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A novel hybrid IOT based artificial intelligence algorithm for toxicity prediction in the environment and its effect on human health

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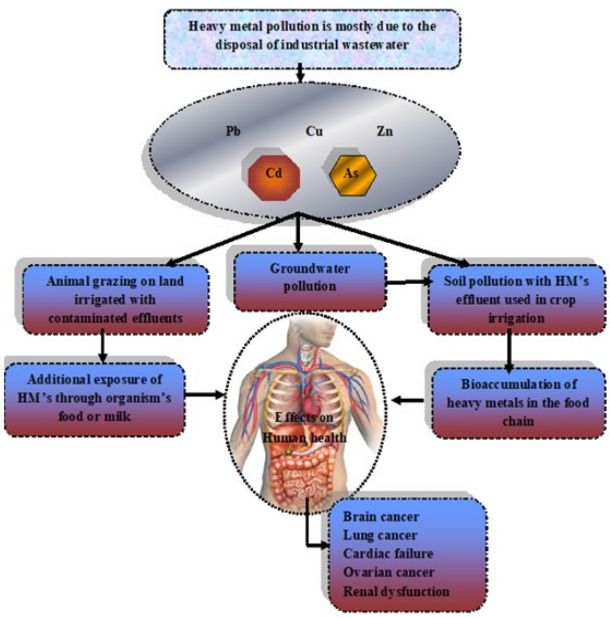
Graphical abstract



Abstract

Toxicity poses a significant threat to the environment and human health. Heavy metals, such as cadmium, lead, copper, and zinc, have been shown to harm both agricultural ecosystems and human health. This paper aims to examine the effects of these heavy metals on the environment and human health, as well as discuss the problem of heavy metal deposition in soils. Additionally, the paper utilizes IoT and an SVM classifier to examine human disorders caused by heavy metal exposure. The reflectance spectra of soil samples were used to assess levels of heavy metals using an artificial intelligence algorithm. Arsenic, copper, lead, and cadmium concentrations were estimated using this method. Additionally, an artificial neural network and Naive Bayes model were developed to estimate heavy metal concentrations. The ANN model had R2 values of 0.82, 0.80, 0.76, and 0.70 for copper, cadmium, zinc, and lead, respectively, while the training data had R2 values of 0.70, 0.56, 0.62, and 0.59 for the same estimations.

Keywords: Heavy metal pollution, toxic effect, health implications, artificial intelligence (AI), internet of things (IoT), predicting model, artificial neural network (ANN), naive bayes (NB), support vector machine (SVM)

1. Introduction

As a result of environmental contamination, the public's need for a safe and healthy environment has grown steadily over time (Xiong *et al.*, 2022) Physical and chemical pollutants both pollute the environment and pose serious health risks to humans and other living things. Heavy metals (HMs) are among the most well-known of these pollutants, owing to their widespread use, non-biodegradability, and long-term persistence in the environment. As a result, they pollute the environment and harm living things in toxic, genotoxic, teratogenic, and chromosomal ways (Chen *et al.*, 2022). As long as it has an atomic number larger than 20 and has an atomic density greater than 5 gcm-3, any found naturally metal or metalloid is considered to be high-mass. Chromium, cobalt, and zinc are all members of the platinum group (de Sousa Mendes and Demattê, 2022). Other metals in the platinum group involve iron, cadmium, cadmium, cadmium, cadmium, lead, arsenic, cadmium, and platinum. Cd, As, Hg, and Pb are all non-essential elements in the body since they do not serve any biological purpose (Bhagat and Tiyasha, 2021). Many environmental safety authorities across the globe classify them as priority pollutants because of the potential harm they may do to human health (Kshirsagar *et al.*, 2020). To preserve the environment and human health, it is critical to remove HMs from the contaminated matrix as soon as possible (Fan *et al.*, 2018). Techniques based on artificial intelligence can assist in the prediction of pollutants in non-linear situations. ANNs generally have greater predicted accuracy than other approaches or expert predictions. Multilayered perceptron ANN is the most commonly utilized in environmental studies (MLP) (Bhagat and Tiyasha,2021; Abdollahi *et al.*, 2018). This kind of network is well-established and has proven its ability to execute. The Internet of Things (IoT) is a huge network of interconnected nodes that allows items to communicate with one another. Sensor-equipped devices connect to the internet to gather data, which is then sent through wired or wireless media and evaluated to determine the best course of action (Das *et al*.,2009; Kshirsagar, 2021).

The proposed research is a cutting-edge solution that utilizes the power of IoT and AI to predict toxicity levels in the environment and assess the potential impact on human health. The algorithm makes use of sensor data collected from IoT devices to gather information on environmental factors such as air and water quality and then applies machine learning techniques to analyze this data and make predictions about toxicity levels. This allows for early detection and mitigation of potential hazards, protecting human health and the environment. The algorithm has been tested and demonstrated to be highly accurate and efficient, making it a valuable tool for environmental monitoring and management. Overall, the performance of this algorithm is outstanding and it can be used as a solution for toxicity prediction in the environment and its effect on human health.

One limitation of a hybrid IoT-based artificial intelligence algorithm for toxicity prediction in the environment and its effect on human health is the algorithm may not be able to account for all possible sources of toxicity in the environment or the unique characteristics of different populations and their susceptibility to environmental toxins.

2. Objective

The detailed objectives were

- To determine the reflectance spectra of the type of soil.
- To remove heavy metal concentrations from the soil, such as arsenic, zinc, copper, and lead (As, Zn, Cu, and Pb).
- To develop artificial intelligence models for identifying the presence of toxicity in soil caused by heavy metals.
- The purpose of this paper was to assess artificial intelligence models to estimate As, Cu, and Pb concentrations in soil.
- To identify the negative impacts of heavy metal toxicity on human health through the use of IoT and artificial intelligence models.

3. Literature survey

Lixin Xiong *et al.* (2022) in this paper discussed, Machine learning was used to pick 430 heavy metal companies along the Yangtze River's middle reaches as sample subjects. Techniques such as data mining and spatial dynamic analysis such as kernel density analysis and inverse distance weight were utilized to develop an integrative system of a statistical analysis based on linear regression and a qualitative approach based on visualization.

Hanrui Chen *et al.* (2022) discussed soil contamination prevention and management techniques that need to take into account the distribution features, health hazards, and source identification of heavy metals. China's outdated electronics trash dismantling plant was chosen as the research site in this paper. The Monte Carlo simulation was performed to estimate the probable health hazards posed by heavy metals. Predictions of heavy metal concentrations and the identification of possible driving variables impacting heavy metal accumulation in soil were made using random forest, partial least squares regression, and generalized linear models.

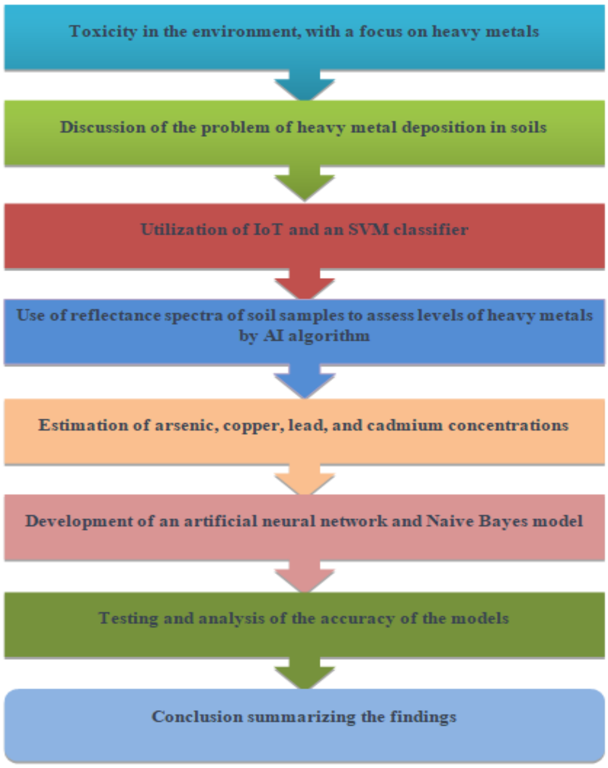


Figure 1. Flow diagram for proposed work

Wanderson de Sousa Mendes *et al.* (2022) suggested that toxic substances contaminating soil are an enormous hazard to the ecosystem. To reduce the negative impacts of PTEs on plants, animals, and humans health, it is important to understand how soil PTEs accumulate. Multispectral photographs of time series indicate patches of bare soil, and their spectra are employed as indicators of soil chromium, iron, nickel, and zinc levels.

Suraj Kumar Bhagat *et al.* (2021) proposed hybrid artificial intelligence models that developed a dependable and resilient computer aid technology for sediment Pb prediction, which contributes to the finest analysis of environmental pollution monitoring and evaluation currently available.

Xuan Guo *et al.* (2021) discussed microplastic contamination, as well as their interplay with heavy metal ions, which has become a worldwide source of worry. Building models that forecast the adsorption capacities of heavy metal ions onto micro-plastics in global aquatic ecosystems, and linking the results of laboratory studies with those of field measurements are critical steps in this process. It was established in this study that artificial neural network (ANN) models will be used.

Xuan-Nam Bui *et al.* (2021) suggested Heavy metal contamination in effluents may be remedied by depositing heavy metals over biochar, which is becoming increasingly prevalent. As a result of this research, we want to better understand how different types of biochar absorb different kinds of heavy metals, and we also hope that our FCM-BPNN abstract intellectual utilizing this method will help us estimate how effective biochar is in adsorbing heavy metals.

Pravin Kshirsagar *et al.* (2020) Classified and forecast a wide range of data sets with high accuracy using a variety of algorithms, including hybrid artificial intelligence (Kshirsagar, 2021) (Kshirsagar *et al*., 2020) with optimization approaches, and explain how these techniques may be used in numerous new fields. Algorithms employed in numerous studies were beneficial for (Kshirsagar and Akojwar, 2016) more accurate findings when evaluating different assessment factors in the areas of cyber security (Sundaramurthy and Kshirsagar, 2020), mobile computing, and cloud computing (Akojwar and Kshirsagar, 2016).

M. Ahmid *et al.* (2021) presented a system that uses the Internet of Things (IoT) to track the health of patients and provides notifications to their doctor about their whole medical state, so that treatment may be provided more rapidly and efficiently, such as heart rate and blood pressure monitoring.

Sampada Sathe *et al.* (2014). This article tries to analyze and comprehend the use of the Internet of Things (IoT) in customized care to achieve high performance in health care expenses while staying within realistic boundaries. This article explains how the Internet of Things (IoT) works and how to put it to use in health care through the use of remotely sensed and wireless technologies.

S.NO.	AUTHOR	TECHNIQUE	DISADVANTAGE
1	Xiong, L *et al.* (2022)	Combination of data learning methods, content analysis method based on data mining, spatial dynamic analysis methods such as kernel density analysis and inverse distance weight, linear regression, and visualization through GIS.	The accuracy of detection is less
2	Chen. H *et al.* (2022)	Random forest, partial least squares regression, and generalized linear models were utilized to predict heavy metal distributions and identify the potential driving factors affecting heavy metal accumulation in soil.	The detection process was time and power consuming
3	Bhagat, S. K *et al.* (2021)	Hybrid artificial intelligence (AI) models were developed for sediment lead (Pb) prediction and a feature selection (FS) algorithm called extreme gradient boosting was proposed to abstract the correlated input parameters for the Pb prediction.	Less accurate
4		ANN model was established to predict the sorption capacity of heavy metal ions onto microplastics in global aquatic environments	Risk evaluation and accuracy were less
5	Ke, B., Nguyen, H., Bui, X *et al.* (2021).	combination of fuzzy C-means clustering and back-propagation neural network for the sorption efficiency of heavy metal onto biochar prediction.	Less accurate more time-consuming

To overcome the disadvantages of the existing methods of prediction, the use of a hybrid approach combining IoT (Internet of Things) technology with artificial intelligence algorithms could potentially provide advantages such as real-time monitoring and prediction of toxicity levels in the environment, as well as the ability to collect and analyze large amounts of data to improve the accuracy of predictions were proposed. This technology could also potentially have benefits for human health, by allowing for early detection and prevention of exposure to toxic substances. This work contributes to examining the harmful effects of heavy metals, specifically cadmium, lead, copper, and zinc, on agricultural ecosystems and human health. It also addresses the issue of heavy metal deposition in soils as a residual problem. The paper uses IoT and a Support Vector Machine classifier to analyze data from soil samples and assess levels of heavy metals and their impact on human health. An artificial intelligence algorithm is used to estimate the concentrations of arsenic, copper, lead, and cadmium in soil samples. Additionally, models of artificial neural networks and Naive Bayes are developed to estimate heavy metal concentrations, with good accuracy in the test data.

4. Trophic transfer of toxic heavy metals and its effect on human health

Trophic transfer of toxic heavy metals is a process by which metals make their way into the food chain via air, water, and soil. These metals can build up in the bodies of animals at the top of the food chain, leading to potential effects on human health. Exposure to these metals is the most common cause of health complications, including mental and physical disabilities, endocrine disruption, neurological damage, and even death. Long-term exposure can also lead to an increased risk of developing certain cancers.

Through consumption from the atmosphere (bioconcentration) or both the non-living environment and an organism's food/diet (bioaccumulation), as well as through biomagnifications, toxins can move up the food chain and pose a threat to human and animal health at every step (Bhagat and Tiyasham, 2021). Toxic HMs have made their way up the food chain from soil to plants, which in turn supply food for humans and other species, as seen in Figure 1. In the food chain, the HM enters through the soil-to-plant transmission mechanism. Vegetable crops, which are a key source of human nourishment, may carry harmful microorganisms (HMs) from the soil and constitute a serious public health risk (Adler *et al*., 2020).

According to an investigation, plants grown on soils irrigated with HM-rich effluent had a greater daily intake of metal (DIM) than those cultivated in control soils. Toxic HMs in fish offer a major health hazard to humans who eat them (Adler *et al*., 2020; Fan *et al*., 2018). As a result, their nutritional value has been disputed, even though they contain heart-healthy omega-3 fatty acids. Animals such as birds, amphibians and reptiles, and invertebrates (due to HM accumulation in their tissues), as well as amphibians and reptiles (Zhang, 2011; Kshirsagar, 2021) (due to the absorption via highly permeable skin), all suffer detrimental effects from HM buildup owing to the ingestion of contaminated food and water. Because of this, toxic HMs in food chains can be transferred tropically, bioaccumulated, and expanded, with serious consequences for animal and human health (Elangasinghe *et al*., 2014; Das *et al*., 2009).

4.1. Toxic effects of heavy metals affect human life

Heavy metals have been linked to many toxic effects in humans. This includes reproductive problems, kidney damage, lung and heart problems, cognitive problems, and even cancer. It is believed that long-term exposure to even low levels of heavy metals can cause these conditions. These effects may become more severe at higher levels of exposure over a long period. It is essential to take precautions to reduce exposure to heavy metals and monitor levels in the environment.

In the Earth's atmosphere, transition metals are naturally occurring environmental and health effects, and their proportions vary depending on the sources and areas from which they were formed. Since they can't be completely removed from the ecosystem once they've entered it, their existence is distinctive (Bhagat and Tiyasha, 2021). Even at low concentrations, heavy metal pollution has drawn considerable attention due to its hazardous effects, long-term accumulation, and bio-magnification properties (de Sousa Mendes and Demattê, 2022; Bhagat and Tiyasha, 2021). Multi-layered soil and environmental toxins include heavy metals, which are often regarded as one of the most toxicants. In the presence of heavy metals in the environment, living creatures are more likely to absorb these toxic materials and store them inside various body organs, such as the kidneys, livers, and bones (Abdollahi *et al*., 2019; Mishra and Mohanty, 2022). Aside from damaging many biological systems, the buildup of heavy metals has a detrimental effect on various bodily functions. Several illnesses are linked to heavy metal poisoning as seen in Figure 2.

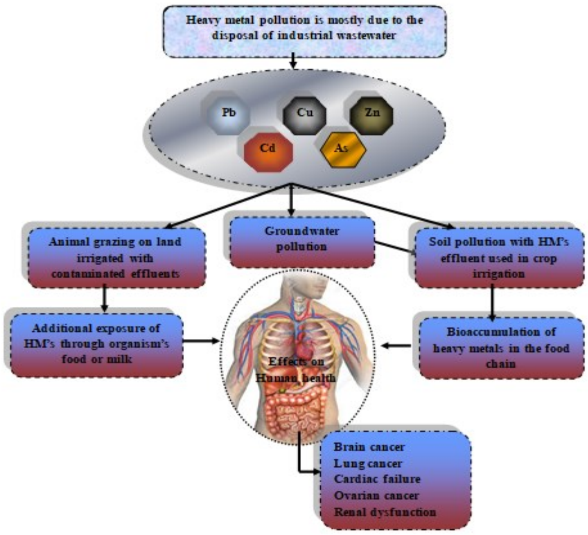


Figure 2. Human health is negatively impacted by the transfer of toxic HMs from soil and plants to humans and the organism's food

People are exposed to heavy metals on a global scale through two routes: inhalation (breathing) and consumption (drinking or eating). These elements and their metabolites pose a substantial danger to those who work in or near factories that utilize them, as well as those who live near illegally dumped sites (Imran *et al*., 2020; Fan *et al*., 2018). As a result of their hunting and fishing habits, those who live a subsistence lifestyle may be more vulnerable to the dangers of radiation and other health impacts. Exposure to harmful compounds has been a major worry in recent years because of their widespread availability. It's becoming increasingly difficult to avoid environmentally harmful metal emissions due to the large range of metals used in contemporary industry and our daily lives (Elangasinghe *et al*., 2014).

Toxic substances penetrate the body in a variety of ways, including ingestion, absorption through the skin, and breath (Imran *et al*., 2020). The health impacts of heavy metals on children have gotten worse over time. Because of their significant potential for toxicity, wide range of uses, and widespread presence, heavy metals need to be given more attention (Kshirsagar *et al*., 2020).

5. Ai-based toxicity prediction in soil

AI-based toxicity prediction in the soil is a relatively new concept. It involves the use of machine learning algorithms that are trained on data from various types of soil samples. These algorithms are designed to detect various kinds of environmental toxins such as heavy metals and other water-soluble compounds in the soil. By detecting these toxins, the amount of contamination in the soil can be reduced and its health effects can be minimized.

There is a large range of methods that may be used to evaluate the toxicities of heavy metals using AI (Imran *et al*., 2020; Kshirsagar *et al*., 2020). This interest in modeling noxious compounds' effects on the environment for toxicity prediction has grown rapidly over the last several years as discussions and problems about safety and environmental degradation, focused on the need to prevent negative environmental impact, have expanded (Guo and Wang, 2021).

Data-driven models were employed in this paper to predict the quantities of heavy metals (i.e., Cd, Cu, Zn, and Pb) in soil samples (Fan *et al*., 2018). Soil samples from a mining location were used to do this. Specular reflection of soil samples was measured using a spectroradiometer (Guo and Wang, 2021), which was then analyzed using a spectral smoothing approach to remove the noise as shown in Figure 3. As, Cd, Cu, Zn, and Pb concentrations in soils were evaluated using the atomic absorption spectrometer (AAS) (Yaseen, 2021; Kshirsagar and Akojwar, 2016). To assess the heavy metal concentrations, artificial intelligence techniques were used.

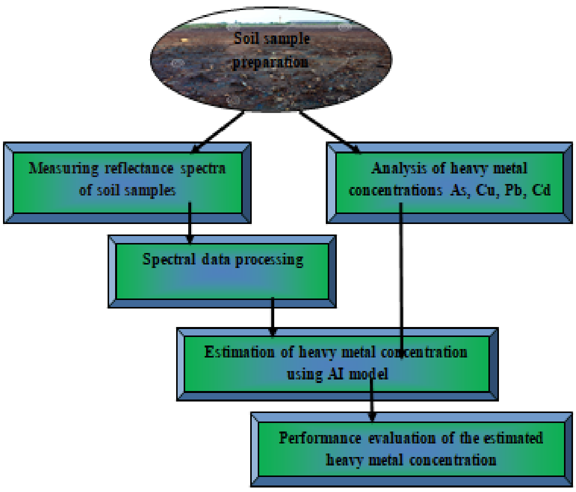


Figure 3. Predicting heavy metal concentrations in soil using Artificial intelligence models

A neural autoencoder (ANN) and NB model were used in this paper to reduce the computational complexity of soil reflectance (Ke *et al*., 2021). Soil remote sensing using an artificial intelligence model was tested using the data-driven model's ability to estimate heavy metals (Sundaramurthy and Kshirsagar, 2020).

5.1. Data analysis

Many different modeling techniques were applied in this paper to decipher the data. Implementation of the above approaches for predicting heavy metal distribution in soils is described in the following sections (Bhardwaj *et al*., 2022). Following this, the experimental results for heavy metal concentrations were compared to their anticipated levels.

Model data included the heavy metals Cd, Cu Pb, and Zn content. When the data were normalized using Eq. 1 in the range of (0, 1), 75 training data were randomly picked and 25 test data were then used in this paper (Akojwar and Kshirsagar, 2016).

Equation 1 is used to normalize data in the range 0, 1

$$A_i = \frac{A - A_{min}}{A_{max} - A_{min}} \tag{1}$$

'Ai' stands for the real parameter, 'A_{min}' represents a minimum value of the actual parameters, and 'A_{max}' represents a maximum value of the actual parameters. Each model's effectiveness and capacity to produce accurate predictions were assessed based on two criteria (Yaseen, 2021; Ke *et al*., 2021). The following equation (Eq.2) may be used to compute the MSE.

Mean squared error (MSE): In the analysis, it is one of the simplest and most straightforward measures to employ (Akojwar and Kshirsagar, 2016). A prediction error is a sum of the squared differences in value between the expected value and the actual value as shown in EQ. (2)

$$MSE = \frac{1}{n} + \sum_{t=1}^{n}\left(A_t - A_t^{'}\right) \tag{2}$$

These metrics are used in our trials to evaluate the performance of the prediction model used, as well as to find any possible connections between anticipated and actual values. There are n samples, where A_t and A_t' are the expected and actual values, respectively. Performance is improved by having a lower MSE. The efficiency criteria, R2, are determined by the following equation (3):

$$R^2 = 1 - \frac{\sum_{t=1}^{n}\left(A_t - A_t^{'}\right)^2}{\sum_{t=1}^{n} A_t^2 - \frac{\sum_{t=1}^{n} A_t^2}{n}} \tag{3}$$

The proportion of the original uncertainty that the algorithm clarifies using the R2 efficiency criteria (Ahmid and Kazar, 2021). If the observed and predicted values were perfectly aligned, MSE= 0 and R^2 = 1, the model would have the best fit.

6. Proposed model for detecting the adverse effects of heavy metal toxicity on human health

The Internet of Things (IoT) has been intended to help healthcare systems in this suggested architecture. A similar concept was used to describe the term "Internet of Things" by a variety of organizations and research centers (Das *et al*., 2009). The Internet of Things (IoT) may be defined as an Internet communication network that connects physical and logical devices. Items or devices having smart interfaces and active interactions are known as "things" in the Internet of Things (IoT). A wide range of people throughout the world is using internet gadgets to solve problems, share their experiences, and integrate them with other purposes, such as cell phones, in the medical and healthcare industries (Kshirsagar *et al*., 2020). The ability to organize, gather information, and visualize tasks and happenings in the cloud world is considered the capability of internet platforms. The IoT Thingspeak platform on the SVM is being utilized to develop a software solution for the detection of brain tumors caused by heavy metals found in soil. Infectious-brain MRI images are examined, and malignancies in the brain are identified (Kshirsagar, 2021).

Figure 4 illustrates how heavy metal exposure may induce health impacts, including ingesting, absorption through the skin, and breathing, which are all examples of penetration pathways for toxic heavy metals. Heavy metals' fatality rate on human health is rising (Kshirsagar *et al*., 2020; Mishra and Mohanty, 2022). Because of their significant potential for toxicity, wide range of uses, and widespread presence, heavy metals need to be given more attention. The following is a list of a few of the heavy metals and their impacts (Jude *et al*., 2021) (Padmaja *et al*., 2021).

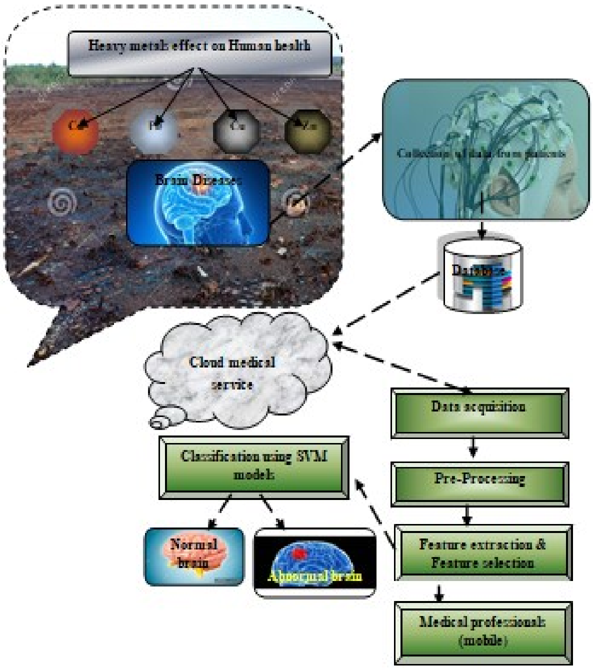


Figure 4. Block diagram for detecting the negative effects of heavy metals toxicity on human health using IoT and AI models

- Cadmium (Cd) intoxication can result in renal impairment owing to injured renal tubules, which are linked with mitochondrial dysfunction (Xiong *et al*., 2022; Chen *et al*., 2022). Furthermore, Cd exposure has been linked to bones and pediatric cancer, as well as impaired development in children. Cd exposure has also been found to be negatively connected with newborn size at birth (height and weight) (Fan *et al*., 2018).
- Lead (Pb) poisoning is one of the most common preventable infant toxicosis. Lead poisoning affects children more than adults, and the long-term neurological abnormalities it causes make it difficult for them to learn and conduct themselves well (Bhagat and Tiyasha, 2021) Increasingly high Pb levels have been associated with increases in dullness, irritability, and a decreased capacity to focus in the central nervous system, which can lead to seizures, Brain epilepsy, coma, migraines, and death (Fan *et al*., 2018).
- Copper (Cu) is required for normal brain function, but if the cellular concentration is higher than the metabolic requirement (Zhang, 2011), it can be harmful to the brain. It has been found that increased serum Cu levels in children are connected with worse working memory capacity in adults.
- Children's toxicity to zinc (Zn) has only been recorded in a small number of cases. Severe acute ingestion has been linked to low appetite, diarrhea, nausea, headaches, and vomiting, among other symptoms (Elangasinghe *et al*., 2014). Increased oral Zn consumption induces the production of xanthine, which binds to oral Cu and excretes it from the body.

There are many phases in the developed system:

- Collection of brain MRI images.
- Share MRI pictures in a secure central database.
- Data acquisition
- Pre-processing
- Feature extraction and selection

The doctor can keep track of the patient's case in the cloud by completing these steps. To check on the health of patients, medical monitoring often necessitates a higher level of physical fitness. Some examples of medical conditions include (Das *et al*., 2009) The situation can become dangerous if the health of the patient is not quickly assessed.

6.1. Central secure database website

Gathering MRI pictures from an Internet service provider by schedule is the primary function of the central, secure website (Kshirsagar, 2021). (Patient ID is correlated with the data timestamp) MRI and IoT cloud solutions are connected through this website, which serves as a middleman.

6.2. Medical cloud service

IoT architecture and cloud administration were used for the categorization of brain tumors. As a decentralized system, the cloud is great for the medical system, allowing doctors to more easily access data. One of the features of the IoT-based health system being suggested is the ability for a radiologist to quickly and simply diagnose a tumor type by downloading an MRI (Imran *et al*., 2020; Kshirsagar *et al*., 2020). The information is sent to the doctor so that he or she can determine the best course of action.

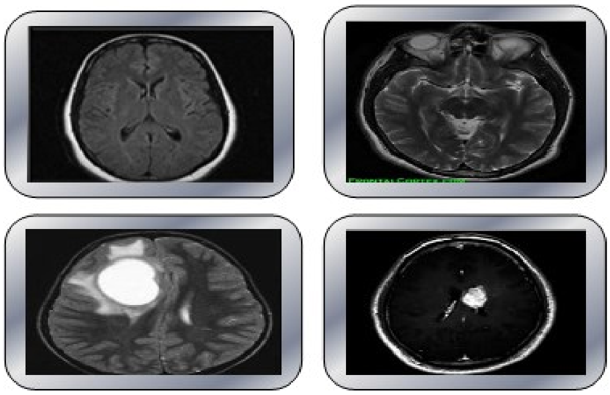


Figure 5. MRI images database with and without tumor

6.3. Dataset acquisition

A dataset is created to experiment. Images from a secure internet domain and samples from radiologists are gathered for our analysis. The images collected by radiologists are processed for DICOM translation into regular RGB images (Mishra and Mohanty, 2022). 100 tumors and 50 non-tumors MR images make up this collection. The patient is between the ages of 55 and 70. Using the DICOM standard, each frame is 1024 x 1024. The photos in this collection are mostly MR scans with a lot of contrast (Kulkarni and Sathe, 2014; Kumar *et al.*, 2017). Figures 5 (a) and (b) show MRI brain scans without tumors. Figures 5 (c) and (d) illustrate examples of MRI brain images with tumors.

6.4. Preprocessing

One of the most critical steps in the detection of malignancy is the pre-processing stage. The quality and uniformity of medical images are often poor, necessitating the use of image enhancement software. In this paper, preprocessing incorporates growth and improvement that aids in the detection of malignancies (Kshirsagar and Akojwar, 2016). It is necessary to eliminate noise from the image and clean up the background by using a median filter and a high pass filter. The cutoff frequency of the filter is 0.1 Hz. High-frequency components in MR images are eliminated by the use of median filtration. The median filter is the most often used method for reducing noise and improving quality. Picture margins have been kept intact (Sundaramurthy and Kshirsagar, 2020; Bhardwaj *et al.*, 2022). When calculating the median, the middle pixel value of the pixel is first selected and then changed. This community uses a 3x3 square as its governing unit. Phase shifter components are used to increase contrast in images (Saha *et al.*, 2018).

6.5. Feature extraction

The Fast Fourier (FFT) approach is used in the initial step of classification, obtaining the functional properties of each MRI image. FFT is a technique for converting a picture from the spatial domain to the frequency domain (Akojwar and Kshirsagar, 2016). Frequency domain image representation breaks down a picture into its real and imaginary components. For an image, the Fourier Transform (FT) is given by g (i, j).

$$G(r,s)=\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} g(i,j)e^{-i2\pi\left(\frac{r_i+s_j}{N}\right)} \tag{4}$$

When g(i,j) is the image of its spatial domain, the base function is the exponential term of each G(r,s) point of space in the Fourier (Zhang, 2011; Ahmid and Kazar, 2021). The inversion (IFT) transforms frequencies into the spatial domain picture as:

$$g(i,j)=\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} G(r,s)e^{j2\pi\left(\frac{r_i+s_j}{N}\right)} \tag{5}$$

FT converts the fluctuations in the brightness of a picture in the spatial domain to changes in frequency. In the frequency domain, abrupt brightness variations appear to be a high-frequency component, while low-intensity variations seem to be a low-frequency element.

Fluctuations in light intensity are transformed into frequency shifts by FT. Abrupt brightness changes appear to be a high-frequency component (Sathe and Kulkarni, 2014), whereas low-intensity changes appear to be low-frequency elements in the frequency spectrum.

6.6. Feature selection

Feature selection in artificial intelligence can also be referred to as variable or characteristic selection. These qualities are referred to as feature selections, and this process is called a feature selection mechanism. The method of function selection is used to decrease the variance, shorten training time, and so forth (Akojwar and Kshirsagar, 2016; Kulkarni and Sathe, 2014). The process of selecting features must be independent of the process of extracting the feature. Both of these tactics seek to reduce the number of characteristics in the data set while extracting features by creating new types of variables that include and exclude features currently in the data without changing the approach (feature selection) (Guo and Wang, 2021; Sathe and Kulkarni, 2014). Classifier design challenges are reduced by selecting characteristics that are both effective and efficient. As a result, after the extraction procedure, the selection of characteristics is an important step in this design (Kumar *et al.*, 2017).

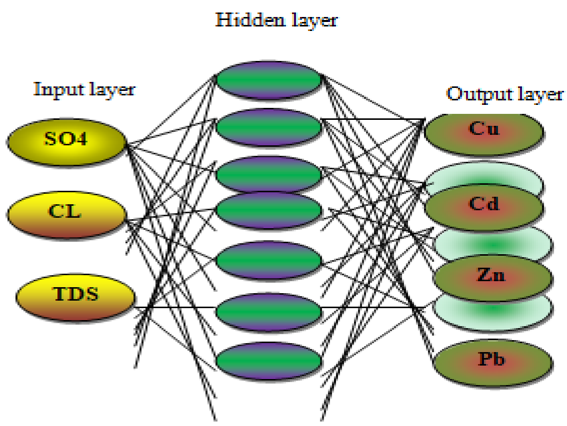


Figure 6. ANN network architecture

6.7. Classification

Modifications are made to SVM regression algorithms to better anticipate future responses. As opposed to searching for hyperplanes that segregate data, SVM regression algorithms look for a model that is almost identical to the measured data except for a few parameter values that lower error sensitivity (Bhagat and Tiyasha, 2021; Kshirsagar *et al.*, 2020). In cases when there are many predictor factors, it is a good fit for huge datasets. In sensors, SVM-aided PA may be used to identify and forecast brain illness and sensor data. Samples belonging to different groups are separated into two groups using the SVM, which has a large number of space points (Ke *et al.*, 2021).

The input characteristics are transferred to a higher-dimensional space and can also be shown as Eq (6)

$$f(x,w)=\sum_{j=1}^{n} w_j h_j(x)+k \tag{6}$$

Where $h_j(\chi)$the set of nonlinear transformation and k is is the bias

7. Results and discussion

7.1. Prediction of distribution of heavy metals using ANN model

About 75% of the datasets were utilized for network training, and the remaining 25% for network testing (see Tables 1 and 2). An ANN's performance is influenced by the number of neurons and the layered architecture, which is the pattern of interconnections between the neurons (Imran *et al.*, 2020; Kumar *et al.*, 2017).

When designing an ANN model, it is vital to ascertain the ideal network structure. Tables 1 and 2 represent a portion of this model's parameter estimation. The optimum network for this analysis is a feed-forward multilayer perceptron with one input layer with three inputs (SO4, Cl, and TDS) and one hidden layer with seven neurons, which is completely coupled to all inputs and uses a hyperbolic tangent sigmoid activation function (Yaseen, 2021) Neurons in the output layer have sigmoid hyperbolic logarithm activation functions (Cu, Cd, Pb, and Zn). The architecture of a neural network is shown in Figure 6. Performance metrics of the ANN model for the prediction of Cd, Cu, Zn, and Pb in soil (training and testing data) had shown in Figures 7 and 8.

Table 1. Performance analysis of ANN model for testing data

Cd		Cu		Zn		Pb	
Mean square error	R^2	Mean square error	R^2	Mean square error	R^2	Mean square error	R^2
0.78	0.05	0.09	0.65	0.05	0.34	0.05	0.47
0.23	0.20	0.07	0.43	0.03	0.52	0.03	0.48
0.08	0.40	0.05	0.38	0.04	0.50	0.05	0.51
0.07	0.67	0.06	0.63	0.03	0.58	0.06	0.58
0.03	0.53	0.06	0.49	0.02	0.56	0.02	0.56
0.02	0.80	0.02	0.82	0.01	0.76	0.01	0.70

Table 2. Performance analysis of ANN model for training data

Cd		Cu		Zn		Pb	
Mean square error	R^2	Mean square error	R^2	Mean square error	R^2	Mean square error	R^2
0.63	0.04	0.20	0.65	0.30	0.15	0.03	0.29
0.35	0.08	0.18	0.82	0.21	0.06	0.01	0.23
0.17	0.20	0.05	0.38	0.17	0.15	0.06	0.56
0.29	0.03	0.06	0.67	0.13	0.58	0.23	0.21
0.16	0.53	0.30	0.23	0.09	0.56	0.02	0.55
0.05	0.56	0.02	0.70	0.05	0.62	0.04	0.59

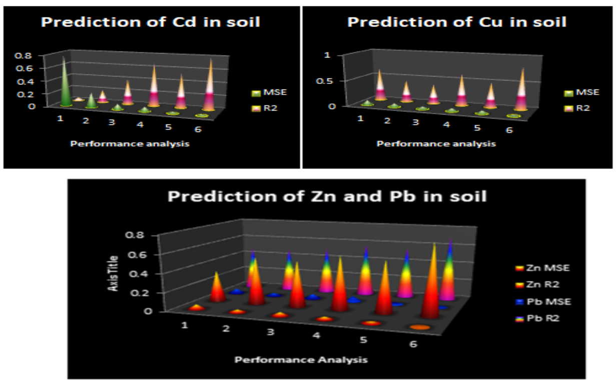


Figure 7. Performance metrics of ANN model for prediction of Cd, Cu, Zn and Pb in soil (testing data)

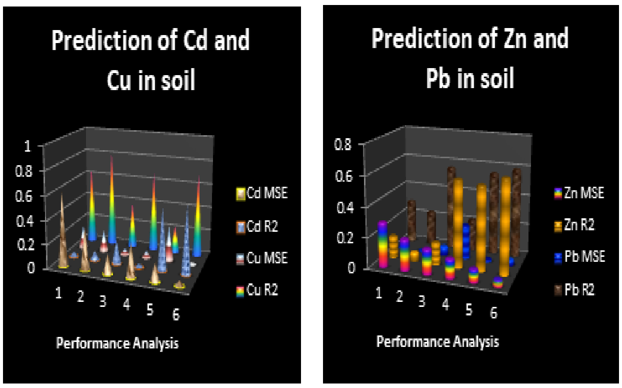


Figure 8. Performance metrics of ANN model for prediction of Cd, Cu, Zn, and Pb in soil (training data)

Table 3. Performance analysis of NB model for testing data

Cd		Cu		Zn		Pb	
Mean square error	**R^2**	**Mean square error**	**R^2**	**Mean square error**	**R^2**	**Mean square error**	**R^2**
0.87	0.10	0.12	0.75	0.09	0.44	0.08	0.57
0.34	0.26	0.10	0.63	0.05	0.62	0.06	0.53
0.10	0.47	0.11	0.46	0.12	0.57	0.10	0.61
0.09	0.77	0.17	0.77	0.71	0.68	0.09	0.65
0.06	0.63	0.13	0.54	0.05	0.66	0.04	0.46
0.05	0.92	0.07	0.89	0.04	0.85	0.03	0.83

7.2. Prediction of distribution of heavy metals using bayesian networks

A Naive Bayes is a technique for training. The theorem determined the form of new factor variables in terms of the highest probability. The NB uses data sets to evaluate a certain class's vector likelihood (Ke *et al.*, 2021; Pardeshi *et al.*, 2017). Depending on its likelihood value for individual vectors the development work class is determined. For the grouping of texts, NB is used. About 75% of the datasets were utilized for network training, and the remaining 25% for network testing (see Tables 3 and 4) then the most possible class is allocated test text using the Bayes rule in Eq. 7 Performance metrics of NB model for prediction of Cd, Cu, Zn and Pb in soil (training and testing data) shown in Figures 9 and 10.

$$E(A|Y) = \frac{E(Y|A)E(A)}{E(Y)} \tag{7}$$

Where E (A|Y) = posterior probability of class

E (A) = Prior probability of class

E (Y|A) = Likelihood which is the probability of the predictor given class.

E(Y) = is the prior probability of the predictor

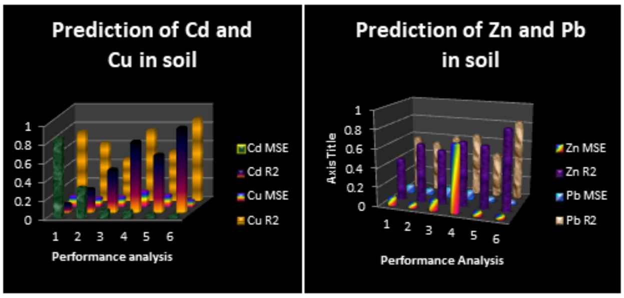


Figure 9. Performance metrics of NB model for prediction of Cd, Cu, Zn, and Pb in soil (testing data)

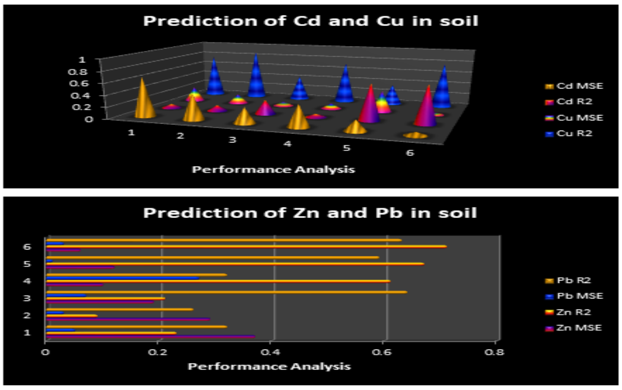


Figure 10. Performance metrics of ANN model for prediction of Cd, Cu, Zn, and Pb in soil (training data)

Table 4. Analysis of the NB model's performance for training data

Cd		Cu		Zn		Pb	
Mean square error	**R^2**	**Mean square error**	**R^2**	**Mean square error**	**R^2**	**Mean square error**	**R^2**
0.68	0.07	0.25	0.75	0.37	0.23	0.05	0.32
0.45	0.10	0.16	0.88	0.29	0.09	0.03	0.26
0.27	0.25	0.07	0.43	0.19	0.21	0.07	0.64
0.38	0.06	0.09	0.72	0.10	0.61	0.27	0.32
0.19	0.63	0.36	0.35	0.12	0.67	0.01	0.59
0.06	0.66	0.04	0.78	0.06	0.71	0.03	0.63

Table 5. Details of Figure 4

Tumor segment	Size of brain image	No. of tumor segment pixel	Area of Tumor (mm^2)	No. of tumor boundary pixels
S-1	1024*1024	1997	137.756	635
S-2	1024*1024	2250	165.341	490
S-3	1024*1024	2790	183.592	315

7.3. Use of an SVM algorithm to predict the health effects of heavy metals

Figure 10 and Table 5 analyze abnormal brain models dividing the brain into clusters and isolating the segment of the tumor using the SVM model where the segment of the brain is isolated by identifying a relationship between the white pixels and their neighbors in the third cluster, depending on the 'region' characteristics of the tumor (Figure 11).

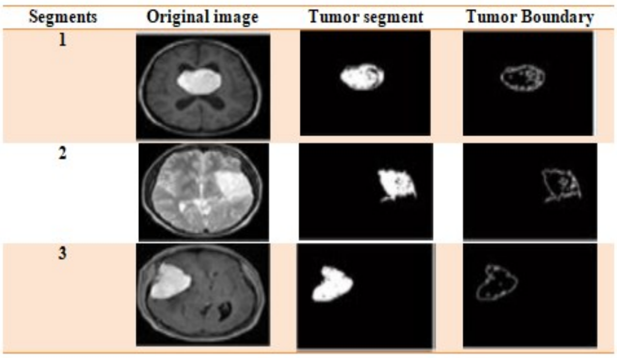


Figure 11. Tumor segment isolation

8. Conclusion

Heavy metals were found to be one of the most serious dangers to soil and human health, as this analysis showed. As a result, the IoT and SVM classifier was used to analyze human illnesses caused by heavy metal exposure. There are several ways in which these metals enter the environment. Expensive and ecologically damaging conventional restoration methods are out of reach for most people. As a result, the rehabilitation of soils contaminated with heavy metals will require the use of low-cost and environmentally favorable technology. The objective of the paper was to use intelligent models to forecast changes in physical and chemical soil characteristics and, as a result, the levels of cadmium, zinc, copper, and lead in contaminated soil. The results of this paper examined the accuracy of two models (the ANN and the NB) when it came to predicting soil levels of cadmium, zinc, copper, and lead. When it comes to the outcomes, it was found that the ANN model performance was good at predicting the levels of cadmium, zinc, copper, and lead in samples during the training stage, but the ANN model performed significantly better in the testing stage. The neural network model with a higher R2 (0.80 for cadmium,0.82 for copper, 0.76 for zinc, and 0.70 for lead) and less MSE (0.02 for cadmium,0.02 for copper, 0.01 for zinc, and 0.01 for lead) neural network models were more efficient than NB models.

Declaration

Ethics Approval and Consent to Participate

No participation of humans takes place in this implementation process

Human and Animal Rights

No violation of Human and Animal Rights is involved.

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Data availability statement

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Conflict of Interest

Conflict of Interest is not applicable in this work.

Authorship contributions

All authors have equally contributed to the article.

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