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An Innovative Deep Learning Approach for Identifying and Restoring Contaminated Soil

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Abstract

Significant environmental risks are presented by contaminated soil; hence, efficient detection and repair techniques are required. To improve soil pollution diagnosis and restoration accuracy, this study presents a unique process called the Weighted Moth Flame Optimized-Adaptive Feed Forward Neural Network (WMO-AFFNN). The suggested WMO-AFFNN model was trained and tested using a dataset of 437 soil samples, each with an assigned level of contamination. The input data was preprocessed using Min-max normalization. To improve the model's ability to detect meaningful patterns in the data, feature extraction using Independent Component Analysis (ICA). The description of the WMO-AFFNN, the central component of the suggested technique, highlights its adaptable nature and the addition of an optimization mechanism to improve its effectiveness. For comparative analysis recall (0.943), accuracy (98.9 %), precision (0.913), F1-score (0.983) and specificity (0.967), are used to assess the efficacy of the WMO-AFFNN method. The suggested methodology shows significant gains in efficiency and accuracy over current approaches, indicating its potential as an efficient method for identifying and restoring soil pollution. This study makes a substantial contribution to the development of computational methods for soil restoration, opening the door to more practical approaches to environmental preservation.

Keywords: Contaminated Soil, Deep Learning, Soil Restoration, WMO-AFFNN

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1. Introduction

Soil classification is an exciting and valuable field of research, starting with the arrangement's composition and going through degree definitions and their applications. Soil texture and color categorization utilizing digital algorithms on soil images has seen a surge in scientific interest [1]. Looking at soils as both a substance and a resource is an excellent place to start when trying to order them. Latin solum, meaning "floor," is an etymological ancestor of the English term soil [2]. The term "soil" refers to the broken-down debris that surrounds the rocks and minerals that a mining engineer is working with. In highway engineering, the soil is the material that will be used to lay the track bed. An agriculturist's view of soil is that of a medium for the growth of plants. It was from soil's capacity to encourage and sustain plant life that the concept of soil as a living entity first emerged [3]. One of the most pressing global environmental issues is the contamination of soils with cadmium (Cd). Soil microbes' biological activity is reduced by soils with high concentrations of Cd, which impacts crop output and quality. When plants absorb Cd, it makes its way into the food chain, where it has harmful effects on humans and other animals. To safeguard the health of animals and humans, it is essential to create a bioremediation method for soils polluted with Cd that is sustainable and efficient [4]. In contrast, bioremediation prioritizes efficiency without sacrificing environmental friendliness or financial viability. Because of their distinct traits, the filamentous fungus has evolved a wide variety of enzymes, including oxidative, organic acid, chelator and extracellular enzymes [5]. Anthropogenic activities, resource exploitation, petrochemical spills, metallurgy, fast expansion of industrial waste, overuse of vehicles coupled with other human activities contribute to soil and environmental contamination by increasing concentrations of metalloids and heavy metals (HMs). Any metallic compound that is relatively dense and poisonous, even at low concentrations, is considered a heavy metal [6]. Because of its high toxicity and extensive bioaccumulation, cadmium is among the most hazardous HMs to living things. It has a negative effect on human health because it builds up in the kidney, where it damages the tubules and can cause emphysema [7]. One of the most problematic priority pollutants is Cd, a non-essential hazardous metal that has a lengthy residence period in soil and a significant risk of human exposure. It ranks seventh among twenty powerful poisons. Over the last few decades, researchers have sought long-term, effective remedial solutions to the growing problem of Cd contamination in agricultural soil [8]. Soil hydrocarbons have a negative effect on plant development and seed germination, making oil spills a hazardous disaster for soil ecosystems [9]. Soil enzymatic activity and earthworm survival were both severely impacted by used motor oil. When petroleum products build up in the environment, it can have a direct impact on human health and ecosystem safety. Therefore, efficient techniques for removing these pollutants are necessary due to the significant effect of oil spills on soil environments [10]. The study introduces the WMO-AFFNN to address soil pollution risks. Using 437 soil samples improves soil pollution diagnosis and restoration accuracy, offering a practical approach to soil restoration. The study [11] focused on the isolation of a pungent fungus (strain PYR-P2) from soil that had been polluted with pesticides. The strain had a high capability for degrading pyrethroids. According to the morphological and molecular features, the strain was determined to be Aspergillus sp. Agricultural and household activities across the globe use type-II pyrethroid pesticides at high rates, which might lead to soil and water contamination. This raised a number of issues about human and environmental health. The study [12] described the toxic waste from a defunct lead mine that was used to cultivate Agrostis stolonifera grasses, which were then examined for endophytic fungus using DNA sequencing. One environmentally beneficial method for cleaning up locations polluted with heavy metals was bioremediation, which makes use of naturally occurring microorganisms like fungi and bacteria. The biological and chemical processes that these microbes use allow them to remove and deactivate contaminants from polluted substrates. Also, the native plants survive the extreme weather by interacting with them and promoted their development. The study [13] determined that a significant contributor to the worldwide decline in habitat and biodiversity, the fast expansion of irrigation agriculture over the last half-century, has enabled food production to match the rate of population increase. Previous production levels can need to be lowered in specific locations due to soil deterioration and overtaxed water supplies. During the sustainability transitions, analytically assisted planning for habitat restoration in agricultural landscapes that were stressed can restore biodiversity and provide co-benefits. The paper [14] described the most cutting-edge restoration tactics that have emerged recently, which was the elimination of environmental contaminants by the use of nanotechnology. These contaminants include heavy metals, organic as well as inorganic pollutants and more. When used in conjunction with biological processes, nanoparticles (NPs) can enhance the removal of harmful chemicals from polluted soils. The study [15] employed a systematic approach to identify petroleum-contaminated grounds. Soil mineral changes, hydrocarbons desorption and pyrolysis all occur within the same temperature ranges, which were determined by using the same analytical methods to examine polluted soil pyrolysis. The article [16] compared to approaches that are more conventional, chemophytostabilization lowers heavy metal concentrations in industrially impacted soil. In most plants, the roots had a greater concentration of Cd, Zn and Pb than the shoots. The study [17] characterized assisted natural remediation (ANR) has gained attention as an eco-friendly, cost-effective and potential method for cleaning up heavy metal-contaminated soil. Proline and malondialdehyde production were assessed, in addition to the amounts of zinc, copper and lead in the plants. The paper [18] covered a variety of soil indicators that can be used to assess ecological restoration approaches in dryland ecosystems across different time and space scales. Both the land's restoration suitability and the restoration solutions' success in reestablishing ecosystem services and functioning can be evaluated using soil indicators. The paper [19] aimed to identify and assess the toxicity of various hydrocarbon fractions found in waste Mobil oil obtained from the vehicle market. Wheat grain was used for this evaluation. Toxic chemicals were released into the environment when the fat was burned. The paper [20] evaluated the fact that technological advancements have made it a large-scale ecosystem function that can repair contaminated soils globally. The lack of a regulatory framework, inadequate understanding of important variables affecting bioremediation costs and the capabilities of such methods for treating contaminated soils were the primary obstacles that need to be overcome. This research aimed to assess the economic performance of bioremediation using bio augmentation, bio stimulation, or a combination of the two methods on an industrial scale for urban soils that have been contaminated with hydrocarbons. The rest of the article follows as: A depth discussion of the methodology follows in section 3. In section 4, we provide a detailed analysis. Section 6 delves further into the relevance of the conclusion.

2. Materials and Methods

This innovative research presents a novel deep learning method for identifying polluted soil and restoring it. It uses cutting-edge techniques and promises vast improvements in cleaning up contaminated areas, as shown in Fig 1.

2.1. Dataset

Aluminum, arsenic, barium, beryllium, calcium, total magnesium, vanadium, cobalt, nickel, iron, lead, zinc, mercury, potassium, sodium, manganese, chromium and copper were among the 18 metals that were tasted in a laboratory from samples obtained at McConnell Air Force Base. In addition, the 437 models were assigned contamination levels after they were mapped to specific geographic areas around the site [21].

2.2. Preprocessing using min-max normalization

There are several approaches for normalizing a dataset. The most effective normalization in this case is Minimax. The normalizing technique converts σ_{max}toσ_{min}, which lies between [B, A]. Equation (1) provides the mathematical formula for it;

$$\sigma^* = \frac{\sigma - \sigma_{min}}{\sigma_{max} - \sigma_{min}} \tag{1}$$

Where, σ_{max} = Optimal level
σ_{max} = The base price and
σ^* = Value that has been normalized

After normalization, every attribute in the data is treated equally. R Represents the minimum value and A means the maximum value.

2.3. Feature extraction using Independent Component Analysis (ICA)

Identifying and restoring contaminated soil to the ICA technique to obtain independent feature vectors from patient data. u is used to train an ICA network to extract independent components and the basis function coefficients V are removed from u using the learned weight matrix. A Linear mixture of the separate elements V is assumed to be the observation by ICA. The columns of A reflect the basis feature vectors of observation Z if F is the inverse matrix of Z.

$$\mathrm{x} = \mathrm{V.Z}, \mathrm{Z} = \mathrm{F.x} \tag{2}$$

A trained mixing matrix, which must be either the unmixing matrix or the mixing matrix to extract basis functions. The learning rule is denoted by equation (2) and it is based on maximizing joint entropy Z(x).

$$\Delta \mathrm{V} \propto \frac{\partial \mathrm{I(x,y)}}{\partial \mathrm{V}} = \frac{\partial \mathrm{y(x)}}{\partial \mathrm{V}} \tag{3}$$

$$\Delta \mathrm{V} \propto [\mathrm{V^C}]^{-1} + \left(\frac{\frac{\partial \mathrm{a(X)}}{\partial \mathrm{X}}}{\mathrm{a(x)}}\right) \mathrm{z^C} \tag{4}$$

$P(u)$ is the approximate probability density function,$p(u_i) = \frac{\partial w_i}{\partial u_i} = \partial c(u_i)/\partial u_i$ for the speech signal component. In this case, the nonlinearity function $g(u)$resembles the source signal U accumulative distribution function, equation (3). A natural gradient is added to equation (4) to increase a converging speed. In particular, this approach eliminates the need for the inverse of matrix X and yields the following rule.

$$\Delta \mathrm{V} \propto \frac{\partial \mathrm{Y(x)}}{\partial \mathrm{V}} \mathrm{V^E V} = [1 - \varphi(\mathrm{X})\mathrm{X^E}]\mathrm{V} \tag{5}$$

Where $\varphi(u)$ is called the scoring function and it is connected to the source probability density function. $X$is iteratively updated in a gradient ascending manner until convergence using the learning procedure in equation (5). Let's use N to represent the size of the training identifying and restoring contaminated soil and Care random-generated speech chunks. The N by N matrix $A\ (A = W^{-1})$ of the ICA network yields N basis vectors from its M inputs and N outputs.

2.4. Classification using weighted moth flame optimized-adaptive feed-forward neural network (WMO-AFFNN)

An innovative approach that improves efficiency in several applications is WMO-AFFNN, which combines weighted optimization with adaptable neural networks. Soil contamination can be quickly and reliably identified and restored using our innovative deep learning approach, which changes the game for soil quality evaluation. To ensure sustainable land management and expeditious restoration, this novel method uses state-of-the-art neural networks to sift through mountains of environmental data.

2.4.2. Adaptive feed-forward neural network (AFFNN)

A fixed-adaptive feed-forward neural network (AFFNN) uses a constant number of inputs and outputs that does not consider historical variable information. The difficulty of the training data set dictates the AFFNN architecture. This section is divided into four parts: algorithms, drawings, training progress and neural network design. A fully-connected AFFNN with two hidden layers, abbreviated as$G$,

$$\hat{Z} = e(G_2X_3 + a_3)G_2 = e(G_1X_2 + a_2)e_1 = e(wX_1 + a_1) \tag{6}$$

In this case, w is the weight matrix, is the layer-wise bias vector and x is the feature vector input. The vector y symbolizes$\hat{Z}$s the outcome. In the current study, the hidden layer tangent hyperbolic activation function e is represented as follows:

$$tang(W) = \frac{f^w - f^{-w}}{f^e + f^{-w}} \tag{7}$$

Rescaling the logistic sigmoid function, this function has an output range of [-1, 1]. Layer values that are not visible are stored in vector W. assuming$z$ to be the objective function; this is the most basic illustration of the AFFNN algorithm.

$$\hat{z} = \hat{z}(W, X, a)\{a, X'\} = Arg\left\{\min_{a,w} L\ (\hat{y}, y)\right\} \tag{8}$$

The trained neural network model with optimal weights W' and biases b' are determined by minimizing$L$ and the loss function is the function of this model. The hidden layers consist of 10 neurons each, with strains ε serving as features and stress σ serving as the outputs of the mode, as shown in Fig 2. The loss equation is believed to be a mean-squared error (MSE) and the following training methods reduce it:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left[\left(X_{target}\right)_j - \left(X_{pred}\right)_j\right]^2 \quad (9)$$

Data collection has to be scaled to a comparable range since stress and strain measurements are different in magnitude. Therefore, the input and target values are first scaled using the following formula to ensure they are in the range [-1, 1]:

$$\hat{X} = \frac{2(x-X_{min})}{X_{max}-X_{min}} + 1 \quad (10)$$

$\hat{X}$is the Value of W in the interval $[-1,1]$ that has been scaled or normalized.

2.4.2. Weighted moth flame optimized (WMO)

Met heuristic algorithms that are based on populations are responsible for it. Fig 3 and Algorithm 1 show that WMO begins by randomly creating moths in the solution space, then determining their fitness values (i.e., positions) and finally, using flames to tag the optimal location**.** The following are three requirements that must be met when using a logarithmic spiral: Starting from the moth, the spiral should go outward. The location of the flame should serve as the spiral's last point. Spiral range fluctuations must be contained inside the search space.

Algorithm 1: Procedure of WMO

Set the Moth-flame settings to their initial values
Start the Moth's flight path N_j accidentally
For $j = 1\ to\ m\ do$
Determine the level of functionse_j
End for
While iteration $\leq Max_{iterations}\ do$
Update the position of N_j
Calculate flame count
Fitness function evaluation e_j
If iteration ==1 then
$E = sort\ (N) and\ OF = sort\ (OM)$
else
$E = sort\ (N_{s-1}, N_s)\ and\ OF = sort\ (N_{s-1}, N_s)$
end if
for$j = 1\ to\ m\ do$
for$i = 1\ to\ c\ do$
Change values of $q\ and\ s$
Finding the value C related to its moth
Update $N(j,) about\ its\ moth$
End for
End for
End while
Print the best solution

3. Results and Discussion

Deep learning models were created using Python 3.8 and Keras, with parallel processing on a desktop computer pre-configured with Tensor Flow and CuDNN library. Performance was assessed using ANN [22], KNN [22], EDL- ASQE [22] and WMO-AFFNN [22]. The accuracy of the technologies used to evaluate and remediate polluted regions is accurately detecting contaminated soil and restoring it. The ratio of true positives to true and false positives is one way to quantify this and it is provided by:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (11)$$

The results of the accuracy measurements were rather similar, as shown in Fig 4 and Table 1. With accuracies of 85%, 69%, 91.2% and 96.7% correspondingly, ANN, KNN, EDL- ASQE and ISQP-DL outperform the methods presently used. Integration of WMO-AFFNN, the proposed technique, achieves a remarkable 98.9% accuracy, making it very successful. The procedures used to detect and restore polluted soil should be as accurate and dependable as possible for them to be considered precise. The calculation of the percentage of accurate findings relative to the total number of true and false positives is an important part of this process**:**

$$Precision = \frac{TP}{TP+FP} \quad (12)$$

At the moment, ANN has a recognition rate of 0.68%, KNN of 0.733%, EDL- ASQE of 0.881% and ISQP-DL of 0.877%. The proposed system, WMO-AFFNN, stands out due to its remarkable 0.913% accuracy rate. This strategy outperforms the status quo, as seen in Fig 5 and Table 1. It is essential to be able to retrieve regions that were polluted when dealing with contaminated soil identification and restoration. A high recall rate means that polluted soil was placed and remedied. Its magnitude is measured by means of the recall equation**.**

$$\text{Recall} = \frac{TP}{TP+FN} \quad (13)$$

The related data for recall measurement comparison can be seen in Fig 6 and Table 1. With recall rates of 0.664%, 0.722%, 0.901% and 0.99%, respectively, the ANN, KNN, EDL-ASQE and ISQP-DL all excelled. A WMO-AFFNN recall of 0.943% was better than the state-of-the-art the suggested method. One measure for assessing how well models can detect and remediate polluted soil is the F1-score. By balancing accuracy and recall, it provides an accurate assessment of a model's performance**.** Here is the equation**:**

$$\text{F1}-\text{score} = 2 \times \frac{P\times R}{P+R} \quad (14)$$

Table 1 and Fig 7 include the pertinent data for comparing the F1-score assessment. With F1-score rates of 0.683%, 0.728%, 0.916% and 0.928%, respectively, the ANN, KNN, EDL-ASQE and ISQP-DL all performed quite well. With a WMO-AFFNN recall of 0.983%, the suggested method outperformed the state-of-the-art. Specificity in locating and remediating polluted soil is defined as the degree to which specific pollutants can be targeted with relative ease. A step of this is the proportion of false negatives to total false

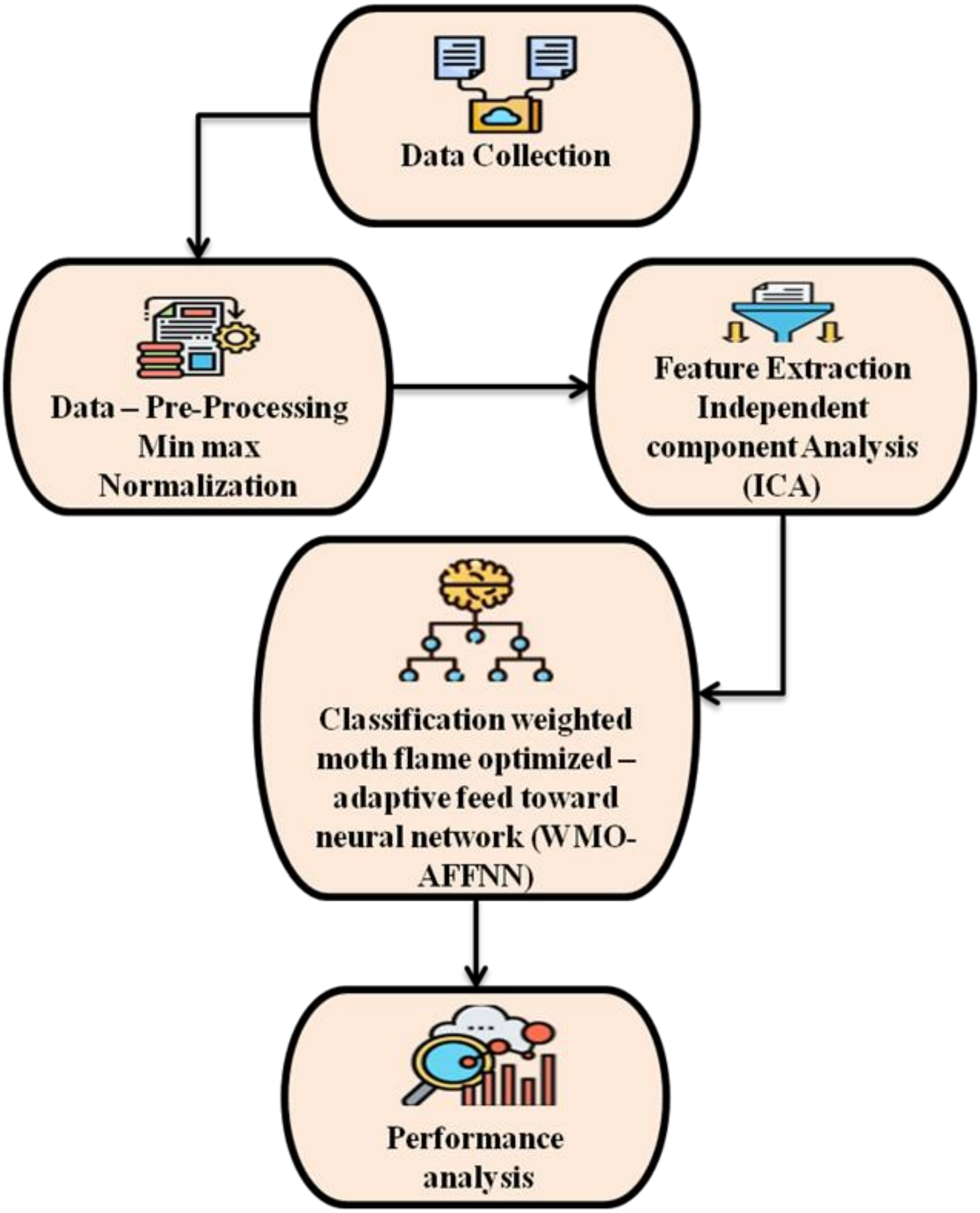

Figure 1. Structure of proposed method

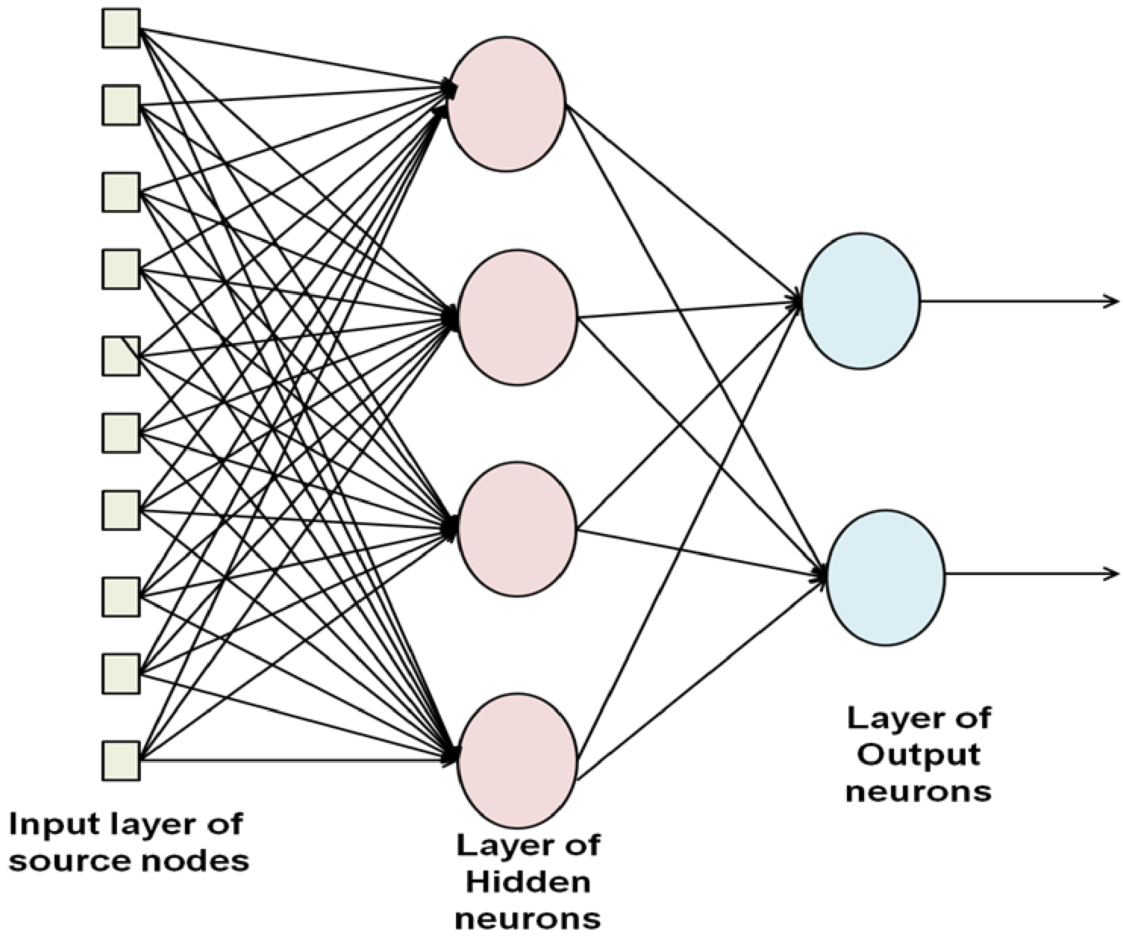

Figure 2. Adaptive Feed Forward Neural Network (AFFNN)

Table 1. Outcomes of evaluation matrix

Evaluation Metrics	Accuracy (%)	Recall	Precision	Specificity	F1-Score
ANN (22)	85	0.664	0.68	0.76	0.683
KNN (22)	69	0.722	0.733	0.784	0.728
EDL- ASQE (22)	91.2	0.901	0.881	0.906	0.916
ISQP-DL (22)	96.7	0.919	0.877	0.913	0.928
WMO-AFFNN (Proposed)	98.9	0.943	0.913	0.967	0.983

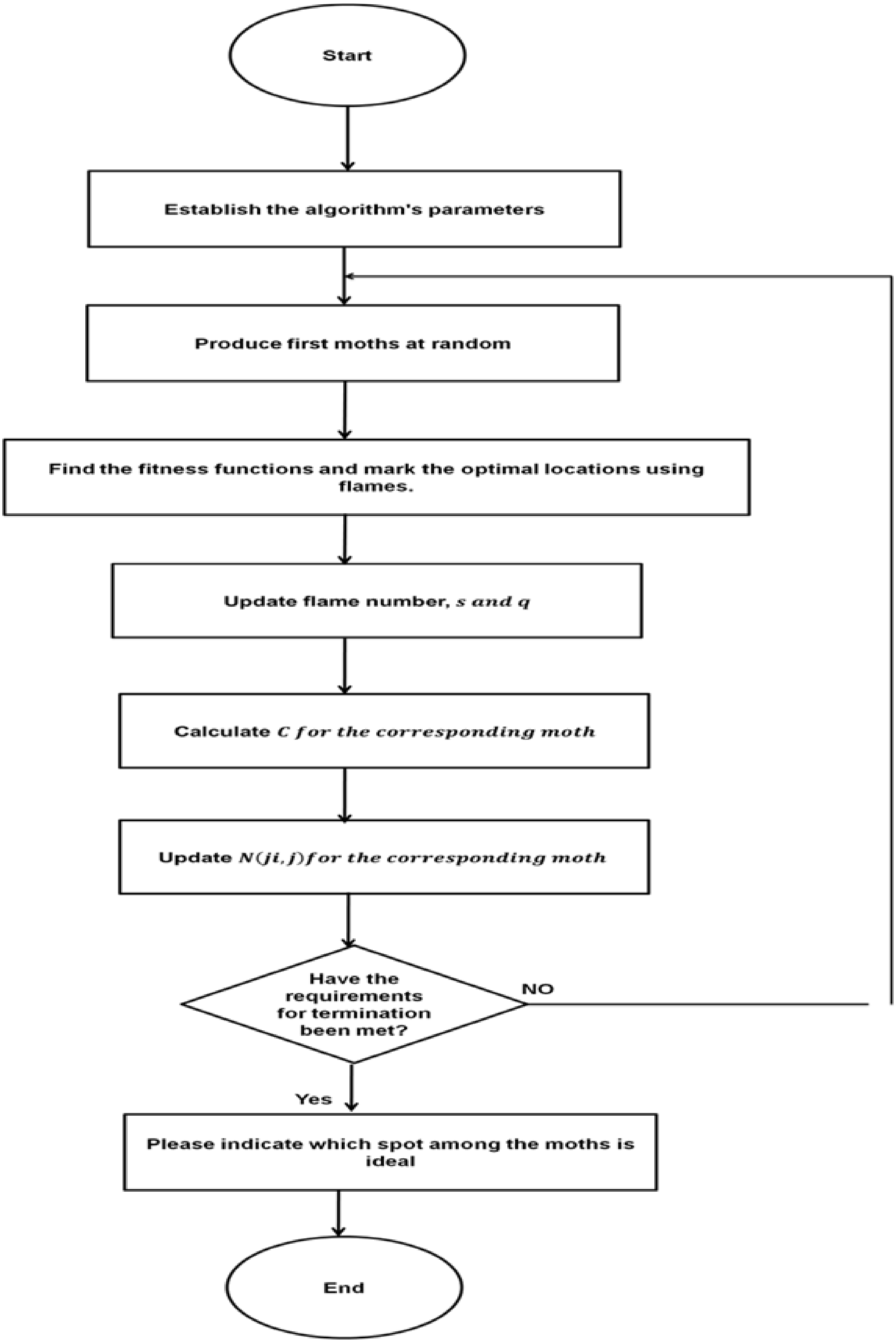

Figure 3. Flow of Weighted moth flame optimized (WMO)

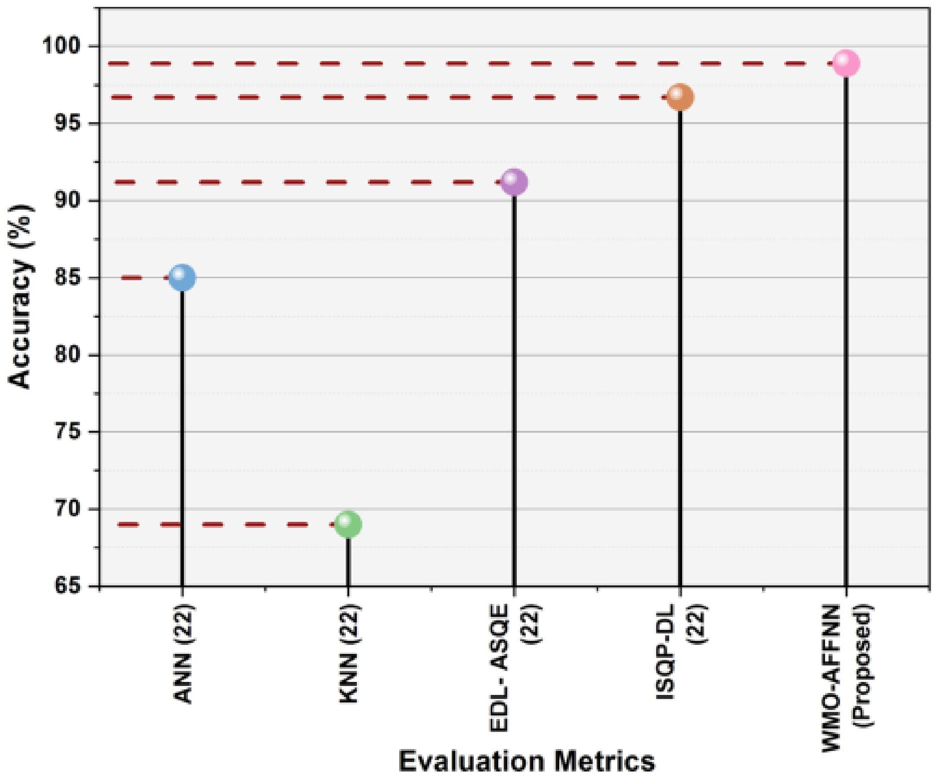

Figure 4. Comparison of the Accuracy

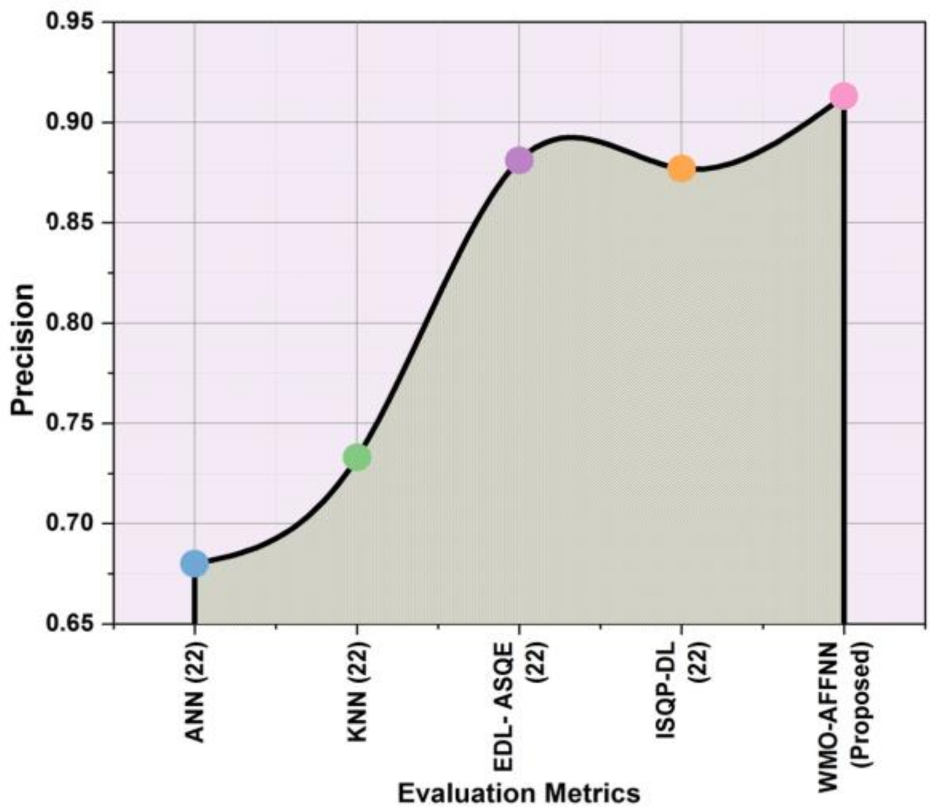

Figure 5. Comparison of the Precision

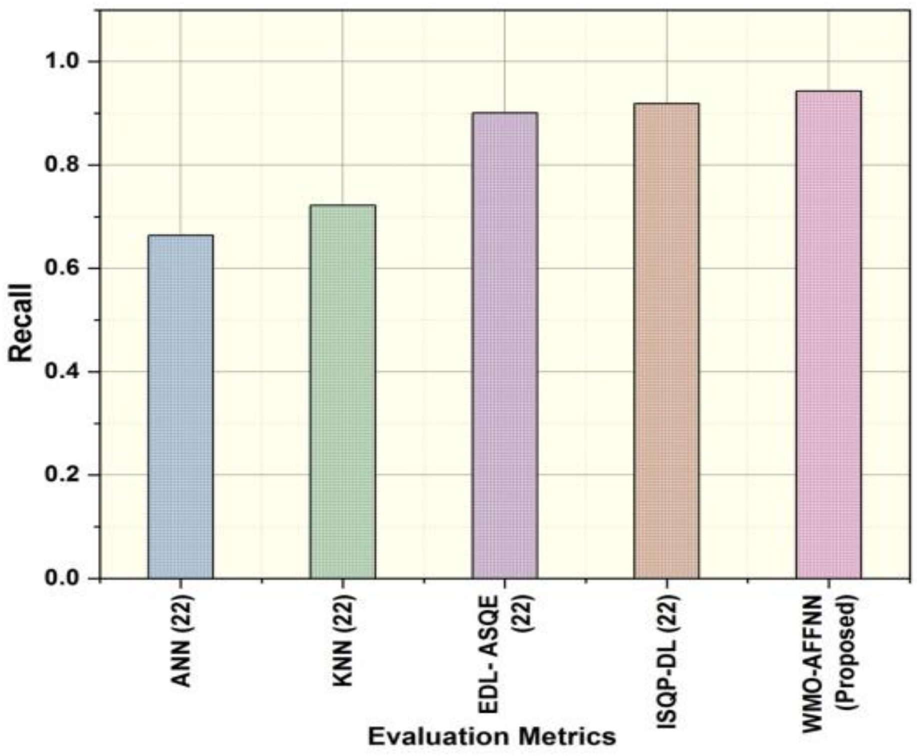

Figure 6. Comparison of the Recall

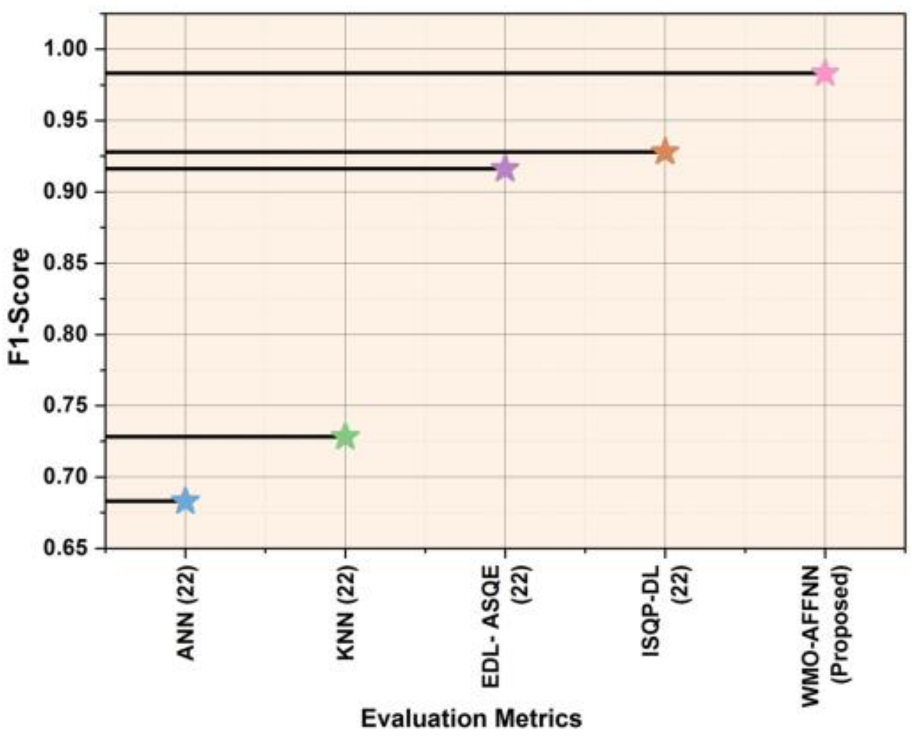

Figure 7. Comparison of the F1-score

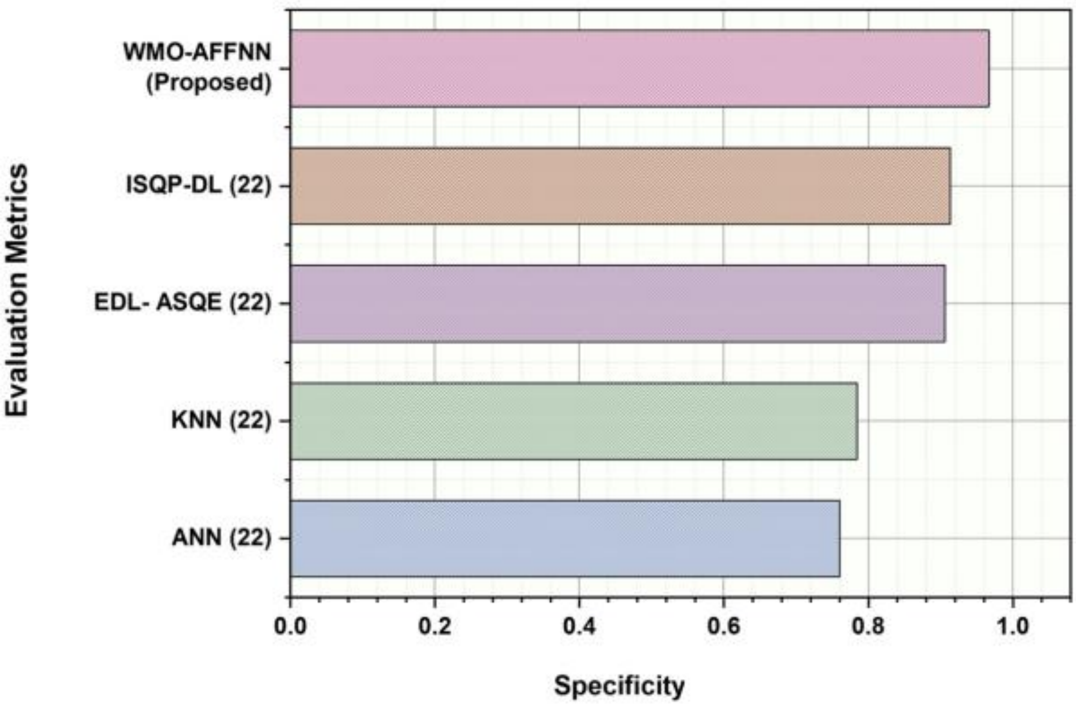

Figure 8. Comparison of the Specificity

negatives and positives. A specificity equation can be expressed as:

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (15)$$

Fig 8 and Table 1 show that the accuracy measures were relatively close to each other. With accuracies of 0.76%, 0.784%, 0.906% and 0.913% correspondingly, ANN, KNN, EDL- ASQE and ISQP-DL outperform the methods presently used. Integration of WMO-AFFNN, the proposed technique, achieves a remarkable 0.967% accuracy, making it very successful. Contaminated soil poses significant threats to the ecosystem. Thus, practical methods for detecting and fixing it are necessary. Overfitting is a problem that ANNs are susceptible and they need a lot of data to improve. When dealing with massive datasets, KNN could be costly. In the group, there could be problems when trying to train varied age-specific models using EDL-ASQE. Performance in specific applications can be affected if ISQP-DL struggles with extended sequences.

4. Conclusions

At some point, WMO-AFFNN proved to be an effective network for identifying and correcting soil contamination. Compared to previous approaches, WMO-AFFNN achieves better results by using optimization mechanisms and Independent Component Analysis for feature extraction. It promises real progress in environmental preservation because of its improved accuracy and efficiency, which is a big step forward in computational methods for soil restoration. The effectiveness of the WMO-AFFNN approach is evaluated by comparison using recall (0.943), accuracy (98.9%), precision (0.913), F1-score (0.983) and specificity (0.967). Data availability, difficulties in generalizing models to different kinds of soil along with the need for substantial field validation to guarantee practicality and efficacy are potential limits. Contaminated soil has the potential to transform environmental cleanup in the future. Technological progress has made this approach possible and it provides automated, effective solutions for soil restoration.

References

[1] P. Srivastava, A. Shukla, A. Bansal. (2021). A comprehensive review on soil classification using deep learning and computer vision techniques. Multimedia Tools and Applications. 80 14887-14914.

[2] H. Moayedi, M. Mosallanezhad, A.S.A. Rashid, W.A.W. Jusoh, M.A. Muazu. (2020). A systematic review and meta-analysis of artificial neural network application in geotechnical engineering: theory and applications. Neural Computing and Applications. 32 495-518.

[3] J. Szulc, J. Nizioł, T. Ruman, A. Kuźniar, A. Nowak, M. Okrasa, B. Szponar. (2022). Biological

and Chemical Contamination of Air, Water and Soil in Illegal, Uncontrolled Refuse Storage Areas in Poland. Water and Soil in Illegal, Uncontrolled Refuse Storage Areas in Poland.

[4] Y. Xie, H. Bu, Q. Feng, M. Wassie, M. Amee, Y. Jiang, L. Chen. (2021). Identification of Cd-resistant microorganisms from heavy metal-contaminated soil and its potential in promoting the growth and Cd accumulation of bermudagrass. Environmental Research. 200 111730.

[5] F.A. Al-Dhabaan. (2021). Mycoremediation of crude oil contaminated soil by specific fungi isolated from Dhahran in Saudi Arabia. Saudi Journal of Biological Sciences. 28 (1) 73-77.

[6] U. Zulfiqar, F.U. Haider, M.F. Maqsood, W. Mohy-Ud-Din, M. Shabaan, M. Ahmad, B. Shahzad. (2023). Recent advances in microbial-assisted remediation of cadmium-contaminated soil. Plants. 12 (17) 3147.

[7] H. Ali, E. Khan, I. Ilahi. (2019). Environmental chemistry and ecotoxicology of hazardous heavy metals: environmental persistence, toxicity, and bioaccumulation. Journal of chemistry, 2019.

[8] M. Xu, Q. Huang, Z. Xiong, H. Liao, Z. Lv, W. Chen, X. Hao. (2021). Distinct responses of rare and abundant microbial taxa to in situ chemical stabilization of cadmium-contaminated soil. Msystems. 6 (5) 10-1128.

[9] A. Benguenab, A. Chibani. (2021). Biodegradation of petroleum hydrocarbons by filamentous fungi (Aspergillus ustus and Purpureocillium lilacinum) isolated from used engine oil contaminated soil. Acta Ecologica Sinica. 41 (5) 416-423.

[10] A.J. Folayan, A. Dosunmu, B. Oriji. (2022). Microbial activity evaluation and aerobic transformation of deep water offshore synthetic drilling fluids in soil: A case study of ternary mixture of synthetic ethyl esters of plants oil (Seep mixture) synthetic drilling fluid in agbami (Niger delta) deep water field. Results in Engineering. 15 100537.

[11] P. Kaur, C. Balomajumder. (2020). Effective mycoremediation coupled with bioaugmentation studies: An advanced study on newly isolated Aspergillus sp. in Type-II pyrethroid-contaminated soil. Environmental Pollution. 261 114073.

[12] E. Soldi, C. Casey, B.R. Murphy, T.R. Hodkinson. (2020). Fungal endophytes for Grass based bioremediation: An endophytic consortium isolated from Agrostis stolonifera stimulates the growth of Festuca arundinacea in lead contaminated soil. Journal of Fungi. 6 (4) 254.

[13] B.P. Bryant, T.R. Kelsey, A.L. Vogl, S.A. Wolny, D. MacEwan, P.C. Selmants, H.S. Butterfield. (2020). Shaping land use change and ecosystem restoration in a water-stressed agricultural landscape to achieve multiple benefits. Frontiers in Sustainable Food Systems. 4 138.

[14] V. D RAJPUT, T. Minkina, A. Kumari, S.S. Shende, A. Ranjan, M. Faizan, R. KIZILKAYA. (2022). A review on nanobioremediation approaches for restoration of contaminated soil. Eurasian Journal of Soil Science. 11 (1) 43-60.

[15] Y. Gao, K. Zygourakis. (2019). Kinetic study of the pyrolytic treatment of petroleum-contaminated soils. Industrial & Engineering Chemistry Research. 58 (25) 10829-10843.

[16] D. Wasilkowski, A. Nowak, J. Michalska, A. Mrozik. (2019). Ecological restoration of heavy metal-contaminated soil using Na-bentonite and green compost coupled with the cultivation of the grass Festuca arundinacea. Ecological Engineering. 138 420-433.

[17] A. Raklami, A.I. Tahiri, N. Bechtaoui, E. Pajuelo, M. Baslam, A. Meddich, K. Oufdou. (2021). Restoring the plant productivity of heavy metal-contaminated soil using phosphate sludge, marble waste, and beneficial microorganisms. Journal of Environmental Sciences. 99 210-221.

[18] T. del Río-Mena, L. Willemen, A. Vrieling, A. Snoeys, A. Nelson. (2021). Long-term assessment of ecosystem services at ecological restoration sites using Landsat time series. Plos one. 16 (6) e0243020.

[19] V.K. Gaur, V. Tripathi, P. Gupta, R.S. Thakur, I. Kaur, R.K. Regar, N. Manickam. (2023). Holistic approach to waste mobil oil bioremediation: Valorizing waste through biosurfactant production for soil restoration. Journal of Environmental Management. 348 119207.

[20] R. Orellana, A. Cumsille, P. Piña-Gangas, C. Rojas, A. Arancibia, S. Donghi, M. Seeger. (2022). Economic Evaluation of Bioremediation of Hydrocarbon-Contaminated Urban Soils in Chile. Sustainability. 14 (19) 11854.

[21] A. Mok. Classification of Soil Contamination. Magnesium. 3 0-371.

[22] P. Sumathi, V.V. Karthikeyan, M.S. Kavitha, S. Karthik. (2023). Improved Soil Quality Prediction Model Using Deep Learning for Smart Agriculture Systems. Computer Systems Science & Engineering. 45 (2).