IoT Enabled Intelligent System for Radiation Monitoring and Warning Approach using Machine Learning

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Summary

Internet of things has revolutionaries every field of life due to the use of artificial intelligence within Machine Learning. It is successfully being used for the study of Radiation monitoring, prediction of Ultraviolet and Electromagnetic rays. However, there is no particular system available that can monitor and detect waves. Therefore, the present study designed in which IOT enables intelligence system based on machine learning was developed for the prediction of the radiation and their effects of human beings. Moreover, a sensor based system was installed in order to detect harmful radiation present in the environment and this system has the ability to alert the humans within the range of danger zone with a buzz, so that humans can move to a safer place. Along with this automatic sensor system; a self-created dataset was also created in which sensor values were recorded. Furthermore, in order to study the outcomes of the effect of these rays researchers used Support Vector Machine, Gaussian Naïve Bayes, Decision Trees, Extra Trees, Bagging Classifier, Random Forests, Logistic Regression and Adaptive Boosting Classifier were used. To sum up the whole discussion it is stated the results give high accuracy and prove that the proposed system is reliable and accurate for the detection and monitoring of waves**.** Furthermore, for the prediction of outcome, Adaptive Boosting Classifier has shown the best accuracy of 81.77% as compared with other classifiers.

Keywords:

Internet of Things (I.O.T), Prediction Model, Monitoring System, Decision Tree, Trained Model, Bagging and Boosting, Ultraviolet Waves, Electromagnetic Waves.

1. Introduction

In today's world everyone is encircled with smart devices and the Internet of Things helps people live and work smarter as well as gain complete control over their lives. In addition, IOT ecosystem consists of web-enables smart devices that use embedded systems, such as processors, sensors and communication hardware [1]. The embedded system was further used to collect, send and act on data they acquire from their environments. Therefore, IOT devices share sensor data they gather by connection to an IOT gateway. Although, this is making life easier and worth living but one cannot overlook some disadvantages of IOT; such as the number of connected devices increased, the potential that a hacker could steal confidential information also increases[2]. Similarly, these smart devices emit rays that are not safe for human health and the example of these rays is electromagnetic waves that are all around us and are significant part of commonly used devices such as cellphones[3], access-points, biometric sensors, Microwave oven, communication satellite and all other Internet of things (IOT) devices[4]. Moreover, these electromagnetic waves are categorized in to seven types: Radio Waves, Microwaves, Infrared Rays, Visible Light, Ultraviolet, X-rays and Gamma Rays. In IOT enabled Intelligent System for Radiation Monitoring and Warning using Machine Learning, there exit wireless systems in which different machine learning algorithms and dual sensors are attached to Mega microcontroller, radiation information is obtained. It cannot be overlooked that the intensity of the electromagnetic waves exists in normal to dangerous range in our surroundings. Therefore, researcher used diverse machine learning classifiers i.e. Logistic Regression, Support Vector Machine, Naïve Bayes, Random Forests, Bagging Trees, Extra Trees, Decision tree and gradient boosting to predict levels of radiations.

Over the past two decades, IOT has different approaches such as smart dustbin, monitoring environment, IOT based irrigation system, smart healthcare system, and traffic control. the devices like cellphones, hand-held devices (iPads, tabs), smart LEDs, microwave ovens, access points, Wi-Fi devices, Bluetooth devices, infrared devices etc. are increasingly being used in our homes and offices. Such devices are harmful for brain and skin cells of infants, patients, people having sensitive skins, etc. because these devices emit high frequency of electromagnetic and other waves and rays[5] .Similarly, the high frequency Radio Frequency (RF) waves and Microwaves are dangerous and have the ability to change the structure of the

Manuscript received May 5, 2023
Manuscript revised May 20, 2023
https://doi.org/10.22937/IJCSNS.2023.23.5.16

specific cells and molecules of brain tissues, bones, cerebrospinal fluid and skull. Such waves and rays are more dangerous for children, specifically infants as they can absorb 50% more radiations than adults[6, 7].Moreover, skin darkening (tanning) and skin-burn happens when the human skin is exposed to high intensity sunlight that has infrared and ultraviolet radiations[8]. High exposure of ultraviolet radiation can cause the skin cancer[9].X-Rays and Gamma rays are more powerful and dangerous for health. Although, these rays are dangerous for all humans but Children are more sensitive to radiation and it is concluded by UN scientific Committee on the Effects of Atomic Radiation[10].

Currently, there is no available device or Predictive Model that can detect the dangerous levels of waves and rays that can hurt infants and patients with sensitive skin according to a layman observation. So, there is a dire need to develop a IOT enabled Intelligent System for Radiation Monitoring and Warning using Machine Learning that uses a set of cheap sensors and IOT technology to protect infants, patients with burns, patients having low immunity and patients having any kind of skin allergy. In this paper, researchers introduce a system that was based on IOT concepts using different sensors that can detect intensity levels different waves. The available sensors are Electromagnetic wave sensor and Ultraviolet wave sensor. In this paper, researchers have used the decision-making power of decision tree for further analysis of the results according to different situations. The results give high accuracy and prove that our system is reliable and accurate for the detection and monitoring of waves. In the past years, many sensors fusion methods have been proposed for autonomous driving applications[11, 12]In addition, [13, 14]examine the existing problems of the current sensor fusion algorithm. According to different data processing methods, sensor fusion can be divided into three levels: the data layer, feature layer and decision layer.

The rest of the paper is divided into following sections: Section 2 is about the related work, Section 3 presents research methodology of the developed system, Section 4 describe the implementation details of the system, Section 5 display the results and Section 6 is about conclusions.

2. Related Work

"Internet of things" (IOT) is a new technology in the area of networking where a number of computing devices and things are connected with each other and share their data using communication technologies and it is one of the most important fields of future technology. IOT and sensor based applications made our life easier. IOT has become the solution of today's problem. There are many popular monitoring applications of IOT that are working well and provide satisfying results such as Health monitoring, environmental monitoring, smart city, smart homes etc.

Environmental monitoring effectively employs the IOT technology for different conditions like rain fall, snow fall, and temperature etc. In this regard Fire detection also comes in Environmental monitoring applications. All of these systems integrate for decision making with global or central system using IOT technology[15]. As an Integrated Environmental Monitoring Device developed by the author of this literature[16] which consisted of temperature, ultraviolet (UV), PM2.5, humidity and sound sensors to collect data for an Android based mobile phone application using a web based database, with the data of location obtained from GPS system of mobile phone. That system presented the evaluated real time data with visualization of data through the mobile phone application and one volunteer tested it in Hong Kong for a brief period of time. The results revealed that the system could respond to evolving environments, such as indoor and outdoor areas.

A multi sensor and intelligent Fire Monitoring and Warning System (FMWS) was developed by [17]which was based on Fuzzy Logic for the identification of the true existence of fire and alert to the Fire Management System (FMS). It used low cost and tiny sensors like flame sensor and temperature sensor. To ensure reliability of the system the alert messages were sent by using the technology of global system for mobile communication (GSM). On the detection of the fire, alternative controlling mechanisms were activated like water showers and it also minimized the false alarm rate. Experimental results proved that the system can identify the fire incidents at initial stages.

An improved integrated environmental monitoring system used to monitor environmental changes developed by [11] .It used Smart City framework and nine environmental parameters like temperature, humidity, CO, Volatile Organic Compounds (VOCs), UV Index, PM10, SO2, PM2.5 and noise for monitoring with nine micro sensors that are combined in a single unit along server-based platform. The values of these parameters transmitted to server and for long term analysis stored in a web database. A calibration test displayed the accuracy of the system on practical experiments. Environmental changes predicted by linear regression and the results showed the effects of some factors on metropolitan areas.

Similarly, a Smart Watering System (SWS) was developed by [12] using IOT Technology and an

Android mobile app for efficient water consumption in medium sized fields and garden. Cheap sensors like Soil Moisture Level, Light Intensity, air humidity and air temperature used to collect real time-data. The Fuzzy logic approach and block chain used in taking smart decisions for water scheduling. The results of the experiment proved that it was a secure and smart application to efficiently manage the process of watering to plants.

A radiation monitoring system based on a microcontroller is presented in this research[18]. The system calculates an accumulated radiation dosage over time and sends out alarms when the rate of the appropriate dose surpasses a particular threshold. A prompt response to emergency situations, such as exceeding the authorized power of the equal radiation dose and accumulator charge regulation, ensures the system's excellent reliability. In addition, they created an electronic circuit for the radiation monitoring system using a microcontroller. Additionally, an operational algorithm as well as software for the Arduino Uno board's ATmega328P microprocessor have been developed.

This paper [19] focuses on the development of the digitized dairy farming system comprised of different computer based technologies including internet of thing, edge computing and artificial intelligence. The system is developed for monitoring and optimizing he performance of dairy form and moreover providing the quality product to the customers with shorter response time. The system is employed on a real scenario of dairy farm with data acquired from barn sensors, air thermometer, hygrometer, cattle sensors and ageo-metreo stations. For the Deployment of the system web services were employed which integrated various machine algorithms from the cloud computing platform.

In this research [20] article author proposed a system named Integrated System Health Management (ISHM) this system is based on the information from the pressure, temperature and vibration sensors and further processing on the data through different machine learning algorithms like regression ensemble methods and deep learning. This system is helpful for the sustainability and health management of the aerospace system. This paper also focuses on the challenges faced by the author for the development of the system and future application of this system in traffic management, urban air mobility and distribution system.

3. Material and Methods

The proposed system has the ability to predict the outcome of radio and ultraviolet waves on the body of human being. For this purpose, sensors are connected with mega Arduino to take data of radiation intensity from surroundings so that intensity levels of the rays can be checked. Infrared Sensor, Ultraviolet Sensor, Electromagnetic Sensor, Gamma Radiations sensors has been connected to Arduino mega and data collected by the system and converted to data file for further use. This approach was based on intelligent decision making system to verify safe and dangerous levels of intensity of rays. All the data stored in Excel sheets and the system alerts the user when intensity level of rays becomes dangerous, through an android mobile application.

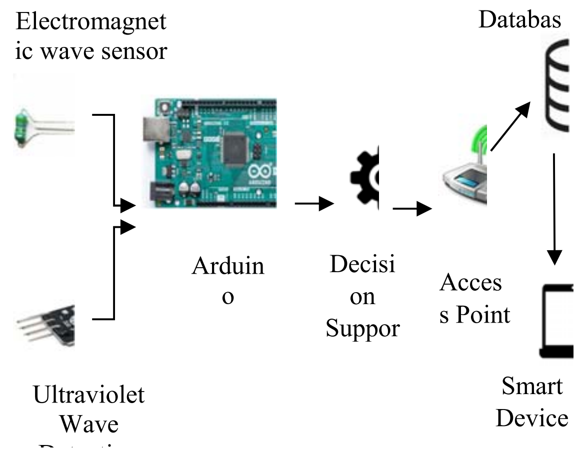


Figure 1: Design of hardware integration of purposed system

Smart Radiation Predictive System (SRPS) use the intelligent decision making system to verify safe and dangerous levels of intensity of waves. All the data stored in database and the system alerts the user when intensity level of waves becomes dangerous, through an android mobile application. This system consists of three modules. The basic structure and the components of the purposed system are:

- Module for Data Collection
- Decision Support System
- Output Module

The working of the system is presented in the block diagram (Figure 2).

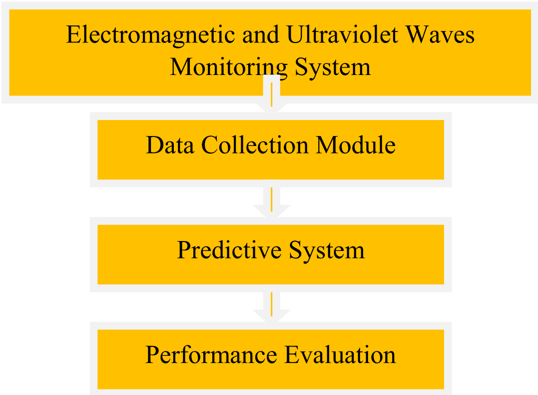


Figure 2: Block Diagram of Smart Radiation Monitoring System

Sensor Based Data Collection

Data collection through sensors was the first step in the proposed system. Such as Electromegnetic Wave Intensity through Electromagnetic Wave sensor and Ultraviolet wave intensity through Ultraviolet Wave detection sensor. For data collection process sensors were connected to the Arduino Mega microcontroller. Electromagnetic wave sensor and Ultraviolet sensor are connected to microcontroller through Analog ports of Arduino. Microcontroller works as a central point that takes inputs from the sensors transmit data of sensors to decision support system. The decision support system sends the data to database after performing some action on the data. Then the data sends to user through Smart Devices.

Predictive System

Predictive molding was a statistical process that uses probability distribution to forecast the output. Prediction was used to build the models. These predictors are basically the variables that make up the future results. When data was collected from various variables a statistical model was design based on probability. In this regard, researchers used different machine learning classifiers i.e. Logistic Regression, Support Vector Machine, Naïve Bayes, Random Forests, Bagging Trees, Extra Trees, Decision tree and Adaptive boosting.

Components of Decision Support System:

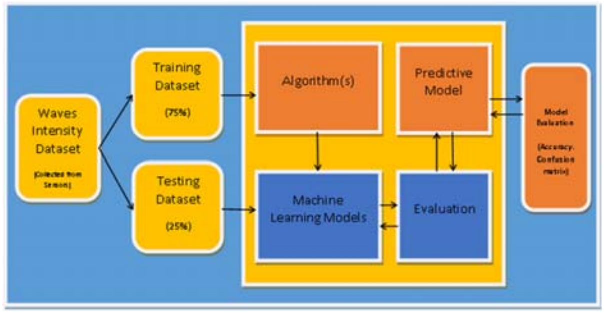


Figure 3: Components of Decision Support System

Figure 3 shows the components of decision support system each component has been separately defined below:

Dataset

The dataset contain total of 2068 mixed instances with no missing values from each of two sensors. The data is preprocessed by identification and removal of black cells that contain any missing value or the numeric value like 9999, this data referred to as cleaned data comprising of 1955 pulses that was necessary for the optimized performance. The former data with missing values used as a baseline data for further processing and model evaluation. The detail of dataset with respect to each sensor and radiation is given below in the table no 1.

Table 1: Details of dataset

Sr.No	Radiation	Sensor	Baseline Data	Cleaned Data
1.	Ultraviolet	Name: Ultraviolet sensor Model: UVM-30A	946	923
3.	Electromagnetic	Name : Electromagnetic Wave Detection Sensor Model: Electromagnetic Wave Detection Sensor V3.0	1122	1032

The Trained Model

The trained model contains all the characteristics, which were validated while constructing the model with training dataset. The trained model (Knowledge Base) performs like a brain while testing with high accuracy and efficiency. While compiling and executing data, some of facts and rules were not modifying themselves. There were some facts that relate to the entire system's specific consultation. These facts extend themselves to generate different decisions in the operational phase along with static knowledge. Overall the trained model was trained with related knowledge which is very helpful in understanding and solving the problems. Present study used 30% data for testing and 70% data for training.

Predictive Model:

The Predictive modeling is a statistical probability process that carries various statistical methods like correlation matrix, probability distribution, testing of hypothesis to forecast the outcomes. In the light of some decision rules (Table 2) set that are:

Table 2: Decision Rules

Sr. No	Electromagnetic (%)	Ultraviolet (Index)	Relative Effects (Labels)
1	0.0-20.0	0-2	Safe
2	0.0-20.0	3-5	Moderate
3	0.0-20.0	6-7	Dangerous
4	0.0-20.0	8-10	Dangerous
5	0.0-20.0	11+	Very Dangerous
6	20.1-40.0	0-2	Safe
7	20.1-40.0	3-5	Moderate
8	20.1-40.0	6-7	Dangerous
9	20.1-40.0	8-10	Dangerous
10	20.1-40.0	11+	Very Dangerous
11	40.1-60.0	0-2	Normal
12	40.1-60.0	3-5	Moderate
13	40.1-60.0	6-7	Dangerous
14	40.1-60.0	8-10	Dangerous
15	40.1-60.0	11+	Very Dangerous
16	60.1-80.0	0-2	Moderate
17	60.1-80.0	3-5	Moderate
18	60.1-80.0	6-7	Dangerous
19	60.1-80.0	8-10	Dangerous
20	60.1-80.0	11+	Very Dangerous
21	80.1-100	0-2	Dangerous
22	80.1-100	3-5	Dangerous
23	80.1-100	6-7	Dangerous
24	80.1-100	8-10	Very Dangerous
25	80.1-100	11+	Very Dangerous

Output Module

An Android mobile application was developed for IOT enabled Intelligent System for Radiation Monitoring and Warning using Machine Learning,so that the user can get alerts when these harmful waves are present. The basic controls of the applications were put in tabbed menus. The user gets the access for main features of the application as monitoring surroundings of the user.

Implementation

In the development of the proposed SRMS, less expensive and tiny sensors were used technically to sense the presence of Radio and Ultraviolet waves. An Ultraviolet sensor UVM-30A was used to detect the ultraviolet radiations and the Electromagnetic Wave Sensor V3.0 is used for the detection of electromagnetic wave strength. These two sensors were involved with the Arduino Mega 2560. The working and properties of sensors and Mega Arduino were discussed below:

Arduino Mega microcontroller

To implement projected Smart Radiation Monitoring System, a mega 2560 microcontroller (Figure 4) was used due to its exclusive structure such as Digital input and digital output, PWM output, analog input, etc.

Figure 4: Arduino Mega 2560 Microcontroller

The microcontroller consists of 16 Analog input pins, 54 Digital Input/output pins out of which 15 can be used as PWM output, a 16 MHz oscillator, a power jack, a USB connection, a reset button and an ICSP header. The sensors were connected with microcontroller through jumper wires to access the data from sensors. Properties of microcontroller Arduino Mega 2560 are showed in (Table 3).

When the Arduino Mega 2560 was linked to computer by USB port, it looks on PC as virtual com port to software. The text information was referred and from Arduino board using sequential monitor in our implementation. Arduino Integrated Development Environment was used for programming. Arduino Mega 2560 in this approach.

Ultraviolet Ray Detection Sensor (UVM-30A): The

Flash Memory	256 KB of which 8KB used
Mega Microcontroller	Atmega2560
Input Voltage (Limit)	6-20V
DC for 3.3V Pin	50mA
Clock	14MHz
DC per I/O Pin	40mA
Digital pins	54 (out of which 15 provide PWM output)

ultraviolet sensor (Figure 6) using the UVM-30A chip, can detect the level of ultraviolet radiation. It operates between the temperature -20ºC to 85ºC, voltage between 3V to 5V and has a high response time < 0.5 s. The operational range of spectral sensitivity is from 200nm to 370 nm which covers all ranges of UVB and 62.5% range of UVA. The strength of ultraviolet radiation is represented by ultraviolet index which was directly proportional to strength of ultraviolet radiation. The intensity of electrical signal emitted by ultraviolet sensor was proportional to the length, depending on the detected wavelength.

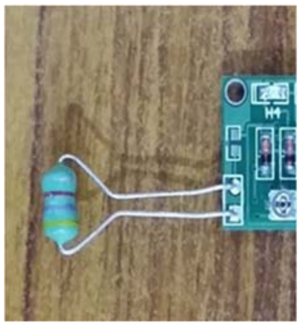


Figure 5: Electromagnetic Wave Detection Sensor V3.0

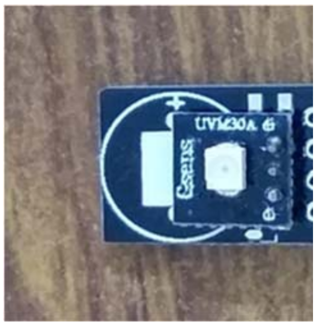


Figure 6: UVM-30A Ultraviolet Wave Detection sensor

Ultraviolet sensor was connected with Arduino Mega microcontroller for implementation. VCC, Output and GND were pins of ultraviolet sensor that were respectively connected with Arduino 5V, A0 and GND pins using jumper wires. After configuration of UV sensor with Arduino, a code was written in Arduino IDE. Properties of ultraviolet sensor were given in the Table

Electromagnetic Wave Detection Sensor V3.0: In the implementation of SRMS, an electromagnetic wave detection sensor (Figure 5) was also used. The purpose of using the electromagnetic wave sensor in the purposed work was to check the presence of radio wave and to measure the strength of radio wave. It detects the radio wave in its surrounding. It covers a small range of radio waves.

The electromagnetic wave sensor has two kinds of output: one way is the voltage display the radio wave strength and the other way LED displays the radio wave strength. Through LED there are four grades to show the electromagnetic strength: A) 10 dB (H1 Light), B) 20dB (H1+ H2 Lights), C) 40dB (H1+H2+H3 Lights) and D) 60dB (H1+H2+H3+H4 Lights). These lights also show the strength of radio wave.

In the implementation, the electromagnetic wave detection sensor is connected to the Arduino Mega microcontroller. The electromagnetic wave sensor 5V Pin is attached with Arduino 5V Pin, module Output Pin was attached with A1 Pin of Arduino and GND Pin of the sensor was attached with Arduino GND Pin using jumper wires. After configuring the electromagnetic wave sensor with arduino, Arduino IDE was used to write a code. Properties of electromagnetic wave sensor are given below in the Table 4.

Table 4: Properties of Sensors

Properties of Ultraviolet Sensor		Properties of Electromagnetic Wave Sensor	
Model	UVM-30A	Model	Electromagnetic Wave Detection Sensor V3.0
Voltage (Input)	DC 3-5V	Input Voltage	5V
Voltage (Output)	DC0-1V (Corresponding 0-10 UV Index)	Output	Digital and Analog
Detected UV Wavelength	200nm to 370nm	Working Current	3mA
Current	0.06mA (0.1mA max)	Respons e Range	50Hz to 100Mhz
PCB Size	28mm*12mm*10m m	Respons e Time	< 0.5s
Temperatur e	-20 ºC to 85 ºC	PCB Size	32mm*18mm*8m m

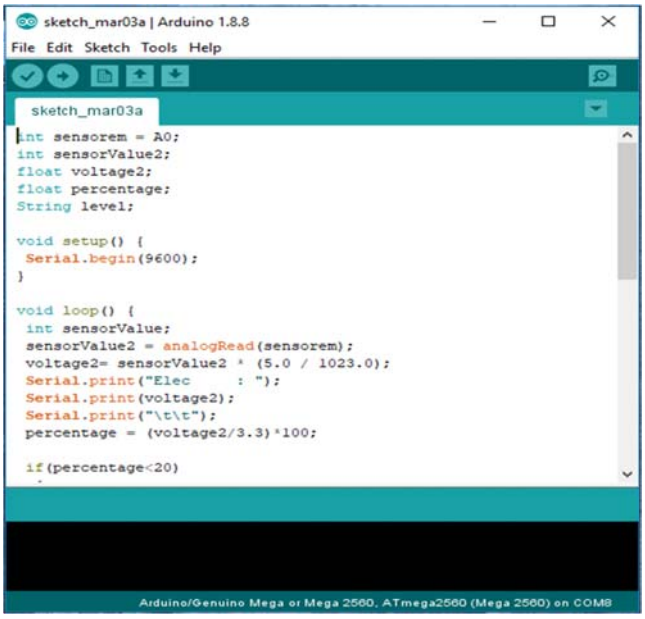


Figure 7: Arduino IDE to write program Coding:

For coding Arduino IDE is used. In the implementation, Arduino IDE Version 1.8.8 was used for programming and hardware configuration as shown in figure 7. However for getting desire output of sensor's data the code was customized. C language was used for writing code in Arduino IDE, and then this code was uploaded on the board and output was displayed on the serial. Data of both sensors was collected in the Excel sheets.

Recording Sensor Data in Experiment:

The data of the sensor appears on the serial monitor of the arduino. For storing data in excel sheets; a software "PLX-DAQ" was used. It was used to store the real-time values of the sensors. The data of the sensors was collected in excel sheets in different scenarios such as for low moderate and high intensities of rays. The values of electromagnetic wave sensor were store in percentage and values ultraviolet sensor in indexes. Initially sensor produces data in voltages then calibrates raw data into proper units.

Python based Jupyter Notebook was open-source software. It generates the accuracy of prediction model. Unbalanced classifications represent a challenge for prediction modelling, since for most classification machine learning algorithms the same number of examples have been developed for each class. This leads to poorly predicted models, particularly for the minority class. The concern was the minority class is usually more important, than the mainstream class to classification errors. So, the data set was balanced by eliminating the outliers in this research. In statistical sense, Correlation Matrix was basically representing the relationship between dependent and independent quantities (x on y and y on x) as well as their positive and negative relationships.

An intermediate result called the correlation describes the best of the linear association. Correlation describes the strength and direction of the linear (straight-line) The correlation was denoted by r that is mention in equation 1, varies from +1 and -1. As shown in equation 1.

$$r_{xy} = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2 \sum(y_i-\bar{y})^2}} \quad (1)$$

Algorithm of Adaptive Boosting Classifier
Input:
Input data $(x, y)N_{i=1}$ to N
Number of Iterations M
Choice of the loss function $\cap$ (y, f)
Choice of the base learner model h(x, $\boldsymbol{\theta}$)
Algorithm:
Initialize f_0 with a constant
For t=1 to M do
Compute the negative gradient g_t (x)
Fit a new base learner function h(x, $\boldsymbol{\theta}_t$)
Find the best gradient-descent step-size p_t
P_t = argmin $_p \sum_{i=1}^{N} \mathrm{yi}, \mathrm{f}(\mathrm{t}-1)(\mathrm{xi}) + \mathrm{ph}(\mathrm{xi}, 0\mathrm{i})$

Adaptive Boosting Classifier

In order to solve the classification problems (discrete data) and regression problem (continues data); the adaptive boosting classifier was adopted by the researcher. The AdaBoost algorithm's main principle is to combine many weak classifiers to create a powerful classifier. A group of base classifiers is sequentially trained in this method. The mistake of previous classifiers is used to train each base classifier. Weights are modified during the training process so that if a prior weak classifier misclassified the samples, the classifier's weight is increased (while the weights of correctly classified samples will be decreased). In each training phase, this form of weight change drives the base learners to focus on different data, resulting in highly efficient and diversified classifiers. It reduces a residual value (Actual – Predicted) by choosing a function that points towards the negative gradient; a weak hypothesis and appeared to be the best classifier.

In hypothesis boosting, deferent steps were involved to observe the trained data that apply on algorithms. These observations were strictly analyzed that the newly created learner model was tested on the set of poorly classified data. This idea based on adaboost (adaptive boosting). In this regards, various decision tress were built based on single split (parent/child relationship).

The weighted mean of observation/instances were measured based on trained data by apply algorithms. In this way, many weak learners were added by reducing loss function in the system in linear way. In addboost, the weak learner models associated to the class gives the best prediction votes. On the maximum votes, the new model was predicted. In weighted minimization context, gradient boosting classifiers and weighted inputs were recalculated. Different steps were involved when Ada boosting was applied. In the first step, the difference between actual class value and predicted class value was obtained to minimize the residual value. This classifier produced a future production model by assembling the weak learner model (Decision tree) into strong model is sequential manners. This algorithm work 70% on training and 30% on testing data approximal. It also reduced the over-fitting of discrete data.

Extra Trees

The whole thing by generating a large number of single split decision trees from the training dataset. Predictions were made by apply the statistical measure on the prediction of the decision trees using maximum votes in the case of discrete dataset (classification). It has reached the accuracy of 79.166% to classify the effects of electromagnetic waves.

Bagging Trees

It uses collaborative algorithm planned to recover the accuracy of machine learning algorithms used in statistical methods. It has shown the correctness of 81.25%. While extra algorithms i.e. Random Forests, Support vector machines, Gaussian naïve Bayes, logistic regression and decision trees has shown the accuracies of 80, 77 ,76, 79 and 71% accuracy respectively. Figure below 15 shows the confusion matrix of correctly and incorrectly classified data point by diverse classifiers.

4. Results and Discussion

The proposed approach was a unique and smarter that uses decision making ability of decision tree model and takes its advantages. It was new idea to use the intelligent approach for sensor-based radiation detection system along real time sensed data. The architecture and implementation details of the proposed system are elaborated in previous sections. The intelligent system consists of multiple sensors, different hardware and software modules and a trained model (knowledge base) with set of predefined rules and datasets of the facts gathered by wave's sensors. The trained model was tested by a rule-based inference engine with new data entries. The performance tests of the proposed system were taken by two sensors (electromagnetic wave sensor and Ultraviolet wave detection sensor) by imbedding them in test fields. The sensors provide the real-time input data and it was forward to Excel sheets, decisions were taken on that data and results were shown on an android mobile application so that in response the user can take some actions for their safety. The two types of sensor's data were gathered from two sensors and the calibrated output of sensors was processed with decision tree approach using the classification.

Table 4: Experimental results

Machine Learning Model	Testing Accuracy on cleaned data	Validation Accuracy on cleaned data
Decision Trees	72.9	71.87
Logistic Regression	80.2	79.16
Gaussian Naïve Bayes	77.90	76.56
Support Vector Machine	78.9	77.08
Random forest	81.8	80.20
Bagging Trees	82.3	81.25
Extra Trees	80.4	79.16
Adaptive Boosting	82.9	81.77

Experimental results were shown in the section. The radiation intensities are measured after applying decision rules on the data set and the results are shown graphically. In the present section all the experiments were performed in Python. Researchers evaluated the model accuracy using that data. Below figure shows the validation accuracy of each machine learning model to predict the dangerous outcome of these wave. Moreover, the testing accuracy and the validation accuracy are mentioned in the above table 4 for each of the classifier.

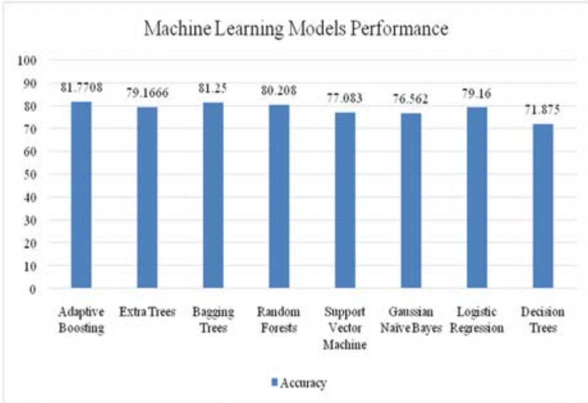
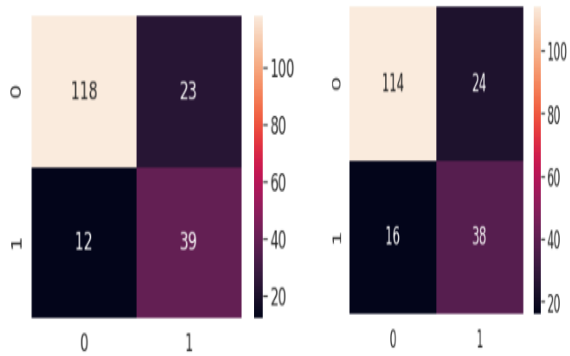
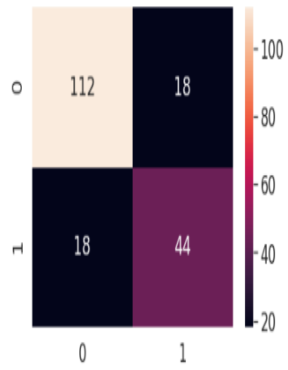


Figure 8: Performance Evaluation of Machine Learning Models

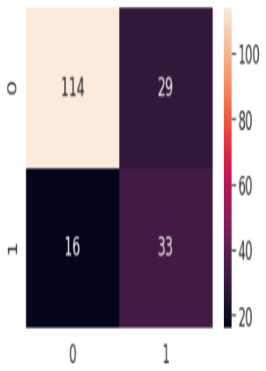
Figure 8 shows the performance of various machine learning models. Dependent and independent features were given as inputs in machine learning algorithms; the output was used as a prediction a future model. In the light of statistical methods, these analytical variables were used to solve the statistical equations. Based on these all scenarios, the target class / label value were categories, because the label contains the target value for the machine learning classifiers based on the training dataset and in order to make a forecast model of any class then you should split the dataset into training dataset (70%) and testing dataset (30%).



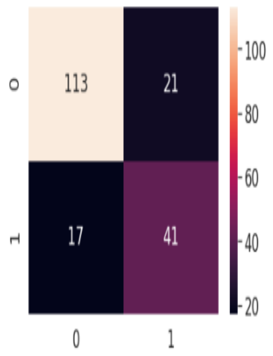
(a) Adaptive Boosting Classifier (b) Extra Trees Classifier



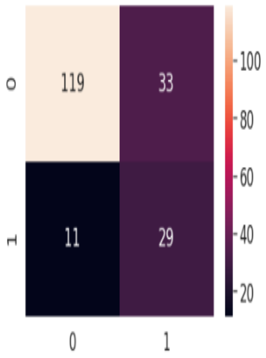
(c) Bagging Trees



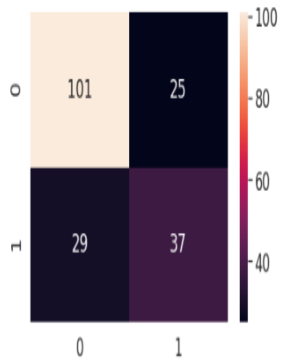
(d) Gaussian Naïve Bayes



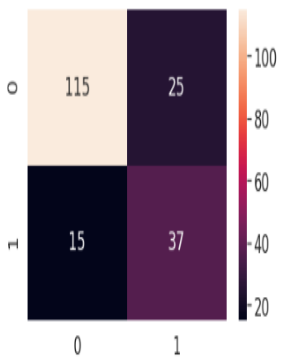
(e) Random Forests



(f) Support Vector Machine



(g) Decision Trees



(h) Logistic Regression

Figure 9: Confusion Matrix of each classification model

The proposed validation dataset contains the up to 500 records. Figure 9 represents confusion matrix of each classification model, classified data by each classifier means it's dangerous and 0 means it was not dangerous, Adaptive Boosting classifier has shown the best performance when considering the best classification of outcome. The accuracy can be calculated from the confusion matrix using equation no 2.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} * 100$$
(2)

Comparison of the results with the state-of-the-art studies

These results obtained through the proposed model are also compared with the recent related studies as shown in the table 5.

In this research [16],) which consisted of temperature, ultraviolet (UV), PM2.5, humidity and sound sensors to collect data for an Android based mobile phone application using a web based database, with the data of location obtained from cheap GPS chipset of mobile phone. The results revealed that the system could respond to evolving environments, such as indoor and outdoor areas. But in this study there is high measure of error. In another research [17]a multi sensor and intelligent Fire Monitoring and Warning System (FMWS) was developed which was based on Fuzzy Logic with overall accuracy of 95.83%.In this study hazardous radiations were not identified. In another paper [12] , a Smart Watering System (SWS) was developed using IOT Technology and an Android mobile app for efficient water consumption in medium sized fields and garden with 95.8% accuracy. In this study the size of the dataset used is not adequate for performance evaluation.

In another research[18] The system calculates an accumulated radiation dosage over time and sends out alarms when the rate of the appropriate dose surpasses a particular threshold. Additionally, an operational algorithm as well as software for the Arduino Uno board's ATmega328P microprocessor have been developed. This study howeverdoes not include any classification of radiation. In another paper [20]author proposed a system named Integrated System Health Management (ISHM) this system is based on the information from the pressure, temperature and vibration sensors and further processing on the data through different machine learning algorithms like regression ensemble methods and deep learning. However this system require a lot of resources.

The proposed study refers to the employment of sensors that detect hazardous radiation and classification of these radiation with adaptive bagging classifier. Experiments were carried out in various ways by employing other state-of-the-art machine learning algorithms including decision trees, SVM, Bagging classifier etc. Dependent and independent features were given as inputs in machine learning algorithms; the output was used as a prediction a future model. In the light of statistical methods, these analytical variables were used to solve the statistical equations. Based on these all scenarios, the target class / label value were categories, because the label contains the target value for the machine learning classifiers based on the training dataset and in order to make a forecast model of any class then you should split the dataset into training dataset (70%) and testing dataset (30%).These implementation provides satisfactory results for the employment of system.

Table 5: Comparison of the results with recent studies

Author's Year	Dataset Used	Sensor Used	Problem Identified	Methodology	Evaluation Measure
[16]	Locally Developed	Ultraviolet, PM 2.5, humidity and sound sensors	Environment Monitoring	Sensors, Bluetooth, GPS and Android Application	Not mentioned
[17]	Locally Developed	Temperature and Humidity Sensor (DHT22), Arduino UNO microcontroller, Flame sensor	Fire monitoring and warning system	Multiple sensors, global system for mobile communication (GSM), Fuzzy logic	95.83%
[12]	Locally Developed	YL-69 Soil Moisture Sensor, DHT-11 Temperature & Humidity sensor, Arduino-UNO R3	Smart watering system	Multiple sensors, Fuzzy logic, Block chain	95.8%
[18]	Locally Developed	ATmega328P microcontroller, SBM-20 Geiger–Mueller counter	Radiation monitoring system	Microcontrollers, Algorithm of the anode voltage adjustment for the Geiger–Mueller counter.	Not mentioned
[20]	Locally Developed	Pressure, temperature and vibration sensors	Integrated System Health Management (ISHM)	Multiple sensors, Regression, ensemble methods and deep learning	Not mentioned
The proposed model	Locally Developed	Electromagnetic Wave Detection Sensor V3.0, UVM-30A, Arduino Mega 2560 Microcontroller	Radiation monitoring and warning system	Microcontrollers, Multiple sensors, Adaptive Boosting, Decision trees	81.77%

5. Conclusion and Future Work

In present age, human beings are surrounded by many dangerous radiations (waves and rays). These radiations badly affected human health especially these rays are very dangerous for infants and patients having skin diseases as well. Moreover, these radiations cause many diseases from a simple infection to deadly diseases like eye infection, headache, skin tanning, skin burn, brain tumor, breast cancer, skin cancer etc. Similarly, these radiations should be avoided but one cannot feel the presence of these waves around oneself. So, there is need of such system which can detect these waves around us. In the said paper low-cost radiation outcome predictive system was introduced that was based on Sensors. The model adopted by present study uses different machine leaning models and the study found that Adaptive Boosting classifier to be the best with accuracy of 81.7% among Logistic Regression, Support Vector Machine, Extra Trees, Bagging Trees, Decision Trees, Gaussian Naive Bayes Theorem and Random Forests Classifier algorithms. In the future, it is recommended for the researchers and scholars to use the Raspberry Pi Microprocessor to increase the efficiency of the system instead of the Arduino Mega Microcontroller. It was a new technology and has its own processing Power, USB ports, built-in Wi-Fi and Bluetooth Modules. The system was used independently and for machine learning models, Hyper tuning and optimization techniques can be effective to improve the performance of models.

Funding Information

This research receive no external funding

Conflict of interest

The author declare no conflict of interest

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