International Journal on Advanced Science Engineering Information Technology

Vol.13 (2023) No. 2
ISSN: 2088-5334

Smart Agriculture: Soil Aggregate Stability Classification for Damaged Crops in India

M. Meenakshi [a], R. Naresh [b,*]

[a] *Department of Computer Science and Engineering, SRM Institute of Science and Technology, Kattankulathur, India*
[b] *Department of Networking and Communications, SRM Institute of Science and Technology, Kattankulathur, India*
*Corresponding author: *nareshr@srmist.edu.in*

Abstract—**Soil health is the most important element in a stable farm environment in soil-based agriculture. Soil aggregate stabilization is mandatory for soil characteristics influencing crop yield and stability. The study was conducted on Tamilnadu delta areas where the alluvial and black soil types for rabi and Kharif crops are used, and soil parameters are analyzed. This study aims to provide an overview of the mechanisms and aggregate-forming agents using ensemble methods. It is difficult to assess and analyze the aggregate stability. However, the most popular farming methods used in commercial crop yields, including artificial fertilizers and monocultures, can weaken the soil throughout the term, resulting in a sequence of issues that necessitate using many more man-made inputs, which contribute to global warming. The soil type's qualities and functions in predicting the crop type that can be grown under specific soil conditions. Remote monitoring of soil parameters can change agricultural practices and boost productivity. We suggest a process in this article for classifying soil based on micro and macro-nutrients and predicting the form of the crop that can be grown in that type of soil. The results obtained were compared to the standardized maximum point for specific crops, and crop inputs varied depending on the variations. Several ensemble methods have been used, such as the bagging meta-estimator, Ada Boost, and XGB. On the held-out dataset, the bagging models estimated an accuracy of 98 percent, showing the technological viability of different soil types.**

Keywords—**Ensemble methods; soil aggregate stability; soil health; crop productivity; smart agriculture.**

Manuscript received 26 Apr. 2022; revised 12 Sep. 2022; accepted 27 Dec. 2022. Date of publication 30 Apr. 2023.

I. Introduction

The type of soil and the nutrients in the soil have a direct impact on the type of crop grown and the crop quality. Soil quality is deteriorating due to rising deforestation, making it difficult to find soil quality. The word "soil damage" has a strong connotation. Soil is necessary for most of our food, lumber, and fabrics, and substantial damage to this asset may leave a growing international community with non-soluble difficulties. Soil is a general population natural resource that is under emerging global strain and, as such, should be preserved sustainably for the benefit of the present and future. This maintenance is impossible without a thorough knowledge of the various soil properties and characteristics.

Aggregate stabilization is an important element in soil protection and preserving its ecological services [1], as deposition harms agricultural productivity in the water cycle, hydropower, and catchment energy generation because it affects the trophic status of water bodies and reduces river storage capacity [2]. Soil erosion might be a gradual, ignored method, or it can happen quickly, potentially causing soil surface loss. Other severe soil degradation conditions that can speed up the soil's ecological status include root penetration, organic matter content, loss of agricultural structure, insufficient management irrigation, salinization, and soil acidity issues [3]. On the other hand, in-situ runoff studies are costly, time-intensive, and have minimal spatial range. Data-driven models and the amount, type, and clarity of required data vary by model. The information for the Ruiru reservoirs catchment might not be available or appropriate to run the models, as seems to be the case for several catchments worldwide, especially in Africa. Climate conditions such as humidity, temperature, and rainfall all play a part in the lifecycle of agriculture. Increased deforestation and waste are causing climate change, making it impossible for farmers to choose how to plant the soil, plant crops, and reap. Each crop of soil requires a different type of nutrition. Soil needs three major nutrients: Potassium (K), Phosphorus (P), and Nitrogen (N). Nutrient deficiency can result in unhealthy crop quality.

Food production is at a critical juncture with a growing population and shrinking Arable Land [5]. There are several ways to increase the amount of crop output [6], but repeated tillage destroys soil structure and reduces soil organic carbon (SOC) [7], which is detrimental to sustainable agricultural growth and environmental health. This strongly impacts soil nitrogen and carbon formation, dispersion, and stabilization. The nitrogen and carbon content of soils and soil aggregates' stability may be greatly improved by restoring and growing vegetation in them [4].

As the deterministic part of the projections, the cubist model was used. A rule-based architecture divides knowledge hierarchy through different file systems that share configuration files. This implies that each piece of data corresponds to a certain subset and cannot be found in another. Each subsection is described by a law, which is expressed by a conditional statement and may contain one or even more coefficients. Therefore, each generated segment is then regressed according to the law that defines it, resulting in the estimation of a particular soil of significance. This implies that perhaps the regression coefficients are specific to the data instances and therefore have lower amplitude defects [8]. Figure 1 shows how health is identified in ensemble techniques.

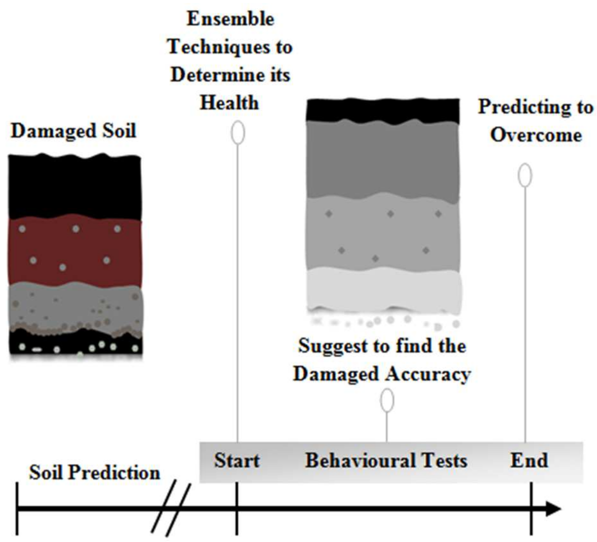

Fig. 1 Damaged soil works in Ensemble Methods

To address the above disadvantages, a device that can benefit through aspects and their interactions is required to recognize complex processes and attain maximum functionality. In those other terms, a machine that can view the universe as a structure of definitions, with each concept determined by its relationship to easier things, would be able to get things done of any complexity. It is close to human experience in that it interacts with the universe and whatever it is instinctively rather than in a confined space.

The current research presented a new and efficient approach for classifying large aggregates collected from a tillage soil surface using Ensemble methods. The learning algorithm found, retrieved, and merged details of damaged crops, allowing it to perform high accuracy in classification. These were achieved after training the bagging and boosting system with multiple levels, including one that featured special and often more complex characteristics. Deep learning is among the earliest experiments in the field of soil erosion, based on machine learning techniques.

II. Materials and Methods

A. Study Area

Machine learning (ML) techniques have been increasingly used in numerous research fields, particularly over the last two decades[9]. Pedometrics, a subfield of soil science analysis, has used mathematical models to study or explain how soil is spread in time and space by information. The growing abundance of soil parameters that can be collected easily globally and preempts, as well as publicly accessible fully accessible algorithms, have increased the implementation of ML techniques for soil data analysis. Scientists have looked at potential solutions to this issue to solve it. Therefore, Pedo-Transfer Functions (PTFs) are always the best option. These techniques are based on easily measured soil parameters to estimate soil properties [9]. While aspects and altitude overperformed, NDVI was one of the most important predictors of aggregate stability.

Vegetation indexes affect landscape dynamics by acting as surrogates for natural vegetation [17]. PH and Organic matter content was found to have a close relationship with aggregate equilibrium, with $r = 0.56$ and $r = 0.73$, respectively. Furthermore, clay content has the highest association with aggregate stability ($r = 0.30$) of the fractions used to measure soil texture. [15]The GLM and ANN models were trained and then tested using these variables. In the cross-validation process, the ANN model outperformed RMSE and MAE, with r2 = 0.82 for checking and r2 = 0.80 for preparation. For training and testing, the GLM generated r2 values of 0.59 and 0.63, respectively. As a result, considering the shortcomings encountered when introducing ANN, its use as a proposed methodology is preferred rather than GLM. Given the limited number of commonly quantifiable factors, this analysis offers two frameworks that can be used in conjunction with those other current soil routines or specifically to complete soil assessments when aggregate stability wasn't assessed [16].

B. Site Description

This study analyzes Tamilnadu delta areas' soil parameters such as nutrients, moisture, humidity, and temperature are analyzed since 88,858 numerous soil damages have been collected [18]. As mentioned in Figure 1, In this data soil type is used for alluvial and black soils for rabi and Kharif crops with minimal, partial, and significant crop-damaging characteristics. Python programming language has been used in the Anaconda distribution framework to incorporate the suggested learning algorithm. This function includes the numerous libraries used to execute the algorithms in contrast to the essential components for machine learning. The Pandas, Matplotlib, and Numpy libraries have been included in the research. Furthermore, the CODs were executed using Colab-Notebooks, a server-client program that manages and updates files via a web browser. [14].There was no reason to link to the Internet while the program was run, so the entire program was run without Internet. Intel(R) Core i3-3250U, 2.6 GHz CPU, and 4 GB RAM were needed for the computer system.

C. Aggregate Sampling and Separation

To determine the soil bulk density (BD) and collect undisturbed soil samples, each plot had three random sampling locations selected from among them. We took samples of the soil at depths ranging from 0 to 20 centimeters, 20 to 40 centimeters, and 40 to 60 centimeters using a soil drill. This used a five-point sampling approach to gather soil from each sample location and then mix the ground before being delivered to determine whether it was collected.

D. Prediction Model

Using a machine learning model known as ensemble learning [15], numerous individuals know to work together to solve a single issue. In supervised learning, ensemble learning is used in several studies [16] to prove that ensemble learning is more effective at predicting outcomes than individual learning algorithms. An enhanced decision tree surpasses current image analysis methods often used in agriculture, as shown by the authors in [17]. More than 4% more accurate than the current state-of-the-art, the suggested model achieves 94.27 percent accuracy. [18] uses stacking to improve crop categorization accuracy.

These include boosting, bootstrap aggregation (bagging), and layered generalization. The variety of the core algorithms in an ensemble seems to provide better outcomes empirically. Random techniques build a more robust ensemble than purposeful methods. This study combines classification techniques and Regression algorithms that use bagging and boosting for various approaches.

The goals of this research were to (1) determine how the stability of soil aggregates, the distribution of soil aggregates, the content of Soil nutrients, and the erodibility of soil vary at various phases after the abandonment of agricultural land; and (2) soil health may be affected by changes in aggregate soil stability after the discontinuation of agriculture in this area.[19]These investigations will increase our knowledge of quality and sequestration following abandonment. This will improve land management for eco-restoration and soil productivity.

III. Results and Discussion

A significant number of regression trees are used in prediction, with each value in a particular tree multiplied or weighted [17]. A spatial map of aggregate stability predicts it was created using readily accessible data as coefficients and calculated point data. The findings showed that the various LULCs had a greater impact on aggregate stability than the terrain attributes.[20]Moreover, the DSM predictor map has been used to describe LULCs of varying levels of aggregate stability. The composite stability charts show vulnerability to water depletion under farmland, tea fields, and roads in the eastern portion of the reservoir, then heavily forested regions on the west coast[1].

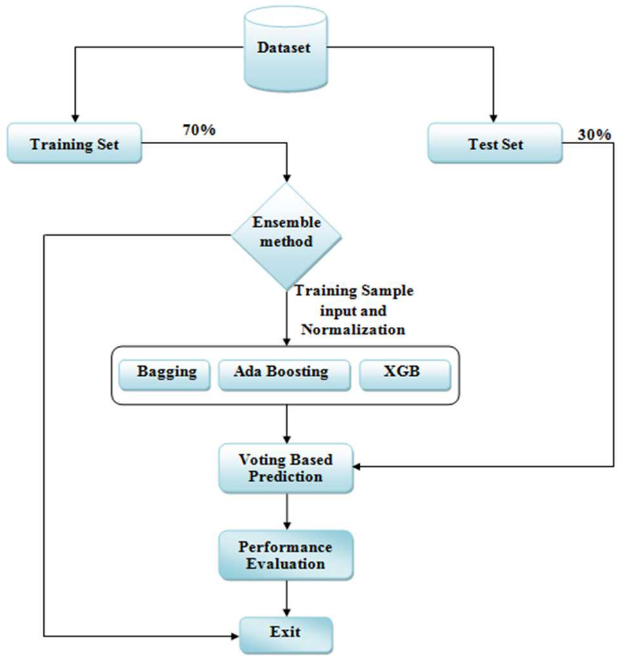

Fig. 2 Flow work of damaged soil using ensemble methods.

TABLE I
Abbreviation

S.No	Formula Symbols with Explanation		
	Symbol	**Quantity**	**Formula**
1	S_n^m	nth observation of the m th random subsets	$\{S^1_{1,}S^1_{2,}\ldots . S^1_n\},\{S^2_{1,}S^2_{2,}\ldots . S^2_n\},\ldots\ldots\ldots\ldots\{S^m_{1,}S^m_{2,}\ldots . S^m_n\}$
2	S_L	Learner Subset	$S_L(.) = \frac{1}{L}\sum_{l=1}^{L} w_l(.)$
3	l	Average Learners	$S_L(.) = S_{l-1}(.) + c_l * w_l(.)$
4	w_l	Weak Learners	$S_L(.) = \frac{1}{L}\sum_{l=1}^{L} c_l * w_l(.)$
5	k	Voting	$S_L(.) = arg_k\, max\left[card\left({}^{l}/_{w_l(.)} = k\right)\right]$

The LDA algorithm will know various topics where each text is allocated based on the testimony in any of them. The first challenge is determining the optimum variety of topics, which must be broad enough yet to catch parallels between papers but precise enough to form a reasonable and sensible set of topics. The ability to strike the right balance between generalization and precision is critical for producing subjects that are grammatically decipherable by individuals [21]. Calculated a cohesion metric suggested for new approaches practiced with a progressively growing variety of categories, ranging from 2 to 30 [14]. This summed metric incorporates a normalized pointwise, cosine vector similarity, reciprocal knowledge cohesion metric, and a 110-point Boolean dimensional vector. It has a scale of 0 to 1, with 1 representing the greatest cohesion. After conducting a variable matrix check, the LDA algorithm's certain variables, including the probability threshold over which a subject is classified as well as the number of additional iterations, were fixed to 0.2 and 1000, accordingly[15]. Figure 2 shows the proposed flow work of damaged soil.

A. Bagging

A bunch of individual models is trained parallel, then the subset of each model is trained randomly. Bagging classifiers are ensemble meta-estimators that suit base classifiers to randomized categories of their original data and then combine their eligible liabilities to form a prediction accuracy. By integrating randomization into a black-box estimator's design procedure, such a meta-estimator can usually be used to reduce the variance. Each base classifier is trained in combination with a training set that is randomly generated and replaced. Figure 3 shows how bagging works on damaged soil.

$$\{S_{1,}^{1}S_{2,}^{1}\ldots\ldots S_{n}^{1}\},\{S_{1,}^{2}S_{2,}^{2}\ldots\ldots S_{n}^{2}\},\ldots\ldots\ldots\ldots\{S_{1,}^{m}S_{2,}^{m}\ldots\ldots S_{n}^{m}\} \quad (1)$$

$$S_L(.) = \frac{1}{L}\sum_{l=1}^{L} w_l(.) \quad (2)$$

(Regression problem average w1 ---> weak learners)

$$S_L(.) = arg_k\, max\left[card\left({}^{l}/_{w_l(.)} = k\right)\right] \quad (3)$$

(Classification problem on voting majority)

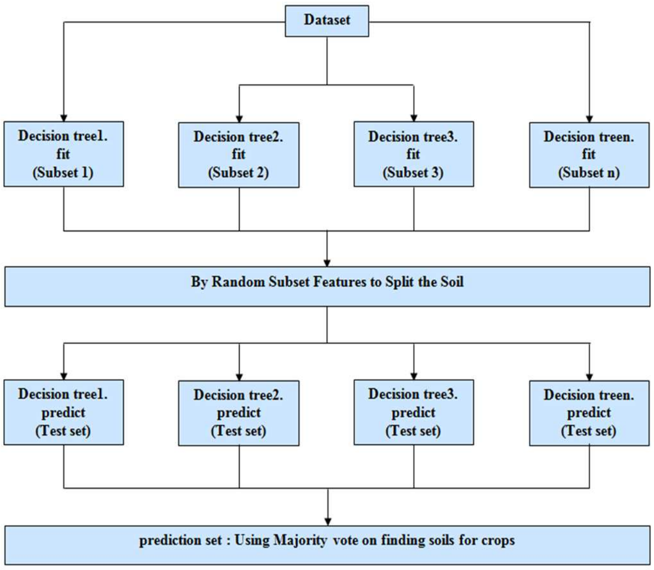

Fig. 3 Bagging architecture to work on damaged soil *Algorithm*:

Step 1: Selecting N Random Subsets for Training sets.
Step 2: Training N Decision trees.
Step 3: Each subset predicts the test set independently.
Step 4: Make the majority of the prediction.

B. AdaBoost (Adaptive Boosting)

A bunch of individual models is trained sequentially from previous model mistakes an individual model learned. By the weight of misclassified data points, AdaBoost learns from its mistakes. Adaptive Boosting is so termed because the weight is redistributed to every instance, with heavier weights allocated to improperly categorized instances. Boosting is used in supervised learning to minimize bias as well as variance. It is based on the sequential development of learners. Except for the first, each successive learner is developed from previously developed learners. Figure 4 demonstrates how it works in AdaBoost.

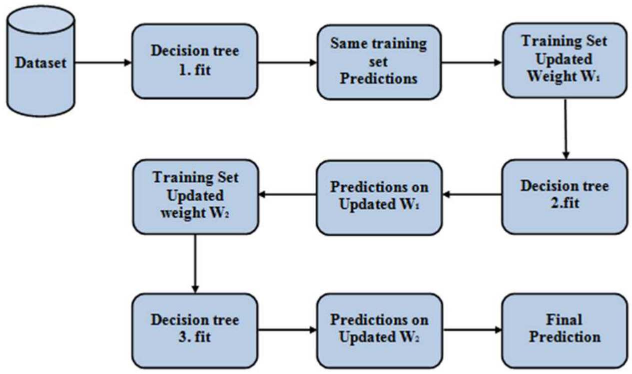

Fig. 4 AdaBoost architecture to work on damaged soil

$$S_L(.) = \frac{1}{L}\sum_{l=1}^{L} c_l * w_l(.) \quad (4)$$

C1 ---> Coefficient of weak learners (w1)

$$S_L(.) = S_{l-1}(.) + c_l * w_l(.) \quad (5)$$

S_{l-1} ---> most potential enhancement
S_l ---> best fit
To calculate weight

$$\left(c_l * w_l(.)\right) = arg_{c*w(.)}\, min\, E\left(S_{l-1}(.) + c * w(.)\right) = arg_{c*w(.)}\, min \sum_{n=1}^{N} e\left(y_n, S_{l-1}(x_n) + c * w(x_n)\right) \quad (6)$$

E(.) ---> error fitting model
E(.) ----> error function
Error fit of gradient opposite

$$S_L(.) = S_{l-1}(.) + c_l * \nabla S_{l-1} E(S_{l-1})(.) \quad (7)$$

Algorithm:
Step1: Initialize Dataset.
Step2: Assign weight to each step.
Step 3: Assign the output weight for the upcoming model input.
Step4: Increase the weight until the prediction model.

C. Extreme Gradient Boosting Machine (XGB)

The framework of XGBM is GBM. Artificial neural networks outperform all other algorithms or programs in prediction problems involving unstructured data. Moreover, for small-to-medium structured/tabular data, decision tree-based algorithms are traditionally regarded as best-in-class. XGBoost, on the other hand, enhances the core GBM architecture through device algorithmic and optimization improvements. This performs based on Parallelised tree pruning, the depth-first approach to tree pruning, out-of-core computing, cache awareness, regularization for overfitting avoidance, missing data is handled efficiently, and cross-validation built in. Figure 5 shows the explanation of XGBoost's works on damaged soil.

$$S_L(.) = S_{l-1}(.) + c_l\alpha_1 E\left(S_{l-1}(.)\right) \quad (8)$$

c1 ---> regularization parameters
α1---> residuals of lth tree

$$(c_1 * w_1(.)) = arg_{c*w(.)} min \sum_{n=1}^{N} e\left(y_n, S_{l-1}(x_n)\right) + c * \alpha w(x_n) \quad (9)$$

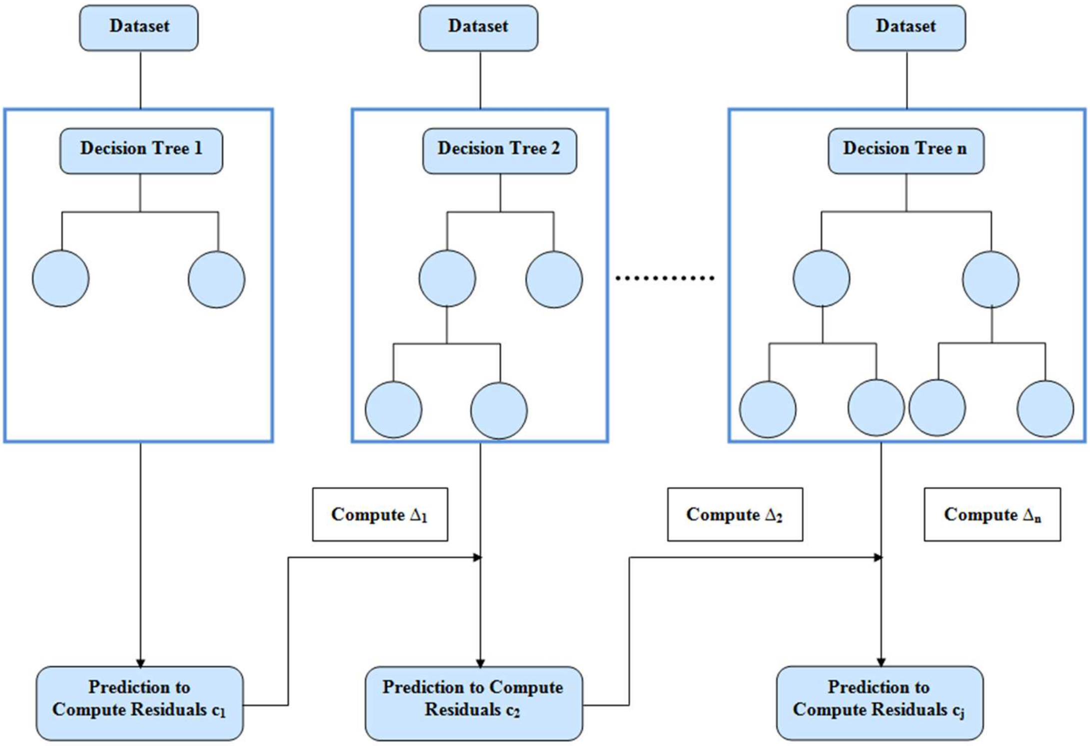

Fig. 5 Bagging architecture to work on damaged soil *Algorithm*.

Step 1: Begin a basic model with modeling data and then examine that error data.
Step 2: Such errors indicate datasets that are difficult to recreate with a simplistic formula.
Step 3: Then, we give particular attention to difficult-to-fit data for later models to make them correct.
Step 4: Finally, we integrate all of the predictor variables by assigning weights to every predictor.

TABLE II
PERFORMANCE ANALYSIS OF TEST AND TRAIN DATA

Performance metrics of algorithm	Performance Analysis					
	TEST DATA			Train Data		
	Bagging	Boosting	XGB	Bagging	Boosting	XGB
Precision	0.99	0.79	0.83	0.99	0.79	0.83
Recall	0.98	0.84	0.83	0.98	0.84	0.83
F1-Score	0.99	0.78	0.82	0.99	0.78	0.82
Accuracy	0.98	0.84	0.8	0.98	0.84	0.8

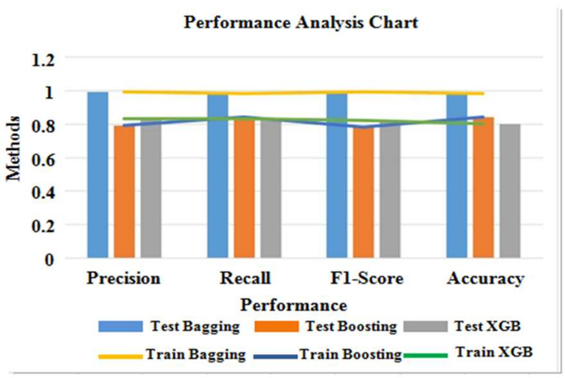

Fig. 6 Performance Analysis of Damaged soil and crops

The classification efficiency achieved by the proposed models was determined using a confusion matrix with an N*N square matrix, where N is the number of correct samples S and the elements of the main diameter. The number of elements in the primary vertex of the matrix is divided by the sum of all its components to obtain the usefulness of a classifier. To avoid this, the relationships in this model are assumed to be beyond the convolution structure and between the layers. These skip connections permit the network to be extended while substantially reducing the number of parameters. Using this trick, the inputs of the previous layers were directly entered into the next layer, and the errors from each layer were transferred to the preceding stage and during the back-propagation phase. In addition to broadening the network, the skip link has an additional benefit, and the gradient descent equations are extended until the training step, allowing the weights of such layers to be included in the training process. This conclusion was consistent with the findings [20]. Table 2 shows the results of the test and trained data, respectively, and Figure 6 shows graphical views.

IV. CONCLUSION

This study proves a system for aggregate-scale description groups with high classification precision, followed by detecting and extracting features used to identify harmed crops. Tests using ensemble approaches to identify damaged soil confirmed the model's capacity to forecast structural stability. Both the rounds of training and assessment provided good outcomes. The machine learning approach of the Python program allowed it to map the geographic range of the four stability studies. The ensemble models accurately predicted aggregate soil stability based on soil content, crop type, pesticide doses, and crop damage. However, the combination of the bagging meta-estimator, AdaBoost and XGBoutputs, was well done with an accuracy of 98%, 84%, and 80%, respectively. Differences in the soil damage data properties can explain differences in the soil damage data properties for massive datasets. It is possible to use prediction maps to identify prospective erosion hotspots, which is helpful when making management decisions. However, certain drawbacks exist, such as the need for a larger sample size. Consequently, adding remotely sensed indices to soil characteristics had little impact on future findings.

REFERENCES

[1] S. Das, S. Chatterjee, J. Rajbanshi, "Responses of soil organic carbon to conservation practices including climate-smart agriculture in tropical and subtropical regions: A meta-analysis", *Science of The Total Environment*, vol. 805, 2022. doi: 10.1016/j.scitotenv.2021.150428.

[2] Y. Bouslihim, A. Rochdi, and N. El Amrani Paaza, "Machine learning approaches for the prediction of soil aggregate stability," *Heliyon*, vol. 7, no. 3, p. e06480, 2021, doi: 10.1016/j.heliyon.2021.e06480.

[3] B. Wang *et al.*, "Using soil aggregate stability and erodibility to evaluate the sustainability of large-scale afforestation of Robinia pseudoacacia and Caragana korshinskii in the Loess Plateau," *For. Ecol. Manage.*, vol. 450, 2019, doi: 10.1016/j.foreco.2019.117491.

[4] S. O. Kwakye and A. Bárdossy, "Hydrological modelling in data-scarce catchments: Black Volta basin in West Africa," *SN Appl. Sci.*, vol. 2, no. 4, 2020, doi: 10.1007/s42452-020-2454-4.

[5] J. B. Wehr *et al.*, "Soil carbon and nitrogen pools, their depth distribution and stocks following plantation establishment in south east Queensland, Australia," *For. Ecol. Manage.*, vol. 457, no. June, p. 117708, 2020, doi: 10.1016/j.foreco.2019.117708.

[6] L. Jiang, S. Guo, G. Wang, S. Kan, and H. Jiang, "Changes in agricultural land requirements for food provision in China 2003–2011: A comparison between urban and rural residents," *Sci. Total Environ.*, vol. 725, p. 138293, 2020, doi: 10.1016/j.scitotenv.2020.138293.

[7] L. He, A. Zhang, X. Wang, J. Li, and Q. Hussain, "Effects of different tillage practices on the carbon footprint of wheat and maize production in the Loess Plateau of China," *J. Clean. Prod.*, vol. 234, pp. 297–305, 2019, doi: 10.1016/j.jclepro.2019.06.161.

[8] H. Zheng *et al.*, "Effect of long-term tillage on soil aggregates and aggregate-associated carbon in black soil of northeast China," *PLoS One*, vol. 13, no. 6, pp. 1–18, 2018, doi: 10.1371/journal.pone.0199523.

[9] H. B. Ly, T. A. Nguyen, and B. T. Pham, "Estimation of Soil Cohesion Using Machine Learning Method: A Random Forest Approach," *Adv. Civ. Eng.*, vol. 2021, no. Ml, 2021, doi: 10.1155/2021/8873993.

[10] A. McBratney, J. de Gruijter, and A. Bryce, "Pedometrics timeline," *Geoderma*, vol. 338, no. December 2017, pp. 568–575, 2019, doi: 10.1016/j.geoderma.2018.11.048.

[11] M. H. J. P. Gunarathna, K. Sakai, T. Nakandakari, K. Momii, and M. K. N. Kumari, "Machine learning approaches to develop pedotransfer functions for tropical Sri Lankan soils," *Water (Switzerland)*, vol. 11, no. 9, 2019, doi: 10.3390/w11091940.

[12] C. Chen, B. Qi, J.B. Huang, S.Z. Ou Yang, Y. Ji, W.Y. Zhang, "Effect of big seedling transplanter on population quality construction and yield of hybrid late rice" Acta Agriculturae Universitatis Jiangxiensis, vol. 43, no. 4, pp. 721-730, 2021.

[13] L. Jing and Y. Wei, "Intelligent Agriculture System Based on LoRa and Qt Technology," *Proc. 31st Chinese Control Decis. Conf. CCDC 2019*, pp. 4755–4760, 2019, doi: 10.1109/CCDC.2019.8833476.

[14] Y. Ming, J. Tang, Z. X. Chen, F. Xu, L. J. Zhang, and Y. Q. Lu, "Generation of N00N state with orbital angular momentum in a twisted nonlinear photonic crystal," *IEEE J. Sel. Top. Quantum Electron.*, vol. 21, no. 3, pp. 225–230, 2015, doi: 10.1109/JSTQE.2014.2382977.

[15] J. Treboux and D. Genoud, "High Precision Agriculture: An Application of Improved Machine-Learning Algorithms," *Proc. - 6th Swiss Conf. Data Sci. SDS 2019*, no. Ml, pp. 103–108, 2019, doi: 10.1109/SDS.2019.00007.

[16] Y. A. Chen, W. H. Hsieh, Y. S. Ko, and N. F. Huang, "An Ensemble Learning Model for Agricultural Irrigation Prediction," *Int. Conf. Inf. Netw.*, vol. 2021-Janua, pp. 311–316, 2021, doi: 10.1109/ICOIN50884.2021.9333852.

[17] J. I. Rivera and C. A. Bonilla, "Predicting soil aggregate stability using readily available soil properties and machine learning techniques," *Catena*, vol. 187, no. November 2019, p. 104408, 2020, doi: 10.1016/j.catena.2019.104408.

[18] Y. Hong *et al.*, "Comparing laboratory and airborne hyperspectral data for the estimation and mapping of topsoil organic carbon: Feature selection coupled with random forest," *Soil Tillage Res.*, vol. 199, no. May 2019, p. 104589, 2020, doi: 10.1016/j.still.2020.104589.

[19] R. Naresh, M. Meenakshi, and G. Niranjana, "Efficient study of smart garbage collection for ecofriendly environment," *J. Green Eng.*, vol. 10, no. 1, pp. 1–9, 2020.

[20] A. W. Kamamia, C. Vogel, H. M. Mwangi, K. H. Feger, J. Sang, and S. Julich, "Mapping soil aggregate stability using digital soil mapping: A case study of Ruiru reservoir catchment, Kenya," *Geoderma Reg.*, vol. 24, p. e00355, 2021, doi: 10.1016/j.geodrs.2020.e00355.

[21] J. John, G. Bindu, B. Srimuruganandam, A. Wadhwa, and P. Rajan, "Land use/land cover and land surface temperature analysis in Wayanad district, India, using satellite imagery," *Ann. GIS*, vol. 26, no. 4, pp. 343–360, 2020, doi: 10.1080/19475683.2020.1733662.

[22] S. J. Blair, Y. Bi, and M. D. Mulvenna, "Aggregated topic models for increasing social media topic coherence," *Appl. Intell.*, vol. 50, no. 1, pp. 138–156, 2020, doi: 10.1007/s10489-019-01438-z.

[23] G. Verma and H. Verma, "Hybrid-Deep Learning Model for Emotion Recognition Using Facial Expressions," *Rev. Socionetwork Strateg.*, vol. 14, no. 2, pp. 171–180, 2020, doi: 10.1007/s12626-020-00061-6.

[24] I. F. Dzakiyah, R. Saraswati, and F. D. Pamungkas, "The Potential of Agricultural Land Drought Using Normalized Difference Drought Index in Ciampel Subdistrict Karawang Regency," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 12, no. 3, pp. 908–914, 2022, doi: 10.18517/ijaseit.12.3.13261.

[25] Y. P. Situmeang, I. D. N. Sudita, and M. Suarta, "Application of Compost and Biochar from Cow, Goat, and Chicken Manure to Restore Soil Fertility and Yield of Red Chili," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 11, no. 5, pp. 2008–2015, 2021, doi: 10.18517/IJASEIT.11.5.13845.

[26] N. Bafdal and B. M. Pareira, "Impact of Soil Water Quality on Yield, Qualities and Water Consumptive Use of Melon (CucumisMelo L)," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 10, no. 5, pp. 2097–2102, 2020, doi: 10.18517/ijaseit.10.5.12217.

[27] H. S. Jat, A. Datta, M. Choudhary, P. C. Sharma, B. Dixit, and M. L. Jat, "Soil enzymes activity: Effect of climate smart agriculture on rhizosphere and bulk soil under cereal based systems of north-west India," *Eur. J. Soil Biol.*, vol. 103, p. 103292, 2021, doi: 10.1016/j.ejsobi.2021.103292.

[28] V. Udutalapally, S. P. Mohanty, V. Pallagani, and V. Khandelwal, "SCrop: A Novel Device for Sustainable Automatic Disease Prediction, Crop Selection, and Irrigation in Internet-of-Agro-Things for Smart Agriculture," *IEEE Sens. J.*, vol. 21, no. 16, pp. 17525–17538, 2021, doi: 10.1109/JSEN.2020.3032438.

[29] R. Kumar, R. Mishra, H. P. Gupta, and T. Dutta, "Smart Sensing for Agriculture: Applications, Advancements, and Challenges," *IEEE Consum. Electron. Mag.*, vol. 10, no. 4, pp. 51–56, 2021, doi: 10.1109/MCE.2021.3049623.

[30] M. Ayaz, M. Ammad-Uddin, Z. Sharif, A. Mansour, and E. H. M. Aggoune, "Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk," *IEEE Access*, vol. 7, no. 1, pp. 129551–129583, 2019, doi: 10.1109/ACCESS.2019.2932609.

[31] B. Umasugi, S. Prijono, Soemarno, and Ariffin, "Soil Moisture Analysis and Rainwater Management at Clove Plantation to Meet the Water Requirement of Clove Plants During Dry Season," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 11, no. 6, pp. 2197–2203, 2021, doi: 10.18517/ijaseit.11.6.15030.