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Modeling Electromagnetic Field Radiation Variability for Minimization of Exposure Rate in Public Health Environments: A Machine Learning Approach

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Abstract: *Public Health awareness of the exposure to radiofrequency electromagnetic fields (Rf-EMF) is necessary for epidemiological studies on possible bio-effects. The Knowledge will promote good health, reduce health risk factors, lower morbidity and mortality rates often associated with public health environment (PHE). Modeling EMF radiation variability and its application is vital given the prospective growth in both the number of mobile devices and equipment radiating electromagnetic fields (EMF) and the increasing concerns in the general public. The main goal of this work is to develop a framework based on Machine Learning (ML) approach to determine the exposure level on time-based variances within and during operational procedures of frequency bands used in mobile telecommunication, digital devices, transmitters, broadcasting terminals etc. The system adopts the measurements and instrumentation methodology, using a handheld Poniie pn8000 multi-field EMF metre and EME Spy exposimeter with a detection limit of 0.0066mW/m (2) with sampling at certain interval in a specific frequency ensemble. The measurements were synthesized as exposure coefficients with assessment based on EMF radiation from emitting devices and matching with International Commission on Non-Ionizing Radiation Protection (ICNIRP) standards endorsed by WHO. Consequently, obtained data was processed and segmented into training and test sets on 70:30 ratios respectively. Computing modeling of the system was performed with R programming language using data obtained from field measurements and records. The prosed system used Ensemble ML-Random Forest Algorithm and Decision Tree algorithm (DTA). Performance evaluation and results obtained clearly demonstrates 87% based on the Confusion Matrix (CM) outcomes for Random Forest and Decision Tree presents 56%. This justifies the capability of ML techniques in accurately classifying EMF radiation to mitigate exposure rate and improve healthcare throughput. The model was transformed and deployed in a production system API environment with Graphical User Interface (GUI) for flexibility. This work revealed relating potential health bio-effects associated with EMF exposure and the different parameters that are currently used for evaluating, limiting, and mitigating the impact of the exposure on the general public.*
KEYWORDS: Public Health Environment (PHE), Radiofrequency Electromagnetic Fields (Rf-EMF), Multi-Field EMF Metre, EME Spy Exposimeter, Non-Ionizing Radiation Protection (ICNIRP), Ensemble ML-Random Forest Algorithm and Decision Tree algorithm (DTA)

INTRODUCTION

Technology has recently evolved into a source of widespread electromagnetic pollution due to created electromagnetic fields and the resulting electromagnetic radiation. This pollution is far more powerful than any natural source of electromagnetic fields or radiation in numerous circumstances. As a result, electromagnetic pollution is emitted by wireless and radio communication equipment, power transmission, and everyday electronics such as cellphones, tablets, and portable laptops. In today's culture, electromagnetic fields are everywhere. They happen as a result of the use of electricity, electronic surveillance devices, and different forms of wireless communication. Despite the fact that these fields differ in terms of strengths and physical qualities, they all cause anxiety among individuals who are exposed to the prospect of health concerns or dangers. Acute health consequences, including burns, can be caused by fields, however exposure restrictions and laws effectively safeguard against these effects. Instead, current worries are focused on the likelihood that long-term exposure to weak fields may have negative health consequences due to an undiscovered biological mechanism [3]. The upsurge in Mobile Broadband Networks (MBBN) in recent time is evident with challenges and opportunities for the telecommunication industries. Mobile Broadband Performance represents qualitative and quantitative process that measures and defines performance ratings of typical active network, [23]. Electromagnetic field usage has become commonplace, ranging from everyday electronic appliances like microwave ovens, tablets, and laptop devices to telecommunication systems like mobile phone towers, radio-television broadcast systems, and electronic power transmission systems, all of which produce electromagnetic fields and associated radiations. At the micro-level, electromagnetic fields (EMFs) can have biological impacts on cells and have the potential to cause cell malfunction manifesting in a variety of biological outcomes [22].

Electromagnetic fields, often known as electromagnetic pollution, have an impact on many aspects of our environment and living organisms. In terms of public health, EMF pollution refers to the danger posed by non-ionizing radiations that have a frequency in the lower half of the *em* spectrum. In the human body, insignificant electrical circuits exist as a component of everyday physical functions such as transmission of electric impulses for brain exercises, heart thumping, and, unexpectedly, chemical responses for food absorption. Because the human body is made up of charged particles, low-recurrence electric fields affect the dispersion of electric charges and produce little flows inside. Essentially, depending on the intensity of the magnetic field, low frequency magnetic fields can also cause circulation currents within the body. Both magnetic and electric fields cause very modest voltages and currents to flow through the body. However, if these currents are powerful enough, they can stimulate neurons and muscles, as well as it affects other biological processes. As a result, effective EMF monitoring and control systems are unquestionably one of the significant advancements in the variety of approaches for evaluating environmental electromagnetic contamination through measurement.

Motivation and Principal Contributions

Machine Learning Approach facilitates the ability to model EMF radiation variability and its application is vital given the prospective growth in both the number of mobile devices and equipment radiating electromagnetic fields (EMF) and the increasing concerns in the general public. Also, modelling emf radiation promote the development of a framework based on Machine Learning (ML) approach to determine the exposure level on time-based variances within and during operational procedures of frequency bands used in mobile telecommunication, digital devices, transmitters, broadcasting terminals etc. Although several studies have considered the use of intelligent and ML techniques in EMF exposure minimization in public health environment, none of these studies consider the comparison of deterministic models - Random Forest (RF) and Decision Tree (DT). Also, most of them evaluated the performance of their models with only one metric while this work compares the prediction accuracy of the two ML models using confusion metrics. Furthermore, this work presents an ML framework for predicting EMF Exposure rates following implementable minimization pathways for efficient and robust minimization. The computational experiment was considered on the basis of data obtained from a study conducted on a typical public healthcare department [22]. The adaptation of ML approach also facilitates precise categorization that helps determine the correlations, hidden patterns and other valuable insights from the vast amount of data with varied properties through the classification process.

RELATED WORKS

In this section, a comprehensive review of previous research works is presented. These works are classified into two major groups namely: statistical and computational approaches to EMF radiation measurements and Machine learning approaches to radiation exposure rate minimization prediction/classification. The second group is predicated on the fact that, to the best of our knowledge in this region no previous works have applied ML methods to the radiation exposure rate minimization. Summaries of the two groups of related works documenting the Authors; Objectives; Methodologies, Tools, Data(bases); Findings and Drawbacks are presented in Table 1 and Table 2.

Earlier works such as that conducted by [14] studied the biological impacts of cell tower base stations and other antenna arrays emitting electromagnetic radiation. A review of previous studies of people living or working near cellular infrastructure, as well as other relevant studies that potentially apply to long-term, low-level radiofrequency radiation (RFR) exposures, was conducted as part of their research. The general public's exposure to RFR from wireless communication devices and transmission towers should be maintained to a bare minimum, according to their research, and should follow the "As Low as Reasonably Achievable" (ALARA) approach. With the growing use of wireless technology, it is becoming increasingly important to understand actual ambient exposures. This covers any potential wildlife consequences. In addition, their research included a review of papers that reported biological impacts from low-intensity radiofrequency radiation (RFR). Despite accumulating evidence as shown throughout this study, multiple biological impacts do occur following short-term exposures to low-intensity RFR. However, possible harmful health effects from such exposures on people are still not fully documented. Unfortunately, little is known about the biological effects of long-term exposures, particularly as the effects of long-term exposure can differ significantly from those of short-term exposure. Long-term, low-intensity exposures are the most common today, and they're on the rise thanks to a plethora of wireless products and services.

Similarly, [15] study of Cell Tower Radiation and Its Health Hazards on the Human Body was the subject of a study. Radio Frequency (RF) radiation from mobile towers and its health effects on the human body were investigated in this study. At the selected neighborhood in Aizawl, Mizoram, India, the power density of RF radiation from a mobile tower was measured in close proximity to the mobile base station (GSM 900). In addition, a questionnaire survey was undertaken on the many health issues that residents living near the base station suffer. The absolute power densities of several houses have been tested and compared to the limitations set by various bodies such as the International Commission on Non-Ionizing Radiation Protection (ICNIRP), Bioinitiative: 2012, and Indian Standards. Their study also took into account at several mobile tower locations, the frequency spectrum was examined. The effects of RF exposure on residents inside 50 meters and outside 50 meters of the tower were studied and compared. The data is also broken down by gender. It was discovered that people who live within 50 meters of each other have higher health problems than those who live outside of 50 meters. Females, on the other hand, have more complaints than males.

In [4] experimental model for ELF-EMF exposure: Human Health Concerns was the title of an essay that was written. Low frequency (LF) electromagnetic fields (EMFs) are prevalent in modern society, according to their research, and interest in the probable effects of extremely low frequency (ELF) EMFs on human health has risen steadily over the last 20 years. According to their findings, epidemiological investigations aimed at determining if EMF exposure is a possible risk factor for health have produced mixed results. The link between EMFs and an increased risk of childhood leukemia, brain tumors, and neurological disorders has yet to be clearly established. EMFs, on the other hand, are commonly employed in neurology, psychiatry, rheumatology, orthopedics, and other medical fields. Dermatology, both in terms of diagnosis and treatment, can be harmful to living organisms. Their findings suggest that more research is needed to see if ELF-EMFs, which are found in both industrial and household settings, can operate as an adjuvant or causal factor in illness development, or as a therapeutic and diagnostic tool.

Basically, [19] studied the effects of radio-frequency electromagnetic radiation from Mobile Tower on Human Health using a case study from Bangalore. They conducted a questionnaire-based survey with a population of 181 people living in five distinct areas of Bangalore South Taluk (Gangondahalli, Nagarabhavi, Moodalpalya, Chandra layout, and Guddadahalli). The participants completed the self-administered questionnaire by giving their responses to the health consequences that have been experienced as a result of the installation of mobile towers. The distances between base stations were used to calculate exposure (less than 10 m, 10-50 m, 50-100 m, 100-200 m, 200-300 m, > 300 m) as well as their relative position to the antennas (facing, besides, behind, beneath in the case of antennas placed on rooftops). The findings indicated that headache, irritability, nausea, appetite loss, pain, sleep disturbance, sadness, memory loss, difficulty concentrating, and dizziness, among other indications of ill-health, are more frequently found in the exposed groups. Mobile phones and cell phone tower radiation were found to be a significant risk factor for high exposure to the human head and the high sensitivity of brain tissue and brain processes.

The work of [20] reveal that, wireless communication has the reputation of being unpredictable. The quality of wireless communication depends on the environment, the part of the frequency spectrum under use, the particular modulation schemes under use, and possibly on the communicating devices themselves. Communication quality can vary dramatically over time, and has been reputed to change with slight spatial displacements. As a result of this, and the paucity of large-scale deployments, it is perhaps not surprising that there has been no medium to large-scale measurements of ad-hoc wireless systems. In [21], Mobile Communication Networks are the fastest growing communications technology in history. This technology is largely attributed to the remarkable exploitation of cellular systems and the distribution of user's terminals. These efforts have tremendously increased the network capacity. The increase has resulted in frequent network defects that have challenge the proper functioning of the network, thus leaving some network operators with no option than to compromise quality.

The work done by [12] performed an investigation into the effects of oxidative stress on antioxidant systems. They observed that Electromagnetic Fields (EMF) have a variety of chemical consequences, including degradation of big molecules in cells and ionic imbalance. They found from multiple investigations that EMF exposure causes oxidative stress in a variety of bodily tissues. EMF has been shown to increase free radical concentrations and traceability, as well as influence radical couple recombination. Nevertheless, according to their findings, the biological effects of EMF exposure are a hot topic for investigation. The findings of recent studies show that not only does EMF exposure produce oxidative stress in numerous tissues, but it also causes significant changes in blood antioxidant indicators. EMF causes fatigue, headaches, impaired learning ability, and cognitive impairment, to name a few symptoms. Because of the dangers that EMF exposure might create, the human body should be shielded from it. Accordingly, [22] proposed a computational intelligence framework to predict patient's LOS in hospital ED. However, they analyzed several factors including Severity of Illness or Emergency Cases (SIC) to assess its performance but the ML framework was implemented using Intuitionistic Type-2 Fuzzy Logic System (IT2-FLS). In [24], a meta-model comprising an ensemble of Adaptive Neuro-Fuzyy Inference System (ANFIS), Feed Forward Neural Network (FFNN) and Recurrent Neural Network (RNN) was used for optimum resource planning in the ED. The results were compared and evaluated in terms of mean absolute percentage error (MAPE) only.

In their studies, [17] researched the dangers of radio-frequency radiation emitted by cell phones and other wireless devices to one's health and well-being. A complete assessment of Radio-Frequency Radiation Emitted by Cell Phones and Other Wireless Devices was undertaken as part of their research, and they found a wide spectrum of negative human health impacts linked with RFR. Furthermore, three large-scale carcinogenicity investigations in mice subjected to RFR levels that approximate lifetime human exposures found considerably higher frequencies of Schwannomas and malignant gliomas, as well as chromosomal DNA damage. The consequences of RFR exposure on the developing brain in children are particularly concerning. When a cell phone is held against a child's head, it exposes deeper brain areas than when it is put against an adult male's head. The youth, thin skull's bone marrow receives a roughly 10-fold higher local dose, exposing structures to higher radiation doses per unit volume. As a result, experimental and observational research show that men who keep cell phones in their trouser pockets had significantly lower sperm counts and significantly decreased sperm motility and shape, as well as mitochondrial DNA damage, according to their review.

The Basic Concepts of Electromagnetic Fields (EMFs)
Research and technological evidences show that Electromagnetic fields, such as those emitted from mobile communication base stations, are distinctly categorized into types: ionizing and non-ironizing radiations [18]; [13]; [11] or Higher frequency EMFs and low to mid frequency EMFs [6] based on their electromagnetic energies where one is capable of breaking chemical bonds, whereas the other is not, according to the Nigerian Communications Commission (NCC). Fields of different energies or frequencies interact with the body in different ways [7] hence, ionizing radiations need extensive radiological safeguards, non-ionizing radiation on the other hand, do not and this is a testament to the variance in their hazard potential.

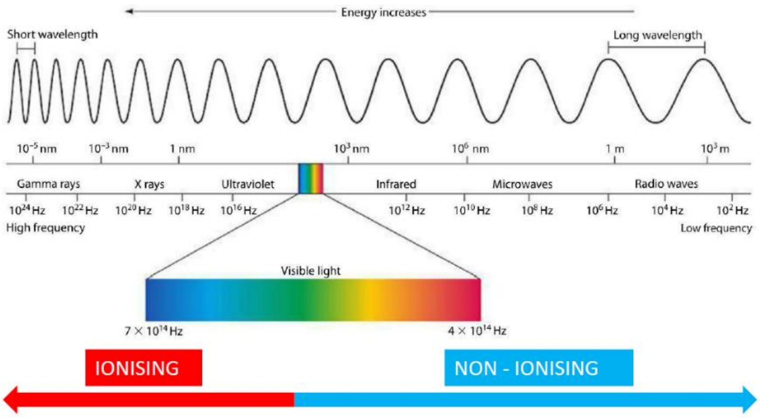

Fig. 1: Electromagnetic Fields Radiation Categories (source: [7])

Types of EMFS and their Descriptions

Table 1 Types of EMFS and their Descriptions

EMF Types	Specific Types	Frequency	Description	Wavelength
Ionization (Higher Frequency) EMFs	High Frequency	3—30 MHz	Radio Waves	100—10m
	Very High Frequency	30—300 MHz	Infrared Ray	10—1m
	Ultra-High Frequency	300 Mhz—3 GHz	Visible Light	1m—10cm
	Super High frequency	3—30 GHz	UV Rays	10—1mm
	Extremely High Frequency	30—300 GHz	X-Ray	1cm—1mm
	Tremendously High Frequency	300 GHz—3 THz	Gamma Rays	1mm—0.1 mm
Non-Ionization (Low-Mid Frequency) EMFs	Extremely Low Frequency	3—30 Hz	Lightening	10^5 - 10^4 km
	Super Low Frequency	30—300 Hz	Power cables, e-devices	10^4 - 10^3 km

	Ultra-Low Frequency	300—3000 Hz	Military com gadgets	10^3 - 100 km
	Very Low Frequency	3—30 kHz	Navigation services, Monitors, TVs	100—10 km
	Radio Frequency	30—300 kHz	Radar Signals	10—1 km
	Medium Frequency	300 kHz—3 MHz	Broadcasting/navigation Radios/beacons	1 km—100 m

Health Complication Associated with EMFs

Table 2: Health Complication Associated with EMFs

Exposure Type	Health Effects	Authors
Short-Term or Low-Level Exposures	Headache	[5]; [10]
	Tremor	[5]
	Nausea, dizziness	[7]; [5]; [10]
	Memory loss	[5]; [10]
	Loss of concentration	[5]; [10]
	Fatigue	[7], [10]
	Sleep disturbance/ disorders	[5]; [10]
	Depression, suicide	[5]; [10]
	Loss of libido	[5]
	Tinnitus	[10]
	Increased temperature, skin irritation	[3], [10
	Chest pain	[10]
	Hormonal disorders	[10]
	Cardiovascular effects	[10]
Long-Term or Higher-Level Exposures	Development of cancer	[10]
	Leukemia in children	[16]

From these, it is evident that findings from studies contain quite a number of shortcomings and contradictions as a result, and we agree with 8 that no firm conclusion can be arrived at about the effects of electromagnetic fields on human health.

Key Criteria for Classification and Evaluation Methods

Table 3: Key Criteria for Classification and Evaluation Methods

Evaluation Methods	Description Features
Computation Speed	Time it takes to implement or use the model
Classification Accuracy	The number of correctly classified examples over the total number of cases
Robustness	Measurement of how the model handles noise and missing values
Scalability	The possibility for the model to be optimized without losing its accuracy
	The possibility for the model to be applicable to a range of similar problems
Interpretability	The possibility for the model to provide insight and be understood
Goodness of Rule	The decision tree size of the model
	The compactness of the classification rules

System Model

Conceptual Architecture of the Proposed Model

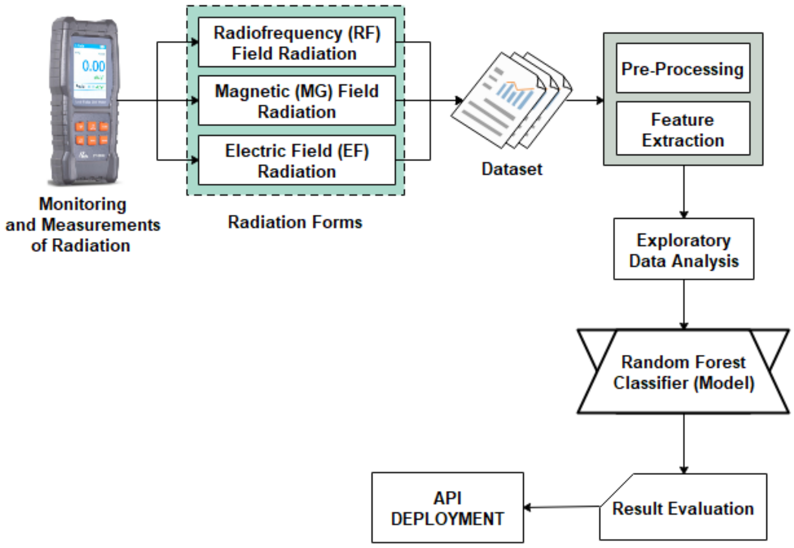

Fig. 2: Conceptual Architecture of the Proposed Model

Description of Key Components of the Proposed System

i. **Monitoring and measurements of Radiation:** Monitoring is the process that encapsulates observation of something thoroughly so that it can be recorded or detected in t our proposed system a smart intelligence meter was procure for the remote monitoring of radiation. Also, measurement entails determine the definite characterization of something, so during our monitoring, measurements were also carried out based on our smart meter.

ii. **Radiation Forms:** Radiation exists in different forms, in this research we have identify major form of radiation which our smart meter is going to measure, includes Radio frequency (RFR) radiation, Magnetic Radiation (MR) and the Electric Radiation (ER) which are all the different forms of radiation this research reflects on.

iii. **Data Processing and Feature extraction:** Cleaning of data is part of the preprocessing process. We will devote a large amount of work to transforming the radiation data into something that will be used in modeling. Also Feature extraction is also a part of the dimensionality reduction process, which divides and reduces a large set of raw data into smaller groupings. As a result, processing will be easier.

iv. **Prediction:** When forecasting the likelihood of a given result, prediction refers to the output of an algorithm after it has been trained on a previous dataset and applied to new data.

MATERIAL AND METHODS

Data Measurements and Analysis

The data used for this work were measured using a portable handheld *Poniie* PN8000 Multi-fields EMF Meter. The device measured radiations from EMF emitting devices based on based on WHO and ICNIRP's standards. Readings were taken from high tension electric power lines, mobile phones, laptops, televisions, MRI Scanning Machines as well as other EMF devices. The measurements were taken in Uyo and Mkpat Enin Local Government Areas both in Akwa Ibom State. The assessment of EMF radiations was obtained through onsite measurement with the multi-field meter used for capturing the data. EMF Radiation data from MRI Machines at the Ibom Specialist Hospital and University of Uyo Teaching Hospital, computers, laptops at the Akwa Ibom State University ICT Units and the Department of Computer Science and power lines at the PHED Sub-station in Uyo were measured, recorded and preprocessed using Microsoft Excel and analyzed using the R programming language. The radiations measurements were taken at distance between 0.02 meters and 20 meters from the target EMF source. Measurements were taken in mW/m^2, v/m and mG

Again, data for this research was gathered through the measurement of EMF Radiations from devices and locations where EMF devices are deployed, using a smart meter, for over a period of 3 months Uyo and Mkpat Enin Local Government Areas of Akwa Ibom State. Different technological devices were accessed, measured and assessed based on the different types of EMF radiations they emit. The data from our assessments were recoded using a smart meter (figure 4) that we procured and the readings were taken at exposure distances between 0.02 meters and 20 meters from the target devices.

Table 4: Field Data Attributes Categorization

Attributes	Category/units
Device Name	Text
Device Type	Text
Mode of EMF	(Magnetic, Radio freq, Electric)
Distance	Numeric(meters)
Electromagnetic Value	Numeric
Result	Text (Slight, Good, Severe, Extreme)

Furthermore, after the attribute's categorization of our statistical flied data, data was processed into table by recording different devices using our procured smart meter.

Participants and Experts

To gain a broader and expert perspective and to further ensure the reliability of this work, we sort inputs and guidance from experts in Radiology. Collaborating with the Head, Department of Radiology, University of Uyo Teaching Hospital and Dr. Nnenna Nwafor, first, we understood what protective measures we had to take while taking the measurements and we achieved more insights to the exposure limits that is advisable from MRI machine radiations. Furthermore, using a device designed by Experts and that conformed to the standards defined by the World Health Organization (WHO) and the International Commission on Non-Ionizing Radiation Protection (ICNIRP), we ensured that our readings were accurate and follows defined standards. Seasoned scholars, especially Dr. Imeh Umoren, from the Department of Computer Science and the ICT Unit both in Akwa Ibom State University participated in the data capturing and the model design process.

Measurements and Instruments

The smart meter used in capturing our EMF data is the PN8000 Multi-fields EMF Meter, a handheld radiation detecting device made *Poniie.* The device is designed to give readings of more than one EMF radiations including the Magnetic, Electric and Radio Frequency radiation.

Fig. 4: PN8000 Multi-fields EMF Meter reading from a Router

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Report Presentation and Datasets

Once we had obtained the data from each target devices, these data were recorded in Microsoft Excel and preprocessed. Each of the data items were categorized in tables and given field names according in order to make more sense of the data. Table 4.2 presents a cross section of captured data.

Table 5: Statistical Field Data for EMF data Categorization

Device Name	Device type	Mode of EMF	Distance (m)	EMF value	Results
Samsung Phone	Mobile Hotspot	R-Field	0.02	58.75mW/m^2	Extreme
Samsung Phone	Mobile Hotspot	R-Field	1	0.08mW/m^2	Good
Samsung Phone	Mobile Hotspot	E-Field	0.02	17v/m	Good
Samsung Phone	Mobile Hotspot	E-Field	1	14v/m	Good
Samsung Phone	Mobile Hotspot	M-Field	0.02	8.6mG	Slight
Samsung Phone	Mobile Hotspot	M-Field	1	4.6mG	Slight
MP3 Player	Bluetooth	R-Field	**0.02**	0.46mW/m^2	Good
MP3 Player	Bluetooth	R-Field	1	0.001mW/m^2	Good
MP3 Player	Bluetooth	E-Field	0.02	13v/m	Good
MP3 Player	Bluetooth	E-Field	1	10v/m	Good
MP3 Player	Bluetooth	M-Field	0.02	1.2mG	Good
MP3 Player	Bluetooth	M-Field	1	0.9mG	Good
HP,Laptop	Laptop Computer	R-Field	0.02	0.02mW/m^2	Good
HP,Laptop	Laptop Computer	R-Field	1	0.00mW/m^2	Good
HP,Laptop	Laptop Computer	E-Field	0.02	765v/m	Extreme
HP,Laptop	Laptop Computer	E-Field	1	50v/m	Slight
HP,Laptop	Laptop Computer	M-Field	0.02	30mG	Severe
HP,Laptop	Laptop Computer	M-Field	1	4.6mG	Slight
300 HP TFM	Transformer	R-Field	1	00.0mW/m^2	Good
300 HP TFM	Transformer	R-Field	20	000mW/m^2	Good
300 HP TFM	Transformer	E-Field	1	1021v/m	Extreme
300 HP TFM	Transformer	E-Field	20	36v/m	Good
300 HP TFM	Transformer	M-Field	1	54.7mG	Extreme
300 HP TFM	Transformer	M-Field	20	9.8mG	Slight
Thermocool Refrigerator	Refrigerator	R-Field	0.02	0.00mW/m^2	Goods
Thermocool Refrigerator	Refrigerator	R-Field	1	0.00mW/m^2	Good

Device Name	Device type	Mode of EMF	Distance (m)	EMF value	Results
Thermocool Refrigerator	Refrigerator	E-Field	0.02	406v/m	Extreme
Thermocool Refrigerator	Refrigerator	E-Field	1	15v/m	Good
Thermocool Refrigerator	Refrigerator	M-Field	0.02	16.5mG	Severe
Thermocool Refrigerator	Refrigerator	M-Field	1	6.1mG	Slight
Sony TV Set	Television	R-Field	0.02	0.00mW/m^2	Good
Sony TV Set	Television	R-Field	1	0.00mW/m^2	Good
Sony TV Set	Television	E-Field	0.02	652v/m	Extreme
Sony TV Set	Television	E-Field	1	36v/m	Good
Sony TV Set	Television	M-Field	0.02	34.9mG	Severe
Sony TV Set	Television	M-Field	1	6.1mG	Slight
High Tension Power Line	High Tension Power Line	R-Field	1	0.00mW/m^2	Good
High Tension Power Line	High Tension Power Line	R-Field	50	0.00mW/m^2	Good
High Tension Power Line	High Tension Power Line	E-Field	1	332v/m	Extreme
High Tension Power Line	High Tension Power Line	E-Field	50	30v/m	Good
High Tension Power Line	High Tension Power Line	M-Field	1	33.0mG	Severe
High Tension Power Line	High Tension Power Line	M-Field	50	7.3mG	Slight
Projector	Projector	R-Field	0.02	0.01mW/m^2	Good
Projector	Projector	R-Field	1	0.00mW/m^2	Good
Projector	Projector	E-Field	0.02	27.6v/m	Extreme
Projector	Projector	E-Field	1	12.6v/m	Extreme
Projector	Projector	M-Field	0.02	41.9mG	Severe
Projector	Projector	M-Field	1	3.7mG	Slight
ATC Nig.	Base Station	R-Field	1	32.7mW/m^2	Extreme
ATC Nig.	Base Station	R-Field	20	0.01mW/m^2	Good
ATC Nig.	Base Station	E-Field	1	68v/m	Slight
ATC Nig.	Base Station	E-Field	20	25v/m	Good
ATC Nig.	Base Station	M-Field	1	39.4mG	Severe
ATC Nig.	Base Station	M-Field	20	6.2mG	Slight
Electric Iron	Electric Iron	R-Field	0.02	0.01mW/m^2	Slight
Electric Iron	Electric Iron	R-Field	1	0.00mW/m^2	Slight
Electric Iron	Electric Iron	E-Field	0.02	349V/m	Extreme

Device Name	Device type	Mode of EMF	Distance (m)	EMF value	Results
Electric Iron	Electric Iron	E-Field	1	32V/m	Good
Electric Iron	Electric Iron	M-Field	0.02	6.1mG	Good
Electric Iron	Electric Iron	M-Field	1	3.4mG	Good
Strong Decoder	Strong Decoder	R – Field	0.02	0.01mW/m^2	Good
Strong Decoder	Strong Decoder	R – Field	1	0.00mW/m^2	Good
Strong Decoder	Strong Decoder	E-Field	0.02	715V/m	Extreme
Strong Decoder	Strong Decoder	E-Field	1	56V/m	Slight
Strong Decoder	Strong Decoder	M-Field	0.02	94mG	Severe
Strong Decoder	Strong Decoder	M-Field	1	6.9mG	Slight
Laptop Charger	Charger	R-Field	0.02	0.00mW/m^2	Good
Laptop Charger	Charger	R-Field	1	0.00mW/m^2	Good
Laptop Charger	Charger	E-Field	0.02	576V/m	Extreme
Laptop Charger	Charger	E-Field	1	26V/m	Good
Laptop Charger	Charger	M-Field	0.02	15mG	Severe
Laptop Charger	Charger	M-Field	1	2.8mG	Slight
Bobby Sound	Amplifier	R-Field	0.02	0.01mW/m^2	Good
Bobby Sound	Amplifier	R-Field	1	0.00mW/m^2	Good
Bobby Sound	Amplifier	E-Field	0.02	426V/m	Extreme
Bobby Sound	Amplifier	E-Field	1	29V/m	Slight
Bobby Sound	Amplifier	M-Field	0.02	31mG	Severe
Bobby Sound	Amplifier	M-Field	1	5.2mG	Slight
X-ray Machine	Xray	R-Field	0.02	0mW/m^2	Good
X-ray Machine	Xray	R-Field	1	0mW/m^2	Good
X-ray Machine	Xray	E-Field	0.02	29V/m	Good
X-ray Machine	Xray	E-Field	1	21V/m	Good
X-ray Machine	Xray	M-Field	0.02	4.9mG	Slight
X-ray Machine	Xray	M-Field	1	4mG	Slight

Data Visualization and Exploratory Analysis

Exploratory data analysis is a simple classification technique that is usually accomplished using visual means. It is a method of examining data sets in order to highlight their most important properties. In order to determine whether or not our data makes sense. EDA is used to solve every machine learning problem. It is, without a doubt, one of the most crucial aspects of a machine learning project. As the market expands, so does the amount of data available. It becomes more difficult for businesses to make decisions without first conducting thorough research. With the use of charts and graphs, one can make sense of the data and determine whether or not there is a relationship. As a result, any conclusions are reached using these numerous graphs. The data visualization entails the graphical display of data and information. Data visualization tools make it easy to examine and comprehend trends, outliers, and patterns in data by employing visual elements like charts, graphs, and maps. Data visualization tools and technologies are critical in the

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Big Data environment for analyzing enormous volumes of data and making data-driven decisions. Nonetheless, we created the following visuals using our model and our data sets.

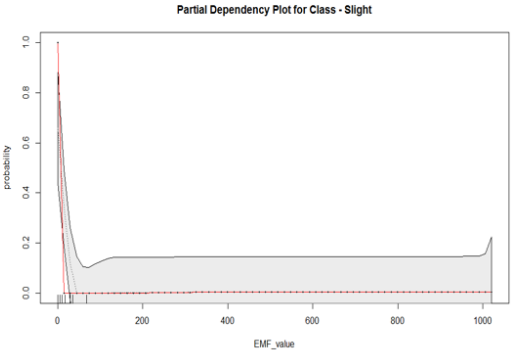

Fig. 4.a EMF vs Probability for class Slight

Figure **4.2a** depicts the partial independencies for EMF values regarded as slight. From the following figures, we illustrate the partial dependencies of the other classes of EMF Radiations values. Also, the probabilities of the EMF values variable based on how it is assigned to a particular class are also illustrated.

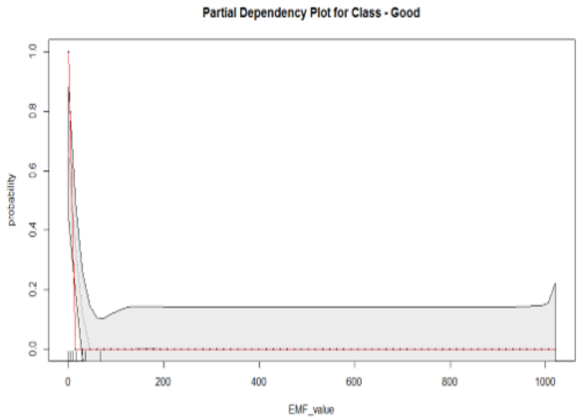

Fig. 4.b EMF vs Probability for class Good

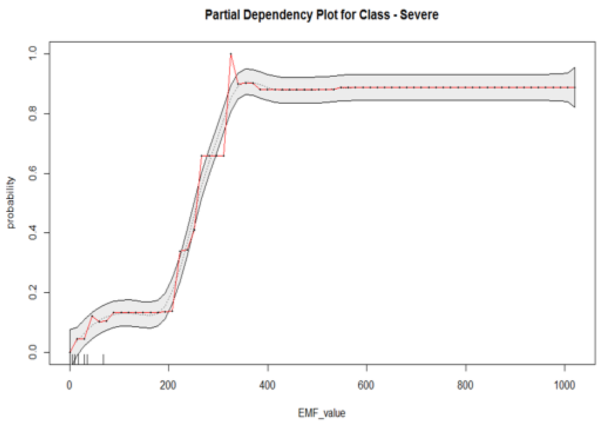

Fig. 4c EMF vs Probability for class Severe

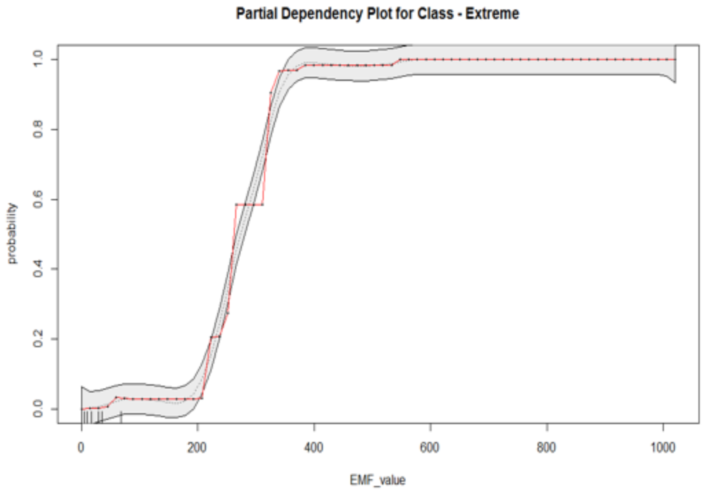

Fig. 4d EMF vs Probability-class extreme

The partial independencies so illustrated represent distance in meters that was use during the measurement of EMF radiation in each device. Elaborately, the probabilities of distance in meters and variable that was covered based on how it is assigned to a particular class are given as well.

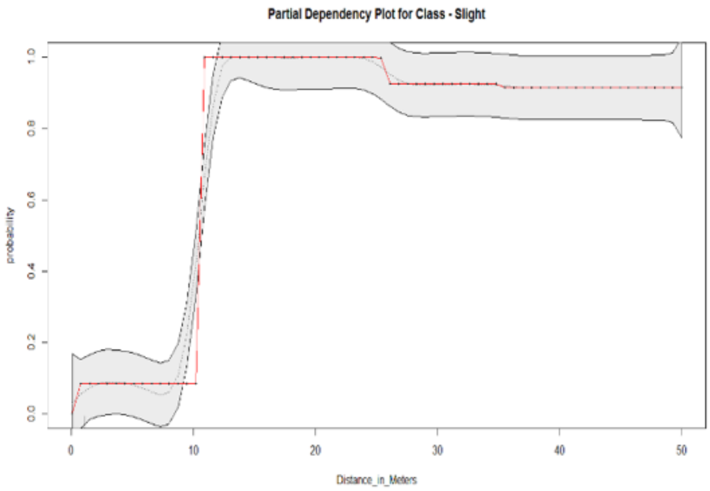

Fig. 5a. Distance vs Probability for Class Slight

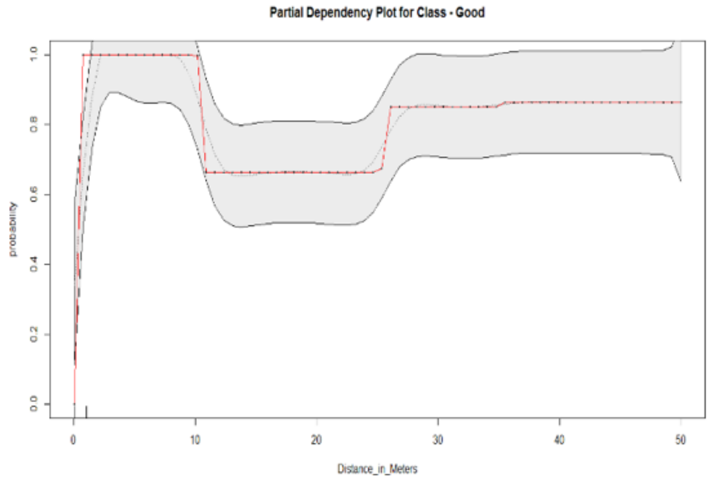

Fig. 5b. Distance vs Probability for Class Good

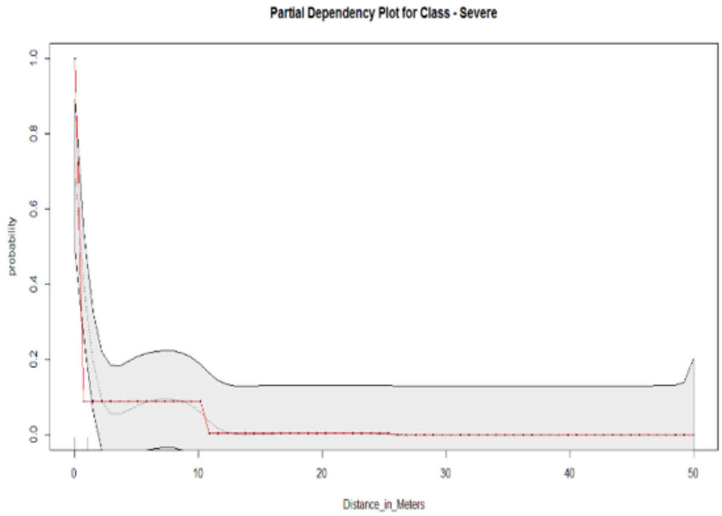

Fig. 5c. Distance vs Probability for Class Severe

Performance Evaluation

In this research, we present first the evaluation of the worst scenario based on the collected data on exposure rate to EMF and secondly, we present the performance of our RF Classifier based on Confusion Matrix and its error during model training.

Table 5.1 depicts the radiation level based on the three modes of measurement from the smart meter where R represent radiofrequency, E-Electric Field and M-magnetic field respectively. Also, the highlighted gold colours on the rows represents the mode of radiation level with highest frequency.

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Table 6: Radiation Level based on Mode of EMF

Mode of EMF	Frequency	Radiation Level
R	1	Extreme
E	11	Extreme
M	1	Extreme
Mode of EMF	**Frequency**	**Radiation Level**
R	0	Severe
E	0	Severe
M	9	Severe
Mode of EMF	**Frequency**	**Radiation Level**
R	1	Good
E	13	Good
M	9	Good
Mode of EMF	**Frequency**	**Radiation Level**
R	2	Slight
E	4	Slight
M	14	Slight

Again, table 5.2 shows the devices with the highest radiation level which is mostly depends on the distance of exposure, and we also use the gold colour to highlight the device with highest emf value generated.

Table 7: Radiation Level based on Devices on worst case scenario

Device_Type	Distance_in_Meters	EMF_value	Radiation Level
Mobile Hotspot	0.02	58.8	Extreme
Laptop Computer	0.02	765	Extreme
Transformer	1	1021	Extreme
Refrigerator	0.02	406	Extreme
Television	0.02	652	Extreme
High Tension Power Line	1	332	Extreme
Projector	0.02	27.6	Extreme
Projector	1	12.6	Extreme
Base Station	1	32.7	Extreme
Electric Iron	0.02	349	Extreme
Strong Decoder	0.02	715	Extreme
Amplifier	0.02	426	Extreme

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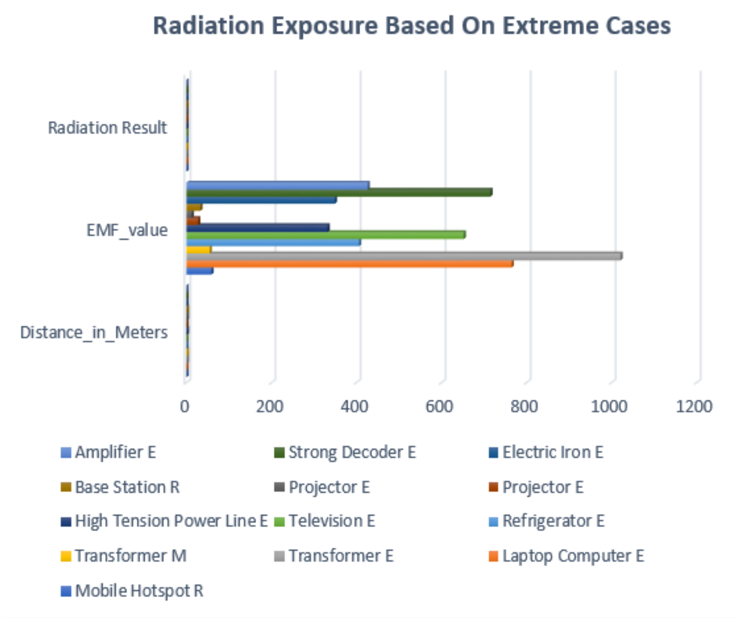
Nevertheless, figure 6 depicts the radiation result on extreme cases of exposure to each device in



our data gathered.

Fig. 6: Radiation Exposure Based on Extreme Cases

Classification and Classification Results

The RF model was trained and the classification was performed using the test data and new datasets and the following results summary were obtained. Figure 7 depicts random forest build model.

```
Call:
 randomForest(formula = Result ~ ., data = train, mtry = 4, ntree = 501,      importance = TRUE)
               Type of random forest: classification
                     Number of trees: 501
No. of variables tried at each split: 4

        OOB estimate of  error rate: 29.51%
Confusion matrix:
        Extreme Good Severe Slight class.error
Extreme       5    2      3      0   0.5000000
Good          1   24      0      6   0.2258065
Severe        1    0      6      0   0.1428571
Slight        1    4      0      8   0.3846154
```

Fig. 7: Random Forest Build Model Result

RESULTS AND DISCUSSION

Result evaluation refers to a systematic and objective appraisal of a current or completed activity. The goal is to identify the amount of significance of project objectives being met, as well as development effectiveness, efficiency, impact, and sustainability. Figure 8 shows variable processing.

```
Device_Type          Mode_of_EMF          Distance_in_Meters   EMF_value          Result
Length:84            Length:84            Min.   : 0.020      Min.   :   0.00   Extreme:14
Class :character     Class :character     1st Qu.: 0.020      1st Qu.:   0.00   Good   :41
Mode  :character     Mode  :character     Median : 1.000      Median :   9.20   Severe : 9
                                          Mean   : 3.722      Mean   :  76.32   Slight :20
                                          3rd Qu.: 1.000      3rd Qu.:  33.48
                                          Max.   :50.000      Max.   :1021.00
```

Fig. 8: Variables Processing

The Random Forest Machine learning technique is used in this study to classify Level of EMF pollution emitted by different device in order to minimize modern toxication in human health. Hence, we use R programming to preprocess all our variable from our filed data to get the summary of all our parameter based on mean, median, max, mode etc. which is depicted in figure 5.1.

Confusion Matrix

A confusion matrix is a summary of prediction results on a classification problem. The number of correct and incorrect predictions are summarized with count values and broken down by each class. This is the key to the confusion matrix. The confusion matrix shows the ways in which our classification model is confused when it makes predictions. It gives us insight not only into the errors being made by a classifier but more importantly the types of errors that are being made. Given a class, C_j, and a tuple, t_i, that tuple may or may not be assigned to that class while its actual membership may or may not be in that class. Furthermore, the accuracy of logistic regression was also computed which is depicted in table 8.

Table 8: Confusion Matrix for Random Forest model

	actual			
predictions	Extreme	Good	Severe	Slight
Extreme	4	0	0	0
Good	0	8	0	0
Severe	0	0	2	1
Slight	0	2	0	6

Hence, from our Random Forest model, the accuracy of our model is calculated has and the result is 0.8695652 which is approximately is 87% accuracy.

Additionally, we use our train data which was segmented from our overall dataset in ratio of 70% in order to and classify each device based on their radiation level. By using random forest model, 501 trees were generated and each individual error were computed. This depicted in figure 9.

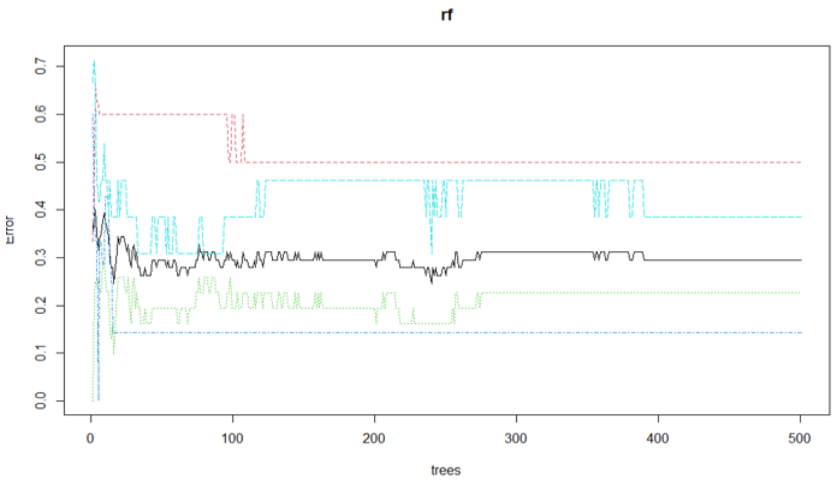


Fig 9 Random Forest Tree Vs Error

Again, we plot our important variables in our random forest model in order to view our mean decreasing accuracy and mean decrease Gini for us to identify those variables that were very important or a contributed factor during our prediction. From figure 10 under mean decrease accuracy, our model indicates that EM value and mode of EMF where the variable that indicates high level of accuracy and under mean decrease Gini, we have EMF value has the highest accuracy parameter in the model depicted in Figure 10.

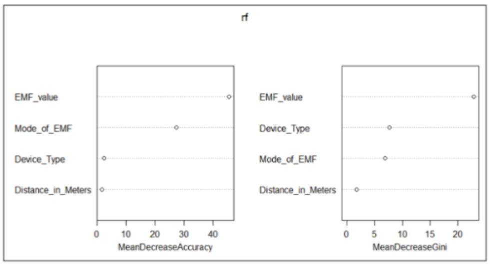


Fig. 10: Mean Decrease Accuracy Vs Mean Decrease Gini

Furthermore, Decision Tree Classifier have a wide range of effective applications. Their ability to extract descriptive decision-making information from the provided data is their key strength. Training sets can be used to create a decision tree. Therefore, in this research we apply a decision tree classifier for the classification of EMF radiation exposure data for efficient comparison of other models in the figure 11 depicts and extract of the most important nodes and causal factors in our decision tree.

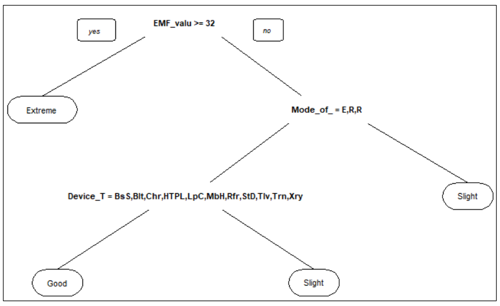


Fig. 11: Decision Tree Node

Also, a decision tree model was applying with the seam data and the result of the accuracy measure is presented in table 9

Table 9: Confusion Matrix for Decision Tree model

pred	Extreme	Good	Severe	Slight
Extreme	8	0	4	3
Good	0	26	0	0
Severe	0	0	0	0
Slight	2	5	3	10

Hence, from our Decision tree model, the accuracy of our model is calculated has and the result is 0.557377 which is approximately is 56% accuracy

Table 10: Comparative Analysis of our Model

Model Type	Confusion Matrix
Random Forest	87%
Decision Tree	56%

CONCLUSION

The research work is very useful in Radiation prediction and control and, and highly effective with regards to deployment of the machine learning model via Application programming interface (API), it can be deployed in any environment or terrain such as Hospital, academic health departments and outlets such has, schools, and personal use sectors so as to yield high Quality of Service (QoS) provisioning. Therefore, the following are the basic contributions to knowledge as many be applicable. It carried out a comprehensive review of most peer-reviewed scientific literature, including thermal and non-thermal effects based on national and international organizations which have formulated guidelines establishing limits for occupational and residential EMF exposure. The exposure limits for EMF fields developed by the International Commission on Non-Ionizing Radiation Protection (ICNIRP) - a non-governmental organization formally recognized by WHO were considered. Generally, there is disparities in EMF standards around the world, this work provides a framework for National Advisory and Regulatory Bodies for policies development and sound decision on health-based EMF standards to serve as outlines for WHO process of harmonization of electromagnetic fields (EMF) standards worldwide. It serves as a framework for policy formulation and decision making in deploying standards for EMF radiation exposure rate and proper utilization of electromagnetic fields (EMF) to greatly improve individual quality of life, health and well-being. It provides a unique prospect to integrate countries to develop a framework for harmonization of EMF standards and to encourage the development of exposure limits and other control measures that deliver the same level of health protection to all people. The system provide outline for standards which are based on evaluations of biological effects that have been established to have health consequences in public environments (PHE).

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