANN model in evaluation of soil quality in the arid area, northwest China. *Soil and Tillage Research*, 208, p.104907.
14. Dahmardeh, M.E.H.D.I., KESHTEGAR, B. and Piri, J.A.M.S.H.I.D., 2017. Assessment chemical properties of soil in intercropping using ANN and ANFIS models. *Bulgarian Journal of Agricultural Science*, 23(2).
15. Pellegrini, E., Rovere, N., Zaninotti, S., Franco, I., De Nobili, M. and Contin, M., 2021. Artificial neural network (ANN) modelling for the estimation of soil microbial biomass in vineyard soils. *Biology and Fertility of Soils*, 57(1), pp.145-151.
16. Jalal, F.E., Xu, Y., Iqbal, M., Javed, M.F. and Jamhiri, B., 2021. Predictive modeling of swell-strength of expansive soils using artificial intelligence approaches: ANN, ANFIS and GEP. *Journal of Environmental Management*, 289, p.112420.

17. Kim, M. and Gilley, J.E., 2008. Artificial Neural Network estimation of soil erosion and nutrient concentrations in runoff from land application areas. *Computers and electronics in agriculture*, 64(2), pp.268-275.
18. Arsoy, S., Ozgur, M., Keskin, E. and Yilmaz, C., 2013. Enhancing TDR based water content measurements by ANN in sandy soils. *Geoderma*, 195, pp.133-144.
19. Liu, Y., Wang, H., Zhang, H. and Liber, K., 2016. A comprehensive support vector machine-based classification model for soil quality assessment. *Soil and Tillage Research*, 155, pp.19-26.
20. Guan, X., Wang, S., Gao, Z. and Lv, Y., 2013. Dynamic prediction of soil salinization in an irrigation district based on the support vector machine. *Mathematical and Computer Modelling*, 58(3-4), pp.719-724.
21. Mustafa, M.R.U., Sholagberu, A.T., Yusof, K.W., Hashim, A.M., Khan, M.W.A. and Shahbaz, M., 2018. SVM-based geospatial prediction of soil erosion under static and dynamic conditioning factors. In *MATEC Web of Conferences* (Vol. 203, p. 04004). EDP Sciences.
22. Wijitdechakul, J., Sasaki, S., Kiyoki, Y. and Koopipat, C., 2016, September. UAV-based multispectral image analysis system with semantic computing for agricultural health conditions monitoring and real-time management. In *2016 International Electronics Symposium (IES)* (pp. 459-464). IEEE.
23. Plier, E.M., Robinson, D.T., Meinen, B.U. and Macrae, M.L., 2020. Pairing soil sampling with very-high resolution UAV imagery: An examination of drivers of soil and nutrient movement and agricultural productivity in southern Ontario. *Geoderma*, 379, p.114630.
24. Krenz, J., Greenwood, P. and Kuhn, N.J., 2019. Soil degradation mapping in drylands using Unmanned Aerial Vehicle (UAV) data. *Soil Systems*, 3(2), p.33. Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 9 September 2024 doi:10.20944/preprints202409.0605.v1
25. Falco, N., Wainwright, H., Ulrich, C., Dafflon, B., Hubbard, S.S., Williamson, M., Cothren, J.D., Ham, R.G., McEntire, J.A. and McEntire, M., 2018, July. Remote sensing to UAV-based digital farmland. In *IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium* (pp. 5936-5939). IEEE.
26. De la Rosa, D., Mayol, F., Moreno, J.A., Bonsón, T. and Lozano, S., 1999. An expert system/neural network model (ImpelERO) for evaluating agricultural soil erosion in Andalusia region, southern Spain. *Agriculture, Ecosystems & Environment*, 73(3), pp.211-226.
27. Kaufmann, M., Tobias, S. and Schulin, R., 2009. Quality evaluation of restored soils with a fuzzy logic expert system. *Geoderma*, 151(3-4), pp.290-302.
28. Ahsanuzzaman, A.N.M., Zaman, M. and Kolar, R., 2004. Simple expert system for evaluation of nutrient pollution potential in groundwater from manure application. *International Journal of Geomechanics*, 4(4), pp.285-295.
29. Fernandes, M.M.H., Coelho, A.P., Fernandes, C., da Silva, M.F. and Marta, C.C.D., 2019. Estimation of soil organic matter content by modeling with artificial neural networks. *Geoderma*, 350, pp.46-51.
30. Mirzaee, S., Ghorbani-Dashtaki, S., Mohammadi, J., Asadi, H. and Asadzadeh, F., 2016. Spatial variability of soil organic matter using remote sensing data. *Catena*, 145, pp.118-127.
31. Somaratne, S., Seneviratne, G. and Coomaraswamy, U., 2005. Prediction of soil organic carbon across different land-use patterns: A neural network approach. *Soil Science Society of America Journal*, 69(5), pp.1580-1589.

32. Bouasria, A., Namr, K.I., Rahimi, A. and Ettachfini, E.M., 2020, October. Soil organic matter estimation by using Landsat-8 pansharpened image and machine learning. In 2020 Fourth International Conference On Intelligent Computing in Data Sciences (ICDS) (pp. 1-8). IEEE.
33. Huang, D., Liu, H., Zhu, L., Li, M., Xia, X. and Qi, J., 2020. Soil organic matter determination based on artificial olfactory system and PLSR-BPNN. *Measurement Science and Technology*, 32(3), p.035801.
34. Swetha, R.K., Bende, P., Singh, K., Gorthi, S., Biswas, A., Li, B., Weindorf, D.C. and Chakraborty, S., 2020. Predicting soil texture from smartphone-captured digital images and an application. *Geoderma*, 376, p.114562.
35. Zhao, Z., Chow, T.L., Rees, H.W., Yang, Q., Xing, Z. and Meng, F.R., 2009. Predict soil texture distributions using an artificial neural network model. *Computers and electronics in agriculture*, 65(1), pp.36-48.
36. Penghui, L., Ewees, A.A., Beyaztas, B.H., Qi, C., Salih, S.Q., Al-Ansari, N., Bhagat, S.K., Yaseen, Z.M. and Singh, V.P., 2020. Metaheuristic optimization algorithms hybridized with artificial intelligence model for soil temperature prediction: Novel model. *IEEE Access*, 8, pp.51884-51904.
37. Sattari, M.T., Avram, A., Apaydin, H. and Matei, O., 2020. Soil temperature estimation with meteorological parameters by using tree-based hybrid data mining models. *Mathematics*, 8(9), p.1407.
38. Behmanesh, J. and Mehdizadeh, S., 2017. Estimation of soil temperature using gene expression programming and artificial neural networks in a semiarid region. *Environmental Earth Sciences*, 76, pp.1-15.
39. John, K., Abraham Isong, I., Michael Kebonye, N., Okon Ayito, E., Chapman Agyeman, P. and Marcus Afu, S., 2020. Using machine learning algorithms to estimate soil organic carbon variability with environmental variables and soil nutrient indicators in an alluvial soil. *Land*, 9(12), p.487.
40. Pathumuthusabana, A.M. and Priyadharsini, S.S., 2021. An Artificial Intelligence-Based Evaluation of Soil Fertility. In *Handbook of Green Engineering Technologies for Sustainable Smart Cities* (pp. 255-275). CRC Press.
41. Rajamanickam, J., 2021. Predictive model construction for prediction of soil fertility using decision tree machine learning algorithm. *INFOCOMP Journal of Computer Science*, 20(1).
42. Zhang, P., Guo, Z., Ullah, S., Melagraki, G., Afantitis, A. and Lynch, I., 2021. Nanotechnology and artificial intelligence to enable sustainable and precision agriculture. *Nature Plants*, 7(7), pp.864-876.
43. Hassan-Esfahani, L., Torres-Rua, A., Jensen, A. and McKee, M., 2015. Assessment of surface soil moisture using high-resolution multi-spectral imagery and artificial neural networks. *Remote Sensing*, 7(3), pp.2627-2646.
44. Gill, M.K., Asefa, T., Kemblowski, M.W. and McKee, M., 2006. Soil moisture prediction using support vector machines 1. *JAWRA Journal of the American Water Resources Association*, 42(4), pp.1033-1046.
45. Prakash, S., Sharma, A. and Sahu, S.S., 2018, April. Soil moisture prediction using machine learning. In 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT) (pp. 1-6). IEEE.
46. Sarmadian, F. and Taghizadeh Mehrjardi, R., 2008. Modeling of some soil properties using artificial neural network and multivariate regression in Gorgan Province, North of Iran. *Global Journal of Environmental Research*, 2(1), pp.30-35.

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doi:10.20944/preprints202409.0605.v1

47. Kurnaz, T.F., Dagdeviren, U., Yildiz, M. and Ozkan, O., 2016. Prediction of compressibility parameters of the soils using artificial neural network. SpringerPlus, 5, pp.1-11.
48. Mohanty, M., Sinha, N.K., Painuli, D.K., Bandyopadhyay, K.K., Hati, K.M., Sammi Reddy, K. and Chaudhary, R.S., 2015. Modelling soil water contents at field capacity and permanent wilting point using artificial neural network for Indian soils. National Academy Science Letters, 38, pp.373-377