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Original Research

Using Artificial Intelligence Algorithms and Spatial Analysis of *Agaricus Bisporus* in the Wilderness near Lake Milh Al-Razzaza-Iraq

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Abstract: Advanced applications of artificial intelligence and geographic information system (GIS) techniques are used to monitor plant growth across their vegetation seasons using morphological parameters. This research presents novel measurements to determine the concentrations of elements such as carbon (C), nitrogen (N), hydrogen (H), lead (Pb), and cadmium (Cd) in the mushroom "Agaricus bisporus" and in the surrounding soil and air. These data are spatially analyzed to contribute to long-term predictions of pollution index and future ecosystem risks. Pollution and element accumulation in the mushroom, soil, and surrounding air were monitored using data accompanied by a geographic map. Pollution was assessed by transforming the system and adopting a methodology that integrates traditional methods with artificial intelligence, aiming to address the challenges with greater efficiency and accuracy. Input parameters were used to develop models using artificial intelligence and statistical methods to detect metal accumulation, monitor carbon, hydrogen, nitrogen, and seasonal changes. The response of plants to heavy metals (lead and cadmium) in soil and air and their impact on their growth and development were analyzed. The techniques showed a significant reduction in the error rate when using fungi as an indicator to predict dietary heavy metal concentrations, as the accuracy of artificial intelligence was remarkable in estimating the concentration of elements and their transfer from soil to plant. The integration of artificial intelligence, machine learning, and GIS technologies enhances environmental management, as it provides the ability to monitor, predict, and provide sustainable assessments. This study provides insights to improve plant growth, reduce pollution, and support long-term food security at a lower cost and with greater accuracy in assessing environmental impacts.

Key Words	Artificial Intelligence, Carbon Hydrogen, Nitrogen Soil Element Storage, Heavy Metals; GIS

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1. INTRODUCTION

Karbala is located on this route together with Anbar governorates where the Lake Al-Razzaza is located and is the second largest lake in Iraq and is influenced by the Euphrates River. Measured about 1810 km2 and has the capacity to store 26 billion m3 of water and the maximum height is 40 m above the sea level. The Mycoflora is essential for maintaining the region's delicate ecosystem of Iraq but is still researched inadequately (Ati, *et al.* 2022); Delineating fungi found in Lake Al-Razzaza and fungi living on palm trees (Al-Joboury, 2022). Nitrogen, carbon and hydrogen are among the elements that when studied helps in explaining the processes that occur in the environment naturally (Al-Qaraghuli, *et al.* 2021) they found that in Iraq after 2003 due to population increase and rise in level of domestic, agricultural and industrial pollution especially in the middle and the south this country is tending towards pollution crisis. In the case of the Karbala desert, there is confusion and technical difficulties in the management of saline water channel and the actual demand for water has gone high in the last few years only (Al-Zuhairi, *et al.* 2018).

Numerous mathematical models and artificial intelligence techniques, including artificial neural networks, along with various analytical methods, are employed for forecasting the quantities of the specified elements (Alengebawy, *et al.* 2022). These models incorporate multiple layers of interference data and an output layer that accurately focuses on heavy metals (HMs). In a study, the WT-MT-SAE and WTMSAE algorithms were used for deep feature extraction from fluorescence spectroscopic data that identified Pb in a sample of lettuce leaves, revealing that WT-MT-SAE performed better than WT-SAE (Alengebawy, *et al.* 2022).

The GA-BPNN, which combines genetic algorithms with back propagation neural networks, shares a similar architecture and parameters with BPNN and was used alongside BPNN to detect mercury in a soil sample analyzed with a spectrometer. The findings indicate that GA-BPNN yielded important results in the study (Ati, *et al.* 2021). In a different study, researchers aimed to identify copper and cadmium in rice leaves using AAS supported by BPNN. The findings indicated that BPNN accurately represented concentration levels in comparison to the statistical model (Arshad, et al. 2015). MLP and RBN were employed to detect Cu, Ni, and Pb in river water samples with the assistance of AAS, where MLP successfully identified Ni and RBN was effective for Cu and Zn, while the ANFIS model was used to detect Pb. In a prior study, both BPNN and general neural regression net algorithms (GRNN) were used to find Cu, Fe, Mg, and zinc in wastewater using AAS data, yielding poor results for Fe (Arshad *et al*., 2015).

Mercury, Iron, Zinc, and Lead were detected through artificial neural networks (ANN) and Multiple Linear Regression (MLR) using Vis-IR spectroscopy data from soil samples, but the effectiveness of these algorithms was predictable (Balali-Mood, *et al.* 2021). In mining soil analysis, Pb was identified using ICP-AES along with multiple linear regression and partial least square regression (Blesser). The PLSR method produced more precise results compared to the identified PLSR MLR (Balaram, 2019). Another investigation involved lead detection in mining soil using AAS and space-based hyperspectral imaging, analyzed through ANN and Fuzzy Neural Network (FNN). In this context, the FNN demonstrated more accurate outcomes than the ANN algorithm. Also, techniques such as the successive Projection Algorithm (SPA), information preservation variables (IRIV), Extreme Learning Machine (ELM), Support Vectors SVM, and GRNN were used to detect Cu and Pb using ICP-OES on maize leaf samples. Thus, the estimation of Cu and Pb was more accurately masked by IRIV as opposed to SPA and GRNN (Fadhel, *et al.* 2019,; Gholami, *etal* .2024).

This research was conducted near Al-Razzaza Salt Lake in the Karbala Governorate, using data from the wild plant *Agaricus bisporus* found near the Al-Razzaza Salt Lake – Iraq. The study employed artificial intelligence algorithms and spatial analysis to evaluate pollution levels and create future prediction maps using the interpolation method for these factors, treating the mushroom as a natural bio-indicator of environmental conditions.

2. MATERIALS AND METHODS

Study Zone, Elemental Examination, and Data Organization

Samples of air and fungus were gathered from the Al-Razzaza area. Soil samples of 500 grams each were taken from different sites, with five replicates collected from each site located 1000m away from the sampling areas. These soil samples were then placed in sterile bags. Following their placement in glass Petri dishes with sterile distilled water for 3-5 hours, they were subsequently dried in an oven at 80°C for 48 hours. The next step involved preparing it for weighing by filtering it through a steel sieve with a pore diameter of 2 mm. The soil samples used ranged in weight from 0. 200-0. Transfer 250 grams into Teflon containers, then add 6 milliliters of 65% HNO_3 (Merck) and 3 milliliters of 37% HCl. Next, 5 ml of deionized water from Merck, and 2 ml of 48% HF from Merck, were included. The digestion samples were prepared using a Berghof-MSW2 microwave. After the process, the samples were transferred into 50 ml sterilized falcon tubes using ultrapure water and a Blue Ribbon filtration Whatman filter. In order to achieve the total volume, the size was set at 50 ml. Focused. The concentrations were measured in milligrams per kilogram of dry weight using the PerkinElmer-Optima 7000DV Inductively Coupled Plasma Optical Emission Spectrometry (ICP-OES) device according to the study by Arshad *et al.* (2015).

Soil quality index

The soil quality index shows that the parameters like nitrogen (N), (H), single carbon (CO) exists in the soil. The quantity of these pollutants in the soil quality during the monitoring period is shown and the level of pollutants is presented in the form of a bar graph. This brings us to the result depicted in the chart below which reveals that the most characteristic pollutant is carbon monoxide. From this we can say that the main pollutant released by industries is carbon monoxide (Balaram, 2019 and Ahmed , *etal*., 2020).

Air samples as per (Huang, *et al.* 2023) filter paper used in the test particles in the ambient air were collected by fine dust sampler. Every last bit of it was sucked through the weighed filter paper before weighing the paper once again. The device was operated contineously twenty-four hrs a day, the mass concentration was estimated by the weight of the material collected per volume. The richness of the air from which the samples were taken, metals are extracted using an acid digestion method in order to isolate and extract heavy metals present in suspended particles of the collected samples and filter papers. A small pieces of filter paper are taken into a conical flask and weighed and added with 20 mL of cone.H_2SO_4 or 10 mL of cone.HNO_3. The next process is of heating the mixture on the hot plate for a period of 4 hours. The filtration and dilution method is used to quantify heavy metals with the help of a photometric analytical ICP-ES device with a sensitivity of up to ppm.

Carbon, N, H by ELEMENTRAC CS-d:

ELEMENTRAC CS d provides method details of the determination of organic carbon, nitrogen and hydrogen in the soil and plant samples using the ‘Thermal Scientific Flash EA 1112 analyzer.’ Carbon and nitrogen contents in all samples shall be determined both before and after acidification.

Acidification is carried out on all types of soil and plant samples, related ELEMENTRAC CS d (QA,QC) : VIO 002: The correct storage and preparation of samples [PRP 003: Soil sample preparation and handling] VOI 003 The correct storage and preservation of samples [PRP 004 Plant sample preparation and handling]. Elemental Analysis is a process that analyses which involves complete combustion of the sample within a high temperature reactor coupled with accurate and precise determination of the elemental gases produced with the help of a thermal conductivity detector to determine carbon and nitrogen present in organic form, Carbon, hydrogen and nitrogen estimations are carried out both before and after the removal of carbonates from the soil sample. Carbonates are extracted from the weighed into Ag capsules soil samples by flooding the samples with aqueous – acid solution. The carbonates are released as CO2 through the following chemical equation; according (Ohyama, *et al.* 2021).

$$\mathbf{CaCO_3 + 2HCl \rightarrow CO_2 + CaCl_2 + H_2O}$$

Development and setup of neural networks along with spatial analysis:

An artificial neural network consists of an input layer (hidden layers) and an output layer. The input layer consists of neurons, known as covariates, and the output layer contains neurons called dependent variables. There are no connections between neurons within the same layer, but they are densely connected to adjacent layers through synapse-like structures. In this way, the data gathered from the surrounding area is utilized for training the neural network in order to forecast the continuous values of the dependent variable. The entire sample of data was divided into three subsets, known as test data, in order to make reliable predictions. The cluster starts with random weights and then uses concentrations from previous tests. The back propagation neural network algorithm with gradient ratios is used to update the concentrations in order to reduce error.

The software SPSS 27 was utilized to achieve the necessary data-driven model during the calculations, with the Multi-Layer Perceptions (MLP) selected as the subunit and 1 chosen as the number of hidden layers. The hidden layer is set to have 2 neurons and the sigmoid function is used as the activation function for both the hidden and output layers Gholami, R.2023. The internal structure of the MLP is created with 4 input variables, with the height (Pb, Cd) set as independent variables in each calculation, and the number of input variables individually represented by (C,H,N).

For each instance of the elements linked to the MLP architecture, the training, test, and rejection data were distributed at 70%, 20%, and 10%. The number of units in the input layer for each variable is determined by the algorithm, starting at 0.4 and using a momentum of 0.9 with the squared error function when running the gradient descent algorithm. The algorithm processes all the data at once and then continues to utilize the stored data until a stopping criteria , is reached such as the maximum number of epochs for the contour maps that are initialized to read spatial distribution semantics according (Uchimiya, *et al*., 2020; Vera, *et al.* 2020).

3. RESULTS AND DISCUSSIONS

Findings have indicated the presence of essential elements (nitrogen, carbon, hydrogen) in the soil and air of Al-Razzaza. Besides, the total elements (lead and cadmium) were also analyzed, with the results outlined in Tables (1, 2).

Table 1: Amounts of (N, C, H, Pb and Cd) in *Agaricus bisporus* and soil of the Al-Razzaza

Code	Soil	C%	H%	N%	Cd ppm	Pb ppm	E: Longitude	N: Latitude
1*	*AbS*	8.68	8	2.17	1.81	0.29	42.243872	32.031541
1	*AbS*	8.06	9	3.13	0.93	0.12	42.252347	32.032871
1	*Abs*	8.99	10	3.07	1.35	0.15	42.254373	32.025972
2**	S	29.24	21.18	6.95	5.9	1.9	42.242483	32.026501
2	S	25.9	18.97	7.93	6.9	1.5	42.246169	32.021261
2	S	27.02	18.88	7.96	7	1.6	42.254928	32.021451

1 Mean concentration between the concentration of elements in Agaricus bisporus with surrounding soil*
*2** Mean concentration in Soil only , AbS: Agaricus bisporus with Soil, S : Soil only*

Table 2: The amount of elements (N, C, H, Pb, Cd) in *Agaricus bisporus* and Air of the Al-Razzaza

Code	Air	C%	H%	N%	Cd ppm	Pb ppm	E: Longitude	N: Latitude
3*	*AbA*	11.2	11.18	1.17	0.92	0.7	42.24387	32.03154
3	*AbA*	12	11.91	1.13	0.84	0.11	42.25235	32.03287
3	*AbA*	16.02	11.81	1.07	0.73	0.15	42.25437	32.02597
4**	A	34.68	16.08	1.95	2.19	1.9	42.24248	32.0265
4	A	30.06	15.67	2.93	3.53	1.9	42.24617	32.02126
4	A	45.99	16.2	2.96	2.59	1.6	42.25493	32.02145

1 Mean concentration between the concentration of elements in Agaricus bisporus with surrounding air*
*2** Mean concentration in Air only , AbS: Agaricus bisporus with Air, A : Air only*

Results indicated that the environmental components (N,C,H) of air and soil are receptors for pollutants in large quantities from various sources. Thus, they can be used in determining the origin of pollution, its characteristics, and the environmental factor that may be exposed to pollutants resulting from climate change, such as dust storms in most seasons of the year, rains, and thunder. The results indicate that the environmental components (N, C, H) of air and soil are receptors for pollutants in large quantities from multiple sources, and thus can be used to identify the source of pollution, its characteristics, and environmental factors exposed to pollutants resulting from climate change, such as dust storms in most seasons of the year, rain, and thunder, bsed on the longitude and latitude lines captured by GPS/Geko 201, a graphic map was determined for spatial analysis of all variables of the study areas based on the affected natural environmental and biological factors, and the graphic images obtained were considered the input variables as indicators indicating small points distributed in the data, so that the environmental indicators of the first level of pollution appear to include soil and air followed by biological levels in *Agaricus bisporus*.

Based on the longitude and latitude lines taken by GPS/Geko 201, a graphical map was determined for the spatial analysis of all variables of the study areas on the basis of the affected natural environmental and biological factors. The graphical images obtained considered the input variables as indicators indicating small points distributed in the data, so that The first level environmental indicators of pollution are shown to include soil and air followed by biological levels in *Agaricus bisporus*, the general maps for the spatial analysis are shown below in Figures 1,2 and 3 approach 1 and 2 Spatial Analysis of Carbon , Hydrogen and Nitrogen concentration in Soil and Air.

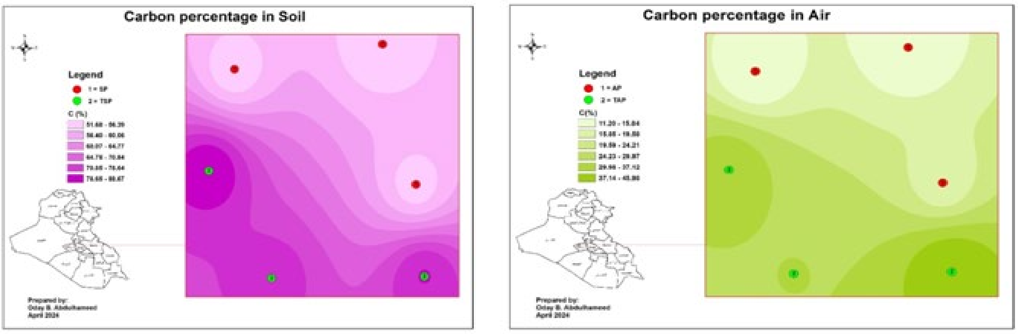

Figure 1: Approach 1 and 2 Spatial Analysis of Carbon concentration in Soil and Air

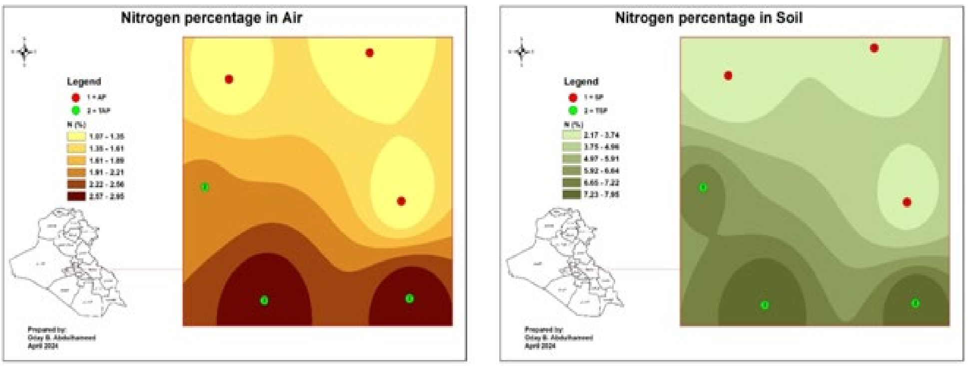

Figure 2: Approach 1 and 2 Spatial analysis Nitrogen in Soil and Air

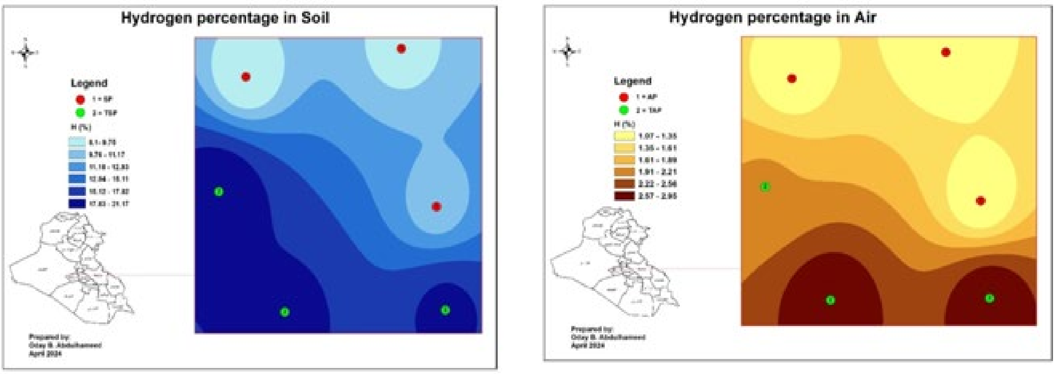

Figure 3: Approach 1 and 2 Spatial analysis Hydrogen in Soil and Air

The resulting contour maps of the investigated metal levels and standard deviation maps are shown in figures 4 and 5 approach 1 and 2 Spatial Analysis Spatial analysis Lead and Cadmium in Soil and Air depending on the type of element, they bear the transportability and absorption of the element that accumulates in their tissues, Metals have accumulated in growing plants in the soil, which has led to a decrease in their concentrations in the air and soil of developing areas, with relatively high concentrations compared areas that were not surrounded by plants. *Agaricus bisporus*, as a biomonitoring device, is directly proportional to the average surrounding bioavailability. (N, H, C) is biologically available to living organisms due to changes in response to environmental conditions and geochemical processes that control its availability within each stage, and any impact on its accumulations leads to an imbalance in the concentrations of the remaining major elements such as lead and cadmium. This was clear in the contour maps and the difference between soil and air of each element.

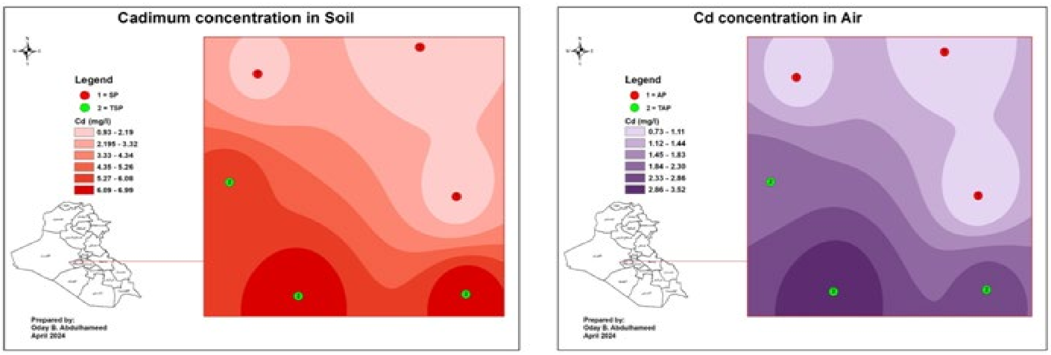

Figure 4: Approach 1 and 2 Spatial analysis Cadmium in Soil and Air

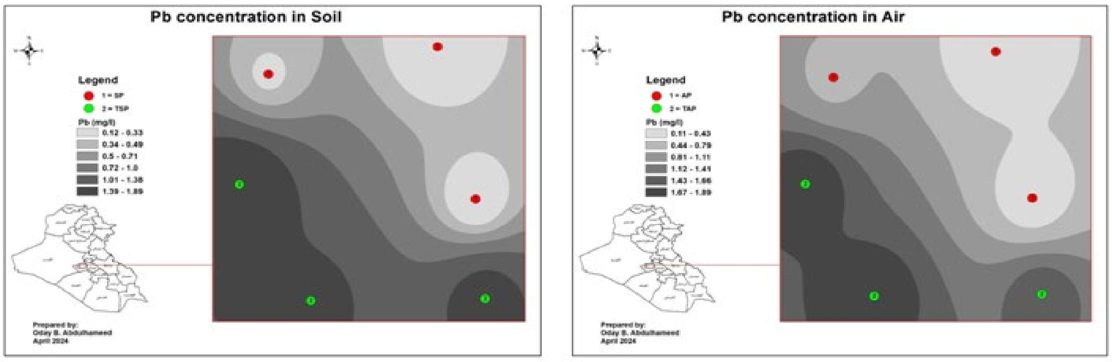

Figure 5: Approch 1 and 2 Spatial analysis Lead in Soil and Air

A balanced amount of essential nutrients and minerals plays a key role in the metabolism of the food chain. These approaches or model equations in our results allowed the use of all available data as a biomarker *Agaricus bisporus* to predict and function the GIS variable and give coefficients with additional accuracy in the supplementary materials because they do not focus on differences in relative size according (Wolski and Kruk 2020) but rather focus on distance-weighted variables such as conditions, soil nature, and activities. Also, the characteristic of spatial data has changed significantly during the last ten years with the increase in population density and conflicts, as mentioned in (Wolski and Kruk 2020).

As a result, materials are at risk of forming significant accumulations during environmental assessment processes, and soil pollution is recognized as a significant threat, especially in open natural areas, as it can lead to serious health and environmental risks (Münzel, *et al.* 2023). The next step involved creating hypotheses based on layers and neurons in artificial neural networks in order to identify and classify complex non-linear relationships between data sets related to *Agaricus bisporus.* This was chosen as the initial modeling method to address scientific problems and make predictions using complex non-linear relationships within the obtained data set.

The study found that increasing the depth of the neural network and the number of hidden neurons could help in dealing with various sources of pollution. It was also determined that the dependent and independent variables play a crucial role in establishing the optimal model for biological neural networks in analyzing plant element concentrations and estimating air and soil pollution (Gholami*, et al.* 2023). While there are significant amounts of certain elements in the soil, they play a crucial role in supporting plant growth and health, including (N, C, H), as well as heavy metals which can have harmful effects on the soil. Nevertheless, an elevated level of these substances in the soil could exceed a specific concentration, leading to harmful effects that are toxic to plants in the future as stated by (Alengebawy, *et al.* 2021; Rashid, *et al.* 2023).

An adequate balance of essential nutrients and minerals is crucial for the food chain's metabolism. The approaches or model equations used in our study allowed for the utilization of all available data to predict and analyze the GIS variable as a biomarker for *Agaricus bisporus*. The coefficients provided in the supplementary materials offer improved accuracy, as they do not emphasize differences in relative size (Wolski and Kruk, 2020) but rather focus on distance-weighted variables such as conditions, soil nature, and activities. Also, the characteristic of spatial data has changed significantly during the last ten years with the increase in population density and conflicts, as mentioned in Jones & Turner 2024 .

As a result, materials can easily accumulate in environmental assessment processes, leading to soil pollution, which is considered a significant risk, especially in undeveloped areas, as it can pose serious threats to both health and the environment (Münzel, *et al.* 2023). The next step involved creating hypotheses using layers and neurons in artificial neural networks to identify and categorize complex non-linear relationships between datasets related to *Agaricus bisporus*. This was chosen as the initial method for modeling, problem identification, and prediction building due to its ability to model the complex relationship between input and output. By increasing the depth of the neural network and the number of hidden neurons, enlightenment can be achieved in dealing with various sources of pollution, as concluded in the study by Gholami *et al.* (2023).

The study also determined that the dependent and independent variables are crucial in determining the optimal model for biological neural networks in estimating the concentration of plant elements and evaluating air and soil pollution. Even though there are significant amounts of elements present, they play a crucial role in the health of plants, including (N,C,H) and heavy metals which can have harmful effects on the soil. Nonetheless, if there is an excessive amount of them in the soil, it may reach a harmful level that could be toxic to plants in the future according to (Alengebawy *et al.* 2021; Rashid *et al.* 2023).

Using deep learning artificial neural networks to predict element levels could serve as a valuable alternative for determining the concentrations of soil and air elements. The current method for making predictions relies on authentic data and results, which are then compared with statistical methods. The current approach's validity was confirmed by splitting the data into three parts and using one of them to verify it. As a result, verification is achieved by analyzing real-world quantitative test data, followed by the use of artificial neural networks to forecast the levels of crucial heavy metals. This is done by establishing a connection between the fluctuations of these metals and the presence or absence of plants in wild areas, whether agricultural or desert, and considering their potential impact on the environment. Additionally, the relationship between these factors and climate changes during the growing season of *Agaricus bisporus* consistent with the findings of Jones, D., & Turner, S. (2022).

The neural network's structure comprises the input layer with three separate spike inputs from the air and soil, denoted as (N,C,H). The concealed layer connects three neurons to the output layer, and the pair (Pb, Cd) signifies distinct states. Before commencing the analysis, the input and output data underwent normalization. The data was then categorized into three groups (*Agaricus bisporus*, Soil, Air) for durability testing. These separate the data into three categories for different trace elements and keep track of rejected data to regulate the accuracy of predictions (Ryoo, *et al*., 2024).

The hyperbolic tangent function is used in the hidden layer, while the sigmoid logistic function serves as the activation function for the output layer. In mathematical biology, sigmoid functions are commonly employed in prediction models. The error function is typically the sum of squared errors, and the maximum impact time on elements such as soil and air is determined by the number of consecutive steps without a decrease in error. This allows the function to represent the relative error value in successive steps. In the soil and *Agaricus bisporus* R. To determine the comparison of some variables in soil and *Agaricus bisporus* R, a programming language and software environment for statistical computing and graphics, is used. A paired t-test was conducted to depict if there are significant differences in the mean average of soil and air variables and absence data *Agaricus bisporus*. Figures 1 and 2 present the outcome of such an analysis. Conventional architecture focus elements of the network diagram in *Agaricus bisporus* with Soil and air.

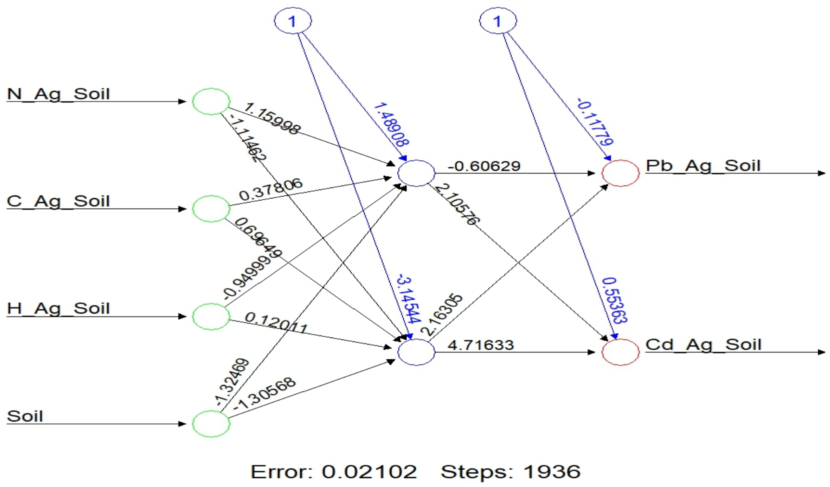

Figure 6. The typical architectural concentration components of the network diagram in *Agaricus bisporus* alongside Soil

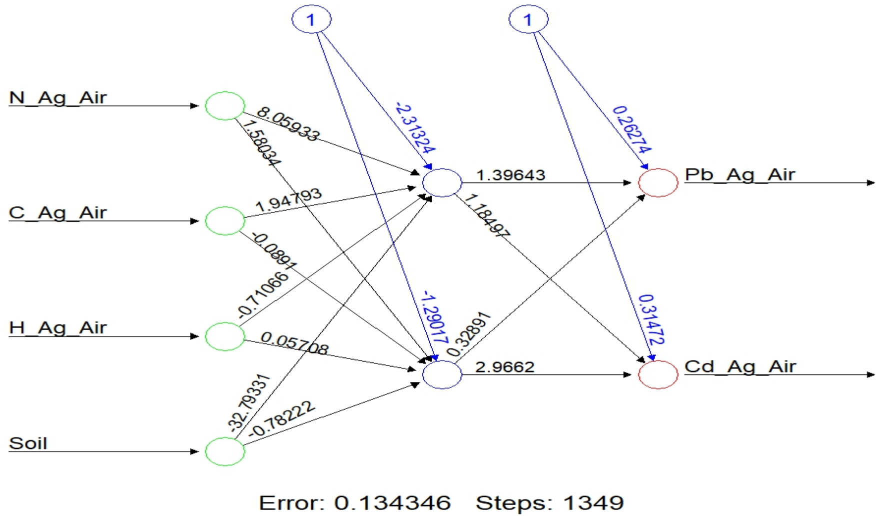

Figure 7: The typical architectural concentration components of the network diagram in *Agaricus bisporus* alongside Air

According (Al-Zuhairi, *et al.* 2018 and Münzel, *etal* .2024). The paired t-test hypotheses show that all p-values in the soil are <0.05, indicating major differences in the mean averages of soil variables before and after planting Agaricus bisporus. The correlation coefficient assesses the strength of the linear relationship between two variables, with a perfect positive linear relationship represented by R2 = 0 – 1. Here, 0 indicates no relationship, while 1 indicates a strong relationship. The null hypothesis is $H0{:}\bar{x}1=\bar{x}2$ (not major), and the alternative hypothesis is $H1{:}\bar{x}1\neq\bar{x}2$ (major).

Linear regression techniques were employed to develop empirical predictive models based on field data. Statistical significance was determined with p-values <0.05, while p-values >0.05 were deemed not major. Regarding air and *Agaricus bisporus*, R, a programming language widely used in statistical analysis, data analytics, and scientific research, was used to compare and analyze soil variable data. Specifically, a paired t-test was conducted to determine if there were major differences in the mean averages of soil and air variables before and after the planting of *Agaricus bisporus.* Since all p-values in air are <0.05, it indicates major differences in the mean averages of air variables before and after the planting of *Agaricus bisporus*. The correlation coefficient, again, measures the strength of the linear relationship between two variables, with a perfect positive relationship signified by R2 = 0 – 1, where 0 means no relationship and 1 indicates a strong relationship.

Linear regression methods were used to build empirical predictive models from field data. Statistical p-values <0.05 were regarded as major, while p-values >0.05 were considered not major. The figure displays predicted Pb values plotted against actual Pb values for the entire dataset, with results aligning closely within an acceptable range around the ideal prediction line. This suggests that the figure remains reasonable when viewed alongside the actual values. Tables 3 and 4 present quantitative results revealing relative errors in the respective test data. Given that the actual values are substantially greater than zero, the relative errors provide plenty insight into the effectiveness of the current technology. What's more, bear in mind that the dataset is major, as evidenced by the calculated sum of square error Ryoo, *etal.* 2024.

The R-squared value, which ranges from 0 to 1, represents a perfect positive linear relationship. A correlation value of 0 denotes no relationship, while a value of 1 indicates a strong positive linear relationship in the soil. This is illustrated through tables (3 and 4), which show that the significance of the correlation among the independent variables can be identified by the increase from 0 (indicating no relationship) to 1 (indicating a strong relationship). The expected values, actual values, and residual values of the elements exhibit nearly perfect alignment, with the remaining values showing a perfectly satisfactory agreement with the expected versus actual values (Guaedoni *et al.,* 2020 ,; Wolski & Kruk , 2024).

5. CONCLUSIONS

Data-driven mathematical models are important for making classifications or predictions, especially when using tools such as dependent and independent variables or artificial neural networks, without addressing causal relationships. Deep learning neural networks can effectively predict soil element levels and their transfer to plants, providing a cost-effective and time-efficient alternative. These predictions are based on real, validated data, which is divided into three segments for validation purposes. Artificial neural networks forecast the prevalence of key heavy metals by correlating them with plants' presence and their environmental impacts. The incorporation of technology, AI, machine learning, and GIS enhances environmental management by allowing for the monitoring and forecasting of contamination levels. By using an interdisciplinary strategy, this approach integrates physical geography, environmental sciences, and social sciences, using GIS to accomplish effective environmental assessment and sustainability goals.

Author’s contributions

Estabraq M. Ati, Rana F. Abbas and Abdalkader Saeed Latif , Reyam Naji Ajmi completed the experiments, while Oday Abdulhameed Jeewan and prepared the draft. All the authors reviewed and finalized and approved the final version of the manuscript.

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Ethical statement

This article does not contain any studies regarding human or Animal

Availability of data and material

Authors declare that the submitted manuscript is our work, which has not been published before and is not currently being considered for publication elsewhere.

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Code Availability

Not applicable.

Consent to participate

All authors participated in this research study.

Consent for publication

All authors submit consent to publish this research.

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