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*Research Article*

# IoT-Enabled Intelligent System for the Radiation Monitoring and Warning Approach

**Muhammad Saifullah, Imran Sarwar Bajwa, Muhammad Ibrahim, and Mutyyba Asghar**

*Islamia University of Bahawalpur, Bahawalpur, Pakistan*

Correspondence should be addressed to Muhammad Saifullah; saif.noraiz@gmail.com

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Radiations are especially harmful to children and infants as their body cells divide rapidly, thus providing radiations more chances to interfere with the organs, leading to a number of diseases, especially those related to the skin. Therefore, the demand for a system that can detect harmful radiations timely and effectively becomes high. Many new and modern techniques comprising radiation protection and alerting systems are being introduced along with improvements and enhancements. This study demonstrates the practical implementation of an IoT-enabled intelligent system based on machine learning for radiation monitoring and warning by classifying radiations and their corresponding effects on infants. The proposed system alerts humans about the danger zones with audio/visual announcements or a buzz so that they can move to a safer place. Along with this automatic sensor system, a real-time dataset is also collected, in which sensor values are recorded along with their effects on infants for experiments. Additionally, the outcomes of the effect of radiations corresponding to the recorded sensor values are classified by using support vector machines, Gaussian naïve Bayes, decision trees, extra trees, bagging classifiers, random forests, logistic regression, and adaptive boosting classifiers. The experiment reveals that the adaptive boosting classifier gives the best accuracy of 81.77% compared to other classifiers.

## 1. Introduction

The usage of devices such as cellphones, hand-held devices, smart LEDs, and laptops is being increased in homes and offices. Radiofrequency electromagnetic rays (RF-EMRs) emitted by such devices are harmful to the brain and skin cells of infants, patients, and people having skin issues. Similarly, long-term exposure to RF-EMR is dangerous and has the ability to change the structure of specific cells and molecules in brain tissues, bones, cerebrospinal fluid, and the skull. Such waves and rays are more dangerous for children, specifically for infants, as they can absorb 50% more radiation than adults. Children and infants' cells divide quickly, giving radiation more opportunities to interrupt the organ system and cause cell damage [1]. RF-EMRs are all around us and are emitted by various devices, such as cellphones, base stations, and access points. The intensity of RF-EMRs ranges from normal to dangerous in our surroundings. Different sources of EMRs have varying levels of intensities, such as mobile phones, communication devices, and base station towers emit radio and microwaves; a microwave oven is the common source of microwaves [2]; the sun produces a large amount of energy including infrared radiation, visible radiation, ultraviolet radiation, and cosmic rays [3]; fire, high-intensity laser beams, and heating objects emit infrared rays [4]; welding devices and photocopier machines emit ultraviolet rays; laboratories and industrial areas emit X-rays, ultrasound, and gamma rays (Figure 1).

Children are more prone to developing cancer through ionizing radiation in their development phase [5]. Because their brain tissues are more absorbent, their skulls are thinner and their relative size is lower, and children absorb more microwave radiation (MWR) than adults. Wireless device MWR has been classified as a potential human

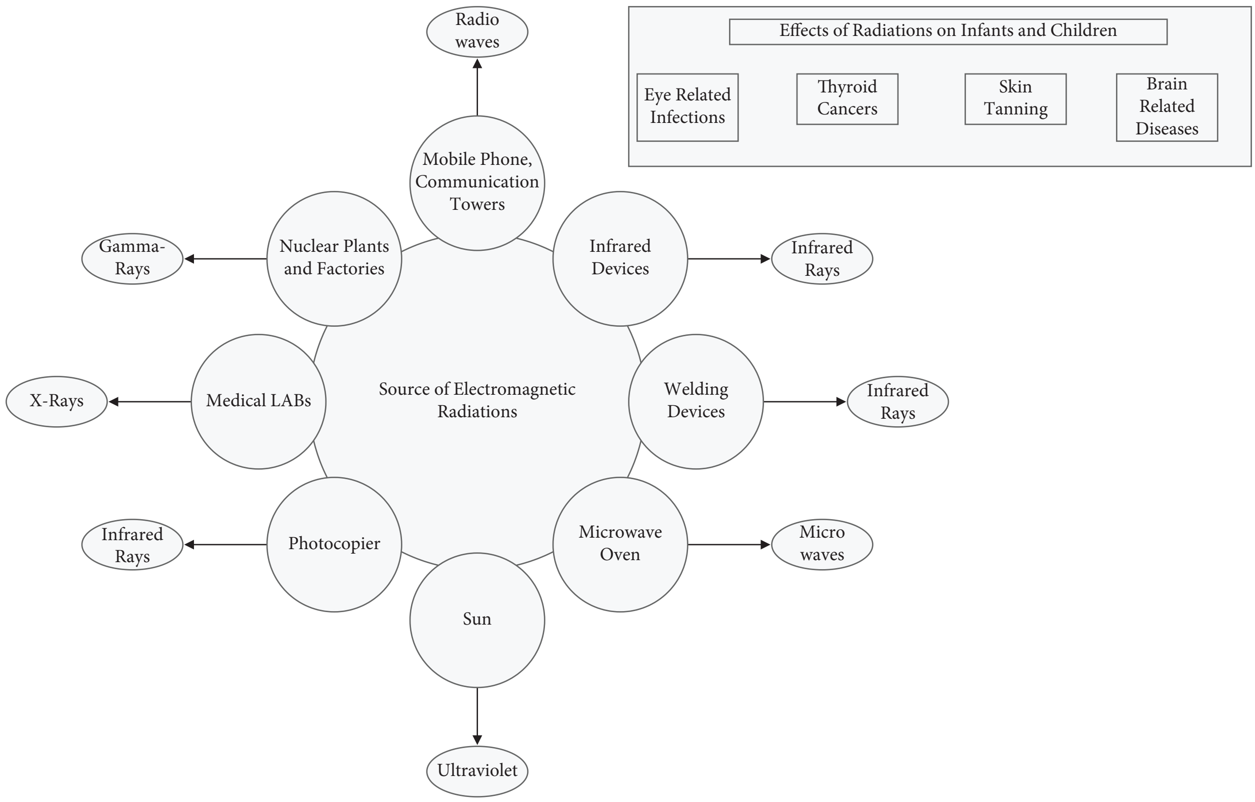


Figure 1: Sources of electromagnetic radiation and their effects.

carcinogen. When children are exposed to any carcinogen, they are at a higher risk than adults. Tumors developing in children may not be diagnosed until adolescence due to the usual delay between first exposure and diagnosis of a tumor, which can take decades. MWR is very harmful to the fetus. MWR exposure can cause protective myelin coating that protects brain neurons to degenerate [6]. Therefore, a specialized mechanism should be developed to save children and infants from harmful radiations.

A research study on rats exposed to 3G mobile phone radiation for 45 days (2 hours per day) resulted in the reduction of the sperm count and modifications in sperm tails [7]. Smart phones when operated in an ideal mode cause lower exposure than those operating at maximum power. The specific absorption rate (SAR) is a parameter that represents the rate at which electromagnetic energy is absorbed per unit of time by a specific biological mass of tissue. In general, SAR is the human body's exposure to RF electromagnetic fields emitted from various sources such as cellular phones. Additionally, it is observed that the specific absorption rate of mobile phones is higher than that of other RF sources. In order to calculate SAR, smart phones, automatic positioning systems (APSs), and head-like phantoms filled with tissue-equivalent liquid are used to assess the SAR for smart phones [8]. In this regard, SAR can be computed using several methods, such as the initial slope method, Box–Lucas method, corrected slope method, and incremental analysis method [9].

Over the past two decades, IoT has different modes of operations, such as access points, Wi-Fi devices, Bluetooth devices, infrared devices, smart trash bins, monitoring environment, IoT-centered irrigation systems, smart traffic control, and healthcare systems. Devices such as cellphones, hand-held devices (iPads and tabs), smart LEDs, and microwave ovens are increasingly being used in our homes and offices. Such devices are harmful to the brain and skin cells of infants, patients, people having sensitive skin, etc., because these devices emit high frequencies of electromagnetic and other waves and rays [10]. An IoT-based architecture along with applications and security for the design and development with sensors in 6G is provided in [11]. Similarly, high-frequency radio waves and microwaves are dangerous and have the ability to change the structure of specific cells and molecules in brain tissues, bones, cerebrospinal fluid, and the skull. Such rays are more dangerous for children, specifically for infants, as they can absorb 50% more radiation than adults [12, 13]. Moreover, skin darkening (tanning) and skin-burn happen when the human skin is exposed to high intensity sunlight that has infrared and ultraviolet radiation [14]. High exposure to ultraviolet radiation can cause skin cancer [15]. X-rays and gamma rays are more powerful and dangerous for health. Although these rays are dangerous for all humans, children are more sensitive to radiation, as is concluded by the UN Scientific Committee on the Effects of Atomic Radiation [16]. Continuous monitoring would substantially assist in taking preventive measures such as raising an alarm in the event of an incident. As a result, many countries throughout the world have suggested creating a variety of ways for monitoring the amount of radiation in the environment to detect any aberrant releases or discharges.

The author in [17] presents a survey that highlights the most relevant healthcare-based Internet of things (H-IoT) applications assisted by smart city infrastructure with the help of new technologies and tools to provide services based on several models with the best use of low-cost sensors, hence focusing on the possible research challenges along with the opportunities in this research area. Moreover, the recent elaborations in terms of sensing principles, sensing integrated with RFID (radiofrequency identification) technology along with its advantages and disadvantages, the scattering behavior of electromagnetic waves, and the bad effects of EMI (electromagnetic interference) on medical devices and patients who depend on these devices are reviewed and listed in [18–23].

There are various methods for monitoring and analyzing effects related to high-energy electromagnetic radiation as described in the radiation early warning system (REWS) [24]. The REWS is made up of multiple electromagnetic detection sensors that are dispersed around a specified area for monitoring radiations and ringing an alarm on long-term exposure to high electromagnetic radiation. Typically, established threshold values are used to determine alerts, which are based on observations (i.e., experience).

Existing REWS are time consuming, labor-intensive, and risky. In fact, when an alarm is produced, the system spends a significant amount of time and effort analyzing metrics derived from the meteorological datasets to evaluate the alert as true or false. Due to the absence of automation, these systems cannot usually classify the alert right away because they must wait for more gamma ray data to determine if they get back to normal.

Currently, there is no available tool approach at homes that can detect and process the dangerous intensity levels of electromagnetic waves, which are hazardous to infants and patients with sensitive skin according to a layman observation. Therefore, there is a dire need of developing an IoT-enabled intelligent system for radiation monitoring and warning using machine learning, which 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 is based on the IoT concept using electromagnetic radiation sensors, which detect the intensity of electromagnetic radiation.

In this paper, researchers after collecting the sensor's data have used the decision-making power of decision trees for further processing and analysis of the data according to different situations. The results show high accuracy and prove that our system is reliable and accurate for the detection and monitoring of radio waves. The main contributions of this study can be summarized as follows: (i) It is the first attempt to combine different machine learning models by incorporating a decision support system that assists IoT-based radiation detection and processing systems; (ii) the proposed method outperforms classical machine learning methods; (iii) the study found that the adaptive boosting classifier has the best accuracy of 81.7% among logistic regression, support vector machines, extra trees, bagging trees, decision trees, Gaussian naive Bayes theorem, and random forest classifier algorithms.

The rest of the paper is divided into the following sections: Section 2 is about the related work, Section 3 presents the research methodology of the proposed system, Section 3.4 describes the implementation details of the system, Section 4 displays the results, and Section 5 is about the conclusion.

## 2. Related Work

The authors in [25] have proposed a new sort of radiation monitors known as CROME (CERN RadiatiOn Monitoring Electronics). These monitors have embedded computing capabilities that allow them to run algorithms, such as calculating the true electric current created by electromagnetic radiation (EMR) detectors on exposure to ionizing fields. This paper gives a case study of a new approach for femtoampere current offset correction. The measured current is sensitive to the surrounding environment at this scale, such as temperature, vibration, and air permittivity. A novel method based on the deep neural network approach is proposed to provide high accuracy in performing real-time operations along with overcoming the restrictions of the field-programmable gate array (FPGA) platform. The neural network improves the accuracy by 7.31 percent and reduces the complexity by 42.9 percent. Hence, the results in terms of computational complexity are quite promising.

A theoretical approach comprising four tissue layers of the human head and a smart GSM-based cellular phone located at a distance of 2 cm from the human head is used to assess SAR values, electric field strength, impedance, conductivity, and power density in the human head. The results show that the SAR values at the skin layer are higher than those at the head layers [26].

Moreover, to address security issues during the communication of sensors' data, various machine learning algorithms, namely, naïve Bayes, linear regression, random forest, adaptive boosting, gradient boosting, decision tree, artificial neural network, support vector machine etc., have been exploited for measuring the accuracy and detecting the botnet attack. The results reveal that tree-based models achieved higher accuracy (>99%) than other models using the same sensors [27].

The authors in [28] proposed the EMR-monitoring system for detecting and monitoring radiation in the surroundings of research reactors in China. Based on the necessary data on monitoring points of four typical research reactors in China, a summary and analysis of the current condition of supervised monitoring of radiation fields, such as monitoring subjects, points, and frequency, was completed. The controlled monitoring of China's nuclear plants was examined in terms of past experiences and current issues. Tips on how to improve the monitoring of the radiation environment near research reactors have been noted. The usage of biomedical and electromagnetic sensing mechanisms integrated with RFID technology in healthcare systems is systematically reviewed by the authors in [29].

Multiple types of passive radiation protection systems based on different ionizing radiation detection mechanisms were subjected to extensive performance testing due to the need for passive radiation protection harmonization and the requirements of international standards in the context of environmental monitoring in radiation protection. In this research article [30], the reaction of 12 distinct passive dosimetry systems from 9 institutions was evaluated as a function of the dose, energy, angle of photon incidence, and response to a natural radiation field (gamma radiation of a sealed Ra-226 source) as part of the preparedness project. OSL and RPL-based systems outperform all other passive dosimetry systems tested in this study in every test. The calculated statistical uncertainties of the instruments' readings were less than 10% for the majority of the experiments; however, two TLD systems and one film system (*J*, *L*, *K*) have significantly greater statistical uncertainties. The average angular response of the tested systems (excluding *K* and *L*) is between 0.8 and 4.5 percent, according to the findings. Differences in the measured data are caused by the employment of various detectors, holders, calibrations, measurement processes, and uncertainties. To establish valid and consistent dose measurements across Europe, prior investigations and standardization of passive radiation protection equipment are required.

In another study [31], the authors have presented the recent advancements in mobile radiation detection since the Fukushima nuclear accident, which is based on four scenarios, (a) radiological and nuclear emergencies, (b) illicit traffic of radioactive materials, (c) nuclear and irradiation services, and (d) naturally occurring radioactive materials.

In [24], a radiation early warning system is proposed that monitors the amount of gamma radiation in the air. Such systems require a lot of manual involvement and rely on expert analysis. This study has made this process autonomous while still allowing the user to make the ultimate decision. The important feature of this research includes data preprocessors, incident extractors, incident classifiers, and data enhancers. A new strategy is offered for making the system more intelligent while also boosting the system's learning from previous experiences.

The authors in [32] describe the tool named commercial off-the-shelf (COTS) that is based on a remote sensing monitor for a nuclear storage scenario to detect both hydrogen concentrations and temperature with the help of two procedures: (1) improvement of a compact, cost-effective, and robust sensor system and (2) validation of the remote sensor system.

A radiation monitoring system is proposed that collects and records nuclear radiation exposure to the facility and its surroundings in the Yogyakarta Nuclear Area (YNA). An Internet of things-based radiation area monitor was created to increase the system's ability to not only measure radiation exposure but also send the data to a cloud server over the Internet. In the nuclear emergency response and readiness system, dispersed radiation data can be used to determine nuclear emerging potential. The area monitor system is a sensor network that includes a Geiger–Muller detector with high-voltage power supply, a signal-conditioning system, an Arduino counter, and a data processor. The detector collects data, which are then transferred to the server through a wireless network utilizing the node MCU communication module. The receiver station system was created to collect data from a database server to display radiation exposure to the environment and determine whether or not there was a radiological emergency. According to the chi-square test and the stability technique, the constructed device has good stability with a probability of 0.75. Sr-90 and an X-ray spectrometer were used as radiation sources in validation tests, and the constructed device was compared with a typical survey meter. The mean square error of this validation testing was 0.37 and 0.24 for Sr-90 at two different source distances, respectively, while the mean square error of the X-ray spectrometer source was 2.48 [33]. The technology can be linked to a smart meteorological system to create an integrated data collecting system for the Yogyakarta Nuclear Area's nuclear and radiological emergency preparedness system. Similarly, a generative adversarial network (GAN) model based on intelligent data analytics can effectively recognize the music data to convey emotions and achieve the accuracy greater than 87% [34]. Another study revealed that the gradient boosting model (GBM) showed optimistic performance in predicting the rate of evaporation over two remote regions; thus, it may support stakeholders to manage water resources efficiently [35].

A radiation monitoring system based on a microcontroller is presented in this research [36]. 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, the authors 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 has been developed.

## 3. Materials and Methods

The proposed system has the ability to predict the outcome of harmful rays on the body of human beings. For this purpose, sensors are connected to mega Arduino to take the data of radiation intensity from surroundings so that the intensity levels of rays can be checked. Infrared sensors, ultraviolet sensors, electromagnetic sensors, and gamma radiation sensors are connected to mega Arduino, and data are collected by the system and converted to data files for further use. This approach is based on an intelligent decision-making system to verify the safe and dangerous levels of intensity of rays. All the data stored in Excel sheets and the system alert the user through an Android mobile application when the intensity level of rays becomes dangerous. The overall design of hardware integration of the proposed system is shown in Figure 2.

The proposed radiation detection system is based on the basic seven-layered architecture.

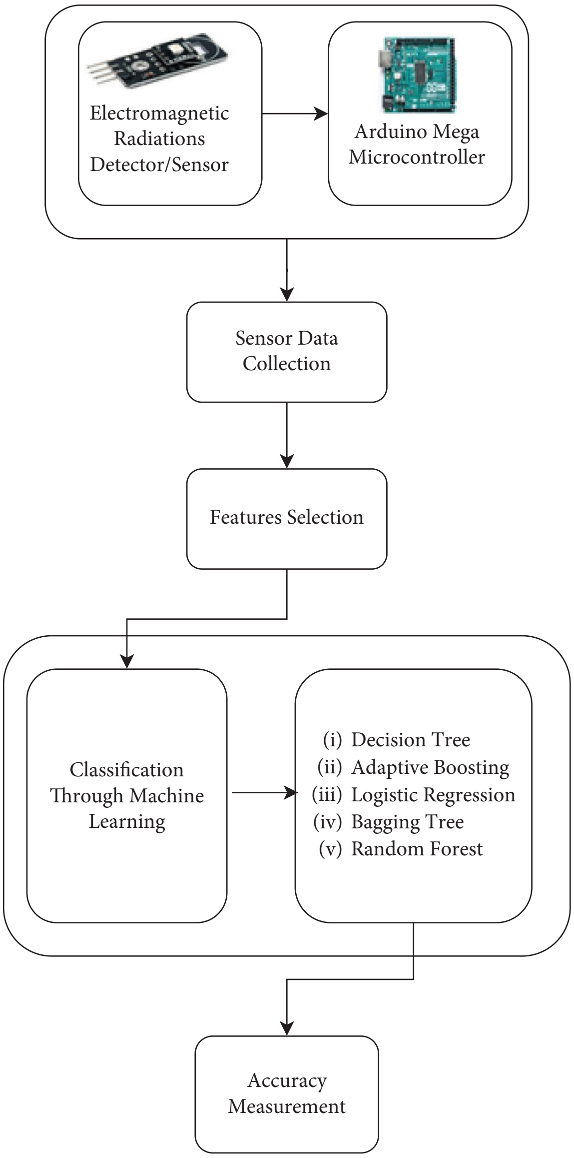


FIGURE 2: Design of hardware integration of the proposed system.

The first layer is called the application layer comprising IoT applications along with actuators, and the second layer is called the management layer having all functions related to device management and database management. The third layer is a networking and connectivity layer based on networking components. Device perception is carried out through sensors and microcontrollers. The final layer comprises machine learning models that provide the final decision results for the system. The overall layered architecture of the proposed model is shown in Figure 3.

The radiation detection system uses the intelligent decision-making system to verify the safe and dangerous levels of intensity of waves. All data are stored in the database, and the system alerts the user through an android mobile application when the intensity level of waves becomes dangerous. This system consists of three basic modules, i.e., a module for data collection, a decision support system, and an output module.

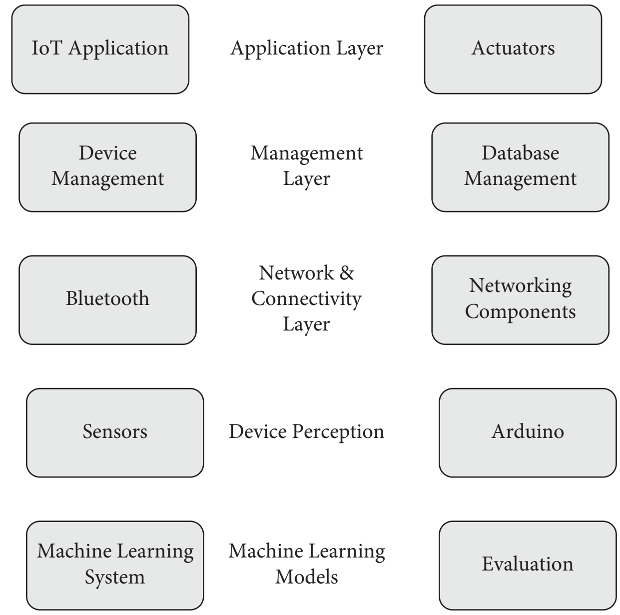


FIGURE 3: Layered architecture of the proposed system.

*3.1. Sensor-Based Data Collection.* Data collection through sensors is the first step in the proposed system, such as electromagnetic wave intensity through electromagnetic wave sensors and ultraviolet wave intensity through ultraviolet wave detection sensors. For the data collection process, sensors were connected to the Arduino Mega microcontroller. Electromagnetic wave sensors and ultraviolet sensors are connected to the microcontroller through analog ports of Arduino. A microcontroller works as a central point that takes inputs from sensors and transmits the data from sensors to the decision support system. The decision support system sends the data to the database after performing some action on the data. Then, the data are sent to the user through smart devices.

*3.2. Predictive System.* Predictive modeling is a statistical process that uses a probability distribution to forecast the output. Prediction was used to build models. These predictors are basically the variables that make up future results. When data were collected from various variables, a statistical model was designed based on probability. In this regard, researchers used different machine learning classifiers, i.e., logistic regression, support vector machines, naïve Bayes, random forests, bagging trees, extra trees, decision trees, and adaptive boosting.

*3.3. Components of the Decision Support System.* The decision support system (DSS) comprises the following components.

*3.3.1. Dataset.* The dataset contains a total of 22086 mixed instances with no missing values from each of the two sensors. The data are preprocessed by identification and removal of black cells that contain any missing value or the numeric value like 9999, and these data were referred to as cleaned data comprising 21987 pulses that were necessary for the optimized performance. The former data with missing values are used as baseline data for further processing and model evaluation. The detail of the dataset with respect to each sensor and radiation is given in Table 1.

*3.3.2. Trained Model.* The trained model contains all characteristics, which were validated while constructing the model with the training dataset. The trained model (knowledge base) performs like the brain while testing with high accuracy and efficiency. While compiling and executing data, some of the facts and rules were not modified 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 problems. The present study used 30% data for testing and 70% data for training.

*3.3.3. The Predictive Model.* Predictive modeling is a statistical probability process that uses various statistical methods, such as correlation matrix, probability distribution, and testing of hypothesis, to forecast outcomes based on decision rules. The graphical representation based on the decision rules (Table 2) for electromagnetic radiations is shown in Figure 4.

*3.3.4. Output Module.* An Android mobile application is developed for the IoT-enabled intelligent system for radiation monitoring and warning (ISRM) so that the user can get alerts when these harmful rays are present. The basic controls of applications were put in tabbed menus. The user gets access to the main features of the application such as dangerous radiation monitoring in neighborhoods of the user.

*3.4. Implementation.* In the development of the proposed system, less expensive and tiny sensors were used technically to sense the presence of harmful rays. The microcontroller consists of 16 analog input pins and 54 digital input/output pins, 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. Sensors were connected to a microcontroller through jumper wires to access the data from sensors. Ultraviolet sensor UVM-30A was used to detect ultraviolet radiation, and Electromagnetic Wave Sensor V3.0 was used for the detection of electromagnetic wave strength. The purpose of using the electromagnetic wave sensor in the proposed work was to check the presence of radio waves and measure the strength of radio waves. It detects the radio wave in its surroundings and covers a small range of radio waves. These two sensors were involved with Arduino Mega 2560.

In implementation, the electromagnetic wave detection sensor was connected to the Arduino Mega microcontroller. The electromagnetic wave sensor 5 V pin was attached to the Arduino 5 V pin, the output pin was attached to the A1 pin of Arduino, and the GND pin of the sensor was attached to the Arduino GND pin using jumper wires. After configuring the electromagnetic wave sensor with Arduino, Arduino IDE was used to write the code.

For coding, Arduino IDE is used. In implementation, Arduino IDE Version 1.8.8 was used for programming and hardware configuration. However, for getting the desired output of the sensors' data, the code was customized. The C language was used for writing the code in Arduino IDE; then, this code was uploaded on the board, and the output was displayed on the serial monitor. Data on both sensors were collected in Excel sheets.

*3.5. Recording Sensor Data.* The data from the sensor appear on the serial monitor of Arduino. For storing data in Excel sheets, PLX-DAQ software was used. It was used to store the real-time values of sensors. The data on sensors were collected in Excel sheets for different scenarios, such as low, moderate, and high intensity of rays. The values of electromagnetic wave sensors were stored in percentage, and values of ultraviolet sensors were stored in indexes. Initially, the sensor produces data in voltage and then calibrates the raw data into proper units.

Python-based Jupiter Notebook is open-source software. It generates the accuracy for the prediction model. Unbalanced classifications represent a challenge for predictive modeling since for most classification machine learning algorithms, the same number of examples has been developed for each class (minority and mainstream class). This leads to poorly predicted models, particularly for the minority class. Moreover, the prime focus is on the minority class as it generates more classification errors as compared to the mainstream class. Therefore, the dataset was balanced by eliminating outliers in this research. From the statistical perspective, the correlation matrix basically represents 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 associations. The correlation describes the strength and direction of the linear (straight line) correlation is denoted by $r$ as shown in Equation (1), varying from +1 to −1.

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

where $r$ is the nature of association, $x$ is an independent variable, and $y$ is a dependent variable.

*3.6. Adaptive Boosting Classifier.* To solve classification problems (discrete data) and regression problems (continued data), the adaptive boosting classifier was adopted by researchers. The AdaBoost algorithm's (see Algorithm 1) main principle is to combine many weak classifiers in order to create a strong 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

Table 1: Details of the dataset.

| Sr. No | Radiation | Sensor | Baseline data (no of rays) | Cleaned data (no of rays) |
|---|---|---|---|---|
| 1 | Ultraviolet | Name: ultraviolet sensor<br>Model: UVM-30A | 11043 rays | 11000 rays |
| 2 | Electromagnetic | Name: electromagnetic wave detection sensor<br>Model: Electromagnetic Wave Detection Sensor V3.0 | 11043 rays | 10987 rays |

Table 2: Decision rules.

| Sr. No | Electromagnetic (%) | Ultraviolet (index) | Relative effects (label) | Effect on infants | Outcome (label) |
|---|---|---|---|---|---|
| 1 | 0.0–20.0 | 0–2 | Safe | Normal | 0 |
| 2 | 0.0–20.0 | 3–5 | Moderate | Harmful | 1 |
| 3 | 0.0–20.0 | 6–7 | Dangerous | Harmful | 1 |
| 4 | 0.0–20.0 | 8–10 | Dangerous | Harmful | 1 |
| 5 | 0.0–20.0 | 11+ | Very dangerous | Harmful | 1 |
| 6 | 20.1–40.0 | 0–2 | Safe | Normal | 0 |
| 7 | 20.1–40.0 | 3–5 | Moderate | Harmful | 1 |
| 8 | 20.1–40.0 | 6–7 | Dangerous | Harmful | 1 |
| 9 | 20.1–40.0 | 8–10 | Dangerous | Harmful | 1 |
| 10 | 20.1–40.0 | 11+ | Very dangerous | Harmful | 1 |
| 11 | 40.1–60.0 | 0–2 | Safe | Normal | 0 |
| 12 | 40.1–60.0 | 3–5 | Moderate | Harmful | 1 |
| 13 | 40.1–60.0 | 6–7 | Dangerous | Harmful | 1 |
| 14 | 40.1–60.0 | 8–10 | Dangerous | Harmful | 1 |
| 15 | 40.1–60.0 | 11+ | Very dangerous | Harmful | 1 |
| 16 | 60.1–80.0 | 0–2 | Moderate | Harmful | 1 |
| 17 | 60.1–80.0 | 3–5 | Moderate | Harmful | 1 |
| 18 | 60.1–80.0 | 6–7 | Dangerous | Harmful | 1 |
| 19 | 60.1–80.0 | 8–10 | Dangerous | Harmful | 1 |
| 20 | 60.1–80.0 | 11+ | Very dangerous | Harmful | 1 |
| 21 | 80.1–100 | 0–2 | Dangerous | Harmful | 1 |
| 22 | 80.1–100 | 3–5 | Dangerous | Harmful | 1 |
| 23 | 80.1–100 | 6–7 | Dangerous | Harmful | 1 |
| 24 | 80.1–100 | 8–10 | Very dangerous | Harmful | 1 |
| 25 | 80.1–100 | 11+ | Very dangerous | Harmful | 1 |

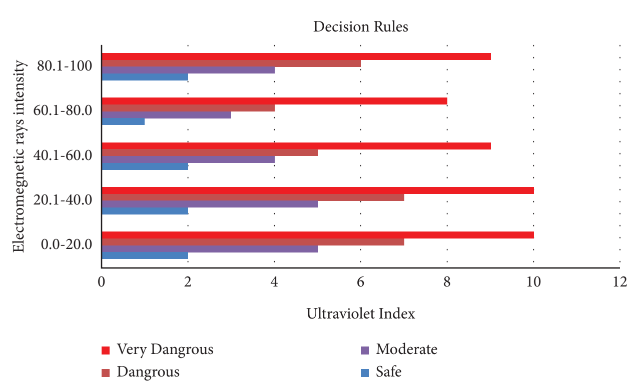


Figure 4: Intensity levels of electromagnetic radiation.

modified during the training process so that if a prior weak classifier misclassifies samples, the classifier's weight is increased (while the weights of correctly classified samples are decreased). In each training phase, this form of weight change drives base learners to focus on different data, resulting in highly efficient and diversified classifiers. It reduces the residual value (difference between actual and predicted) by choosing an appropriate function that points towards the negative gradient.

In hypothesis boosting, different steps were involved to observe the trained data that are applied to algorithms. These observations were strictly analyzed so that the newly created learner model can be tested on a set of poorly classified data. This idea is based on AdaBoost (adaptive boosting). In this

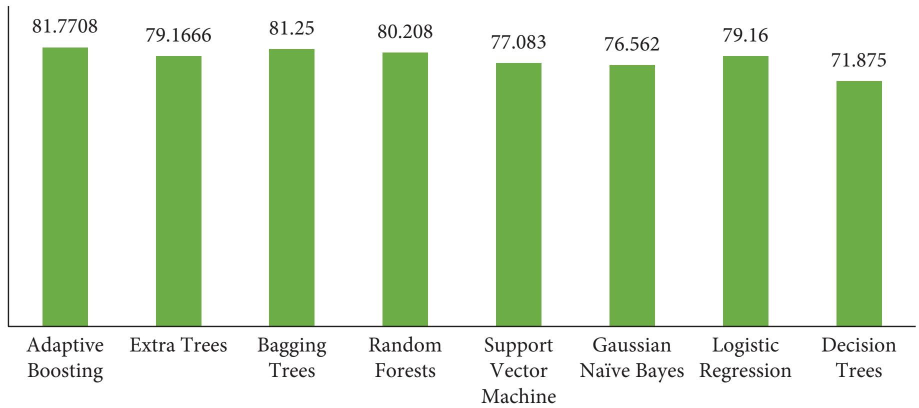


Figure 5: Performance evaluation of machine learning models.

**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 $h\ (x, \theta)$
**Output**: Powerful classifier
Step 1: Initialize weights: $w_i = 1/N_i$ (start with the null classifier $f_o(\vec{x}) = g_o(\vec{x}) = 0$)
Step 2: Iterate the function from $t = 1$ to $M$ for generating the training dataset by sampling
Step 3: Fit some weak learners $g_t(\vec{x})$.
Step 4: Update the weights and get a new base learner function for better results.
Step 5: Find the best gradient-descent stepsize $p_t$
$P_t = \text{argmin}_\text{p} \sum_{i=1}^{N} yi, f\,(t-1)\,(xi) + ph\,(xi, 0i)$
Step 4: Output the final model

Algorithm 1: Adaptive boosting classifier.

regard, various decision trees were built based on a single split (parent/child relationship).

The weighted mean of observations/instances are measured based on trained data to apply them to algorithms. In this way, many weak learners are added by reducing the loss function in the system in a linear way. In AdaBoost, the weak learner model associated with the class gives the best prediction votes. With the maximum votes, the new model is predicted. In the weighted minimization context, gradient boosting classifiers and weighted inputs are recalculated. Different steps are involved when AdaBoosting is applied. In the first step, the difference between the actual class value and the predicted class value is obtained to minimize the residual value. This classifier produces a future production model by assembling the weak learner model (decision tree) into a strong model in a sequential manner. This algorithm works 70% on training and 30% on testing proximal data. It also reduces the overfitting of discrete data. The final output classifier is expressed as follows:

$$G(x) = \text{sign}\,(f\,(x)) = \text{sign}\left(\sum_{m=1}^{M} \beta_m * b_m(x)\right), \tag{2}$$

where sign $(f(x))$ is a function that convert values into actual classes, $\beta_m$ is a parameter controlled by how each weak base learner is added, and $b_m$ is base learning controlled by parameter $m$.

*3.7. Extra Trees.* Decision tree is used because it is very easy to understand and make decisions, and it can be applied on large datasets. Furthermore, it does not require previous knowledge for making decisions rather it splits the datasets into training and testing. And a large number of single split decision trees are generated from the training dataset. Predictions were made by applying the statistical measure to the prediction of decision trees using maximum votes in the case of the discrete dataset (classification). It has achieved an accuracy of 79.166% to classify the effects of electromagnetic waves. The final output classifier is expressed as follows:

$$G(x) = \arg \min_{y\epsilon\{-1,1\}} \sum_{t=1}^{T} \left\|(\epsilon_t(x) = y)\right., \tag{3}$$

where $\epsilon(x)$ is the base learner and $T$ is the number of base learners.

*3.8. Bagging Trees.* It uses a 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 have shown an accuracy of 80, 77,76, 79, and 71%, respectively. Figure 6 shows the confusion matrix

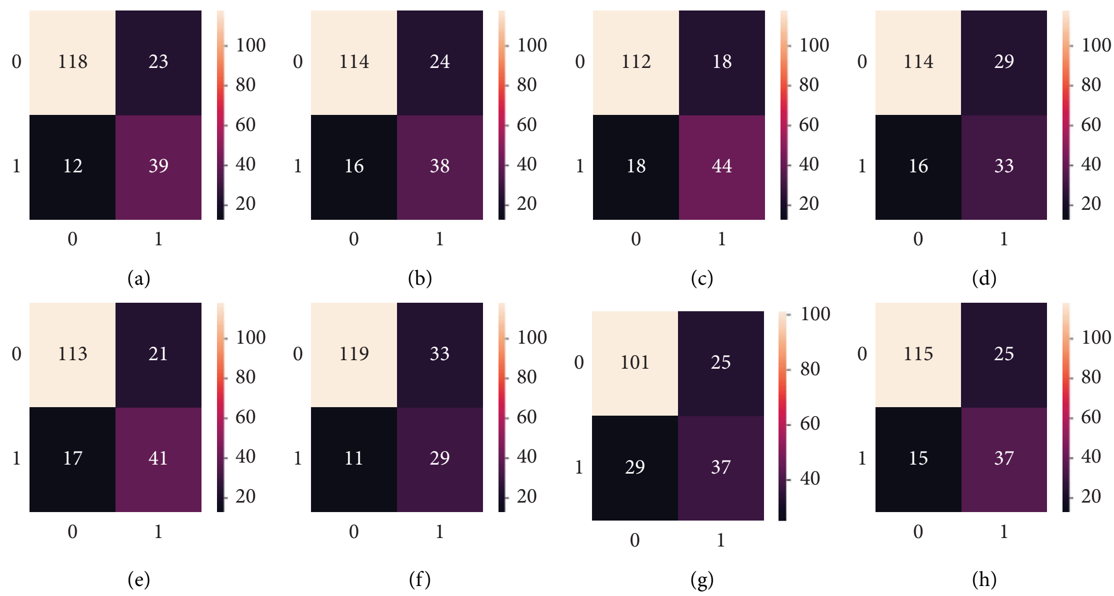


Figure 6: Confusion matrix of each classification model. (a) Adaptive boosting classifier. (b) Extra tree classifiers. (c) Bagging trees. (d) Gaussian naïve Bayes. (e) Random forests. (f) Support vector machines. (g) Decision trees. (h) Logistic regression.

of correctly and incorrectly classified data points using diverse classifiers. The final output classifier is shown in Equation (3) with updated parameter values.

## 4. Results and Discussion

The proposed approach is unique and smarter because it uses the decision making ability of the decision tree model and takes its advantages. It was a new idea to use the intelligent approach for a sensor-based radiation detection system along with real-time sensing data. The architecture and implementation details of the proposed system are elaborated in the previous sections. The intelligent system consists of multiple sensors, different hardware and software modules, and a trained model (knowledge base) with a set of predefined rules and datasets of facts gathered by wave sensors. The trained model was tested by using a rule-based inference engine with new data entries. The performance tests of the proposed system were taken using two sensors (an electromagnetic wave sensor and an ultraviolet wave detection sensor) by embedding them into the test fields. The sensors provide the real-time input data, which are forwarded to Excel sheets, decisions are taken based on those data, and the results are shown to an Android mobile application so that in response, the user can take some actions for their safety. The calibrated output of sensors is processed with various machine learning algorithms, and the best accuracy is obtained by the adaptive boosting classification algorithm.

The experimental results comprising the testing accuracy and validation accuracy are shown in Table 3. Radiation intensities are classified after applying decision rules to the dataset, and the results are shown graphically in Figure 5. In the present section, all experiments are performed using the Python programming language. Researchers evaluated the model accuracy using those data. Figure 5 shows the validation accuracy for each machine learning model to predict the dangerous outcome of these waves. Dependent and independent features were given as inputs in machine learning algorithms; the output was used as a prediction future model. In the light of statistical methods, these analytical variables were used to solve statistical equations. Based on these all scenarios, target class/label values were categories because the label contains the target value for the machine learning classifiers based on the training dataset, and to make a forecast model of any class, then you should split the dataset into the training dataset (70%) and the testing dataset (30%).

*4.1. Comparison with State-of-the-Art Studies.* These results obtained through the proposed model are also compared with those of the recent related studies, as shown in Table 4. In [11], the authors have developed a new generation of radiation monitors known as CROME (CERN RadiatiOn Monitoring Electronics). These monitors have embedded computing capabilities that allow them to run algorithms, such as calculating the true electric current created by using radiation detectors when they are exposed to ionizing fields. The results revealed that the system could not respond to evolving environments, such as indoor and outdoor areas. Moreover, this study requires more improvement in results. In another research [12], the author examined the supervised mode, monitoring basis, and monitoring system of radiation environment monitoring for typical research reactors in China. In this study, hazardous radiation levels were not identified. The author in [13] evaluated the reaction of 12 distinct passive dosimetry systems from 9 institutions as a function of the dose, energy, angle of photon incidence, and response to a natural radiation field (gamma radiation of a sealed Ra-226 source) as part of the preparedness project. In this study, there was a high measure of errors.

Table 3: 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 |

Table 4: Comparison of existing approaches.

| Reference | Dataset used | Problem identified | Methodology | Evaluation measure |
|---|---|---|---|---|
| [11] | Real-time data | Radiation detection | Neural networks and field-programmable gate arrays (FPGAs) | 7.31% accuracy improvement |
| [12] | Data from typical integrated research reactors | Radiation detection | Monitoring units based on air absorption | Not reported |
| [13] | 12 dosimeter systems | Radiation detection | LiF: Mg, Ti/TLD-100 and LiF: Mg, Cu, P/(MCP-N, RADCARD) | 0.8%–4.5% average angular response |
| [10] | Real-time data and external data | Radiation detection | Machine learning and radiation detection sensors | Not reported |
| [37] | Real-time data | Wound detection | Temperature and humidity sensors and decision trees | 94% |
| [38] | Real-time data | Health monitoring | Sensors, microcontrollers, fuzzy neural networks | 97% |
| [39] | Real-time data | Fire monitoring and warning systems for smart buildings | Sensors, microcontrollers, fuzzy control algorithms | Not reported |
| Proposed system | Real-time data | Radiation monitoring and warning approach | Radiation detection sensors, microcontrollers, adaptive boosting classifiers | 81.7% |

In [10], the authors proposed a radiation early warning system that monitors the quantity of gamma radiation in the air. Such systems require a lot of manual involvement and rely on expert analysis. This study has made this process autonomous while still allowing the user to make the ultimate decision. This study, however, does not include any fully automated system and requires human intervention. In another paper [37], a radiation monitoring system is proposed that collects and records nuclear radiation exposure in the facility and its surroundings in the Yogyakarta Nuclear Area (YNA). An Internet of things-based radiation area monitor was created to increase the system's ability to not only measure radiation exposure but also send the data to a cloud server over the Internet. However, this system requires a lot of resources.

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

## 5. Conclusion and Future Directions

In the present age, human beings are surrounded by many dangerous radiations. These radiations badly affect human health, and especially, these rays are very dangerous for infants and patients having skin diseases as well. Moreover, these radiations cause many diseases from simple infection to deadly diseases, such as eye infections, headache, skin tanning, skin burns, brain tumors, breast cancer, and skin cancer. Similarly, these radiations should be avoided, but one cannot feel the presence of these rays around oneself. Therefore, there is a need for such a system which can detect the intensity of rays around us. In this paper, a low-cost radiation outcome predictive system is introduced that is based on sensors. The model adopted by the present study uses different machine learning models, and the study found that the adaptive boosting classifier is the best with an accuracy of 81.7% among others, such as logistic regression, support vector machines, extra trees, bagging trees, decision trees, Gaussian naive Bayes theorem, and random forest classifier algorithms.

In the future, it is recommended for researchers and scholars to use the Raspberry Pi microprocessor in order to increase the efficiency of the system instead of the Arduino Mega microcontroller. It is a new technology and has its own processing power, USB ports, built-in Wi-Fi, and Bluetooth modules. Hypertuning and optimization techniques can be effective in improving the performance of models.

## Data Availability

All data generated or analyzed during this study are included in this article.

## Disclosure

The funders played no role in the design of the study, collection, analysis, and interpretation of the data, or preparation, review, or approval of the manuscript.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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