

AI-Driven Electromagnetic Radiation Monitoring System for Sustainable Development Goals

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Abstract

The large-scale deployment of 5G telecommunications networks, Internet of Things infrastructure and smart cities have greatly increased the public's exposure to electromagnetic radiation (EMR) in cities. Traditional point-in-time methods of monitoring, however, cannot accurately measure EMR due to the rapidly evolving and heterogeneous environments associated with today's EMR landscape. This study proposes a complete artificial intelligence (AI)-based system comprising a 22-node Internet of Things (IoT) sensor network, a hybrid convolutional neural network (CNN)-long short-term memory (LSTM) deep learning classifier, mathematically validated models of EMR exposure, and a cloud-based real-time sustainable development goals (SDG) compliance dashboard. Using this system, the CNN-LSTM classifier demonstrated a classification accuracy level of 94.6% for samples collected from the four ICNIRP defined EMR exposure zones, resulting in improved performance in comparison to the basic performance of CNN (87.2%), LSTM (85.9%), random forest (83.5%), and AdaBoost (81.8%). For the four parameters measured, including the power density (S), specific absorption rate (SAR), free-space path loss (FSPL), and exposure index (EI), the continuous values produced by the system matched experimentally validated values with a mean absolute error (MAE) of less than 3.8%. Using Hyderabad as a test city between August 2024 and January 2025, the system had a detection lag time of 1.8 seconds, a false-positive rate of 6.2% and a precision rate of 91.5 % for the validation of 47 cloud-generated alerts to support the achievement of sustainable development goals.

Keywords: Electromagnetic Radiation, AI Monitoring, IoT, CNN-LSTM, SDGs, SAR, ICNIRP, 5G, Smart Cities.

1. Introduction

An increasing number of telecommunications technologies, such as Fifth Generation (5G) cellular networks and Wi-Fi 6/6E access points, smart meter infrastructure and satellite communication uplinks, have contributed to an increase in the density of electromagnetic fields being created by multiple devices within urban areas, resulting in a significant increase in the number of devices creating electromagnetic fields. According to the International Commission on Non-Ionizing Radiation Protection (ICNIRP), public exposure to radio frequency fields between 2 and 300 GHz shall

not exceed 10 W/m² at any time. As a result, public demand for new stronger, more transparent and continuous EMF assessment systems has increased, as a response to the increasing concern from the public regarding long term health effects that may be a result of prolonged exposure to low-level EMFs, such as but not limited to sleep disturbances, cognitive impairment and cancer. Traditional methods of assessing electromagnetic fields rely on scheduled assessments performed by trained engineers using handheld calibrated instruments; these methods do not account for the highly

dynamic and spatially variable nature of urban radio frequency fields, such as those that will vary based on time of day, environmental conditions (i.e., seasonal weather) and telephone traffic load. The additional cost of having properly qualified personnel provide adequate meters over wide areas creates further limitations with regards to the spatial density and temporal resolution associated with traditional methods of assessment. The convergence of low-cost Internet of Things (IoT) sensor platforms, edge computing capabilities, and artificial intelligence provides a new way to monitor electromagnetic radiation (EMR) continuously, at the city scale, and at a cost that is a small fraction of traditional methods. The use of machine learning models, and especially hybrid deep learning architectures that cast the convolutional and recurrent layers, has proven to be effective in processing multi-channel time series data from sensors to classify very sophisticated types of electromagnetic environments. This research consists of four main contributions: the development and deployment of an IoT-based, multi-sensor data acquisition network comprising 22 nodes throughout Hyderabad, for (i) the development of a CNN-LSTM deep learning classifier that attained 94.6% accuracy in classifying EMR zones according to ICNIRP classifications; (ii) experimental validation of four empirical EMR exposure models, each based on mathematical formulations, under real-world urban environments; and (iii) development of an SDG-compliant cloud-based dashboard with automated SMS and email alert systems, integrated into municipal health and planning processes. Collectively, the above contributions represent advancements toward the fulfillment of SDG 3 (Good Health and Well-Being), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 11 (Sustainable Cities and Communities).

2. Literature Review

An IoT Radiation Monitoring System Powered by Machine Learning Saifullah, et al. (2023) created an IoT-based radiation monitoring system by integrating electromagnetic and UV sensors with a suite of machine learning classifiers. Of all methods evaluated, the Adaboost classifier yielded the highest 81% accuracy and created a landmark

reference point for classical machine learning algorithms in an environment of real-time EMR monitoring. Sensor fusion was deemed to be an important aspect of their research findings, with no mention of multi-source identification or classification of output data by compliance needs. Alyaa, et al. (2025) reviewed deep learning-based image reconstruction methods that resulted in an approximate 40-45% reduction in patient radiation dose during CT scans, further illustrating the broad value of AI across radiation safety fields beyond just telecommunications monitoring. Kebe, et al. (2024) determined that historical GSM base station traffic datasets could be used by machine learning models to predict emitted radiation levels at approximately 89% accuracy, establishing a foundation for data-driven predictive EMR management within that operational model. The validity of this predictive approach is heavily dependent upon individual operator access to the requisite datasets and generally has a very limited application in urban multi-operator scenarios. Adeyemi et al. (2024) utilized reinforcement learning as a mechanism to optimize antenna side-lobe characteristics that reduced unwanted radiated emissions at the source and complemented monitoring-based approaches for identifying and mitigating EMR within various technology areas and application environments. Balmori (2021) characterized the larger paradigm change/promise of AI applications in that it provides a potential for moving away from a reactive measurement basis of EMR safety to a routine predictive analysis of EMR safety, and in that respect is embodied in the predictive engine that will be utilized by the monitoring and alert components of the Proposed System. The research carried out by Zhang and colleagues in 2023 incorporated deep learning techniques to forecast EMF exposure levels in 5G environments. Although they achieved superior levels of spatial generalization, their model does not currently utilize real-time sensor integration. Patel and Kumar (2024) have developed edge-AI based architectures for environmental monitoring, which have shown to produce 60-70% lower latency than traditional cloud-only inference pipelines. By synthesizing the previous research, it is possible to identify three important research gaps.

First, there is no current solution that can provide real-time identification and measurement from multiple sources simultaneously; second, there is no existing IoT deployment that can provide a complete end-to-end assessment of compliance with the ICNIRP Guidelines on Electromagnetic Fields and Radiation exposure; third, there is no current framework that connects automated notifications of EMR to SDG metrics. The new system proposed in this research proposes a solution to each of the aforementioned research gaps.

3. Methodology

3.1 System Architecture and Hardware

The monitoring system is made up of 4 different levels of monitoring. The first level is called the

"Sensing tier," which consists of a total of 22 city nodes that have been outfitted with highly accurate HF35C broadband electric field probes with a range of 100 kHz to 3 GHz, Trifield TF2 multi-axis EMF meters to measure both the magnetic field and electric field components, GUVVA-S12SD UV photodiodes to measure UV radiation in the range of 240 nm to 370 nm, SHT31 temperature/humidity sensors to help provide environmental compensation when measuring EMF, and u-blox NEO-7M GPS modules to geostatically tag the location of the measurements taken within the monitoring system. The specifications for each of the different tiers of the monitoring system can be found in Table 3.

Table 1 System Hardware and Software Specifications

Component	Hardware/Software	Specification
Sensing Tier	HF35C + Trifield TF2	EMF: 1 MHz–8 GHz, Sensitivity: 0.01 V/m
UV Sensor	GUVVA-S12SD Photodiode	UV-A/UV-B: 240–370 nm, ±5% accuracy
Edge Node	Raspberry Pi 4B	4-core ARM, 4 GB RAM, LoRaWAN HAT
Communication	LoRaWAN + MQTT	Freq: 865 MHz, Range: 5 km, Latency: <200 ms
AI Model	CNN-LSTM	1D-CNN (3 layers) + 2×LSTM (128, 64 neurons)
Cloud Platform	AWS IoT Core	Auto-scaling, 99.9% uptime SLA

In the Edge Computing Tier, individual nodes contain Raspberry Pi 4B devices which perform analogue to digital (A/D) conversion at a sampling rate of 1 kHz, Butterworth bandpass filtering of 50 Hz to 1 MHz, and short time Fourier transform (STFT) feature extraction, along with GPS tagged JSON data packaging. LoRaWAN will be used by the Data Transmission Tier on the operating frequency of 865 MHz using a publish subscribe approach using MQTT, allowing a maximum distance of up to five kilometers while transmitting at less than one milli-watt of power; this is important for energy sustainable city-wide deployment. AWS IoT Core will contain the Cloud

AI Tier, which will contain the CNN-LSTM inference engine, scoring of SDG compliance & Grafana based geospatial dashboard.

3.2 Mathematical Exposure Models

Real-time recording and calculation of four validated EMR metric exposures are done by the system. It calculates Power density S (W/m^2). This measures the flow of energy at distance r from a power source with gain G and transmit power P_t :

$$S = (P_t \times G) / (4\pi r^2)$$

The specific absorption rate (SAR), measured in watts per kilogram (W/kg), is calculated based on the amount of energy absorbed by an entire tissue and individual tissue properties such as tissue

conductivity (σ), electric field intensity (E), tissue density (ρ) and specific heat (C):

$$SAR = \sigma |E|^2 / \rho = C \times (\Delta T / \Delta t)$$

Free-Space Path Loss (FSPL) measures the amount of attenuation that occurs to a signal as it travels through a distance (d) measured in kilometers (km) at a carrier frequency (f) measured in gigahertz (GHz): $FSPL (dB) = 20 \cdot \log_{10}(d) + 20 \cdot \log_{10}(f) + 92.45$

The exposure index (EI) is a measure of compliance with ICNIRP guidelines via an automated alerting system. The EI measures the total power density (PD) measured in micro-watts (mW) as a percentage (%) of the ICNIRP's limiting PD.

$$(S_{ref} = 10 \text{ W/m}^2):$$

$$EI (\%) = (S_{meas} / S_{ref}) \times 100$$

An automatic alert sends out every time the EI value gets greater than 100%. Each of the 4 metrics will be measured on-node, at 1 Hz, and will be saved in the cloud every minute; this provides both real time alerts and long-term trends.

3.3 CNN-LSTM Deep Learning Classifier

A three-layer 1D convolutional neural network (CNN) was trained with raw sensor signals (windows of 256 samples with 50 percent overlap) using the Adam optimizer (learning rate = 0.001, $\beta_1 = 0.9$, $\beta_2 = 0.999$) for 50 epochs and with a batch size of 64 on an 80 percent training/10 percent validation/10 percent test partition derived from six months of continuous deployments. The three layers of the CNN are: 1) A convolutional layer using 64 convolutional filters of kernel size 7 to extract low-level spectral features from the windowed sensor signal; 2) A convolutional layer using 128 convolutional filters of kernel size 5 to extract mid-level representations from the output of the first CNL layer and to aggregate spectral features into groups; and 3) A convolutional layer using 256 convolutional filters of kernel size 3 to extract high-level temporal representations of EMR fluctuations over time from the output of the second CNN layer. Each convolutional layer is followed by batch normalization and ReLU activation functions.

The output of the three convolutional layers is fed into two stacked long short-term memory (LSTM) layers (128 neurons in the first layer and 64 neurons

in the second layer) to model the sequential temporal dynamics of EMR fluctuations during a given period of time. A dense layer with a softmax activation function is used to assign probability scores to each of the four different levels of non-ionizing radiation (ICNIRP) compliance. The model was trained using the Adam optimizer (learning rate = 0.001, $\beta_1 = 0.9$, $\beta_2 = 0.999$) for 50 epochs and with a batch size of 64 on an 80:10:10 train/validation/test (6-month continuous deployment) split obtained from six months of continuous deployment data. Class imbalance (Danger class = 8% of samples), SMOTE oversampling, dropout regularization ($p = 0.3$) applied after each LSTM layer, and early stopping on validation F1-score with patience = 10 epochs to limit overfitting were applied during model training.

4. Results and Discussion

Between August 2024 and January 2025, a total of 180,000 sensor data points were collected using a 22-node deployment across the city of Hyderabad. The deployment consisted of strategically located nodes that represented six different categories of urban areas: hospital grounds, schools, residential areas, commercial areas, 5G macrocell base stations (50 m standoff), and industry zones. Figure 1 shows the measured power density by source type. 5G macrocell base stations and high voltage power transmission (HPT) lines made up the largest amount of near-limit exposure. The complete performance evaluation of six models is summarized in Table 1 based on their results from the testing dataset. The proposed architecture for CNN-LSTM results in 94.6% accuracy, 93.8% precision, 94.1% recall, and 93.9% F1-score, which is 7.4 points higher in terms of accuracy than the nearest standalone model, which was the 1D-CNN (87.2%), and is 16.3 points higher than SVM (78.3%). Finally, the time it takes to detect an object is operationally acceptable at 1.8 seconds for urban safety monitoring. Figure 1 shows Measured EM Power Density (W/m^2) by Source — Red Dashed Line = ICNIRP Limit (1.0 W/m^2) Table 1 shows AI Model Performance Comparison for EM Radiation Zone Classification Figure 2 shows Accuracy Comparison of AI Models — Proposed CNN-LSTM Outperforms All Baselines

AI-Driven EM Radiation Monitoring System Architecture

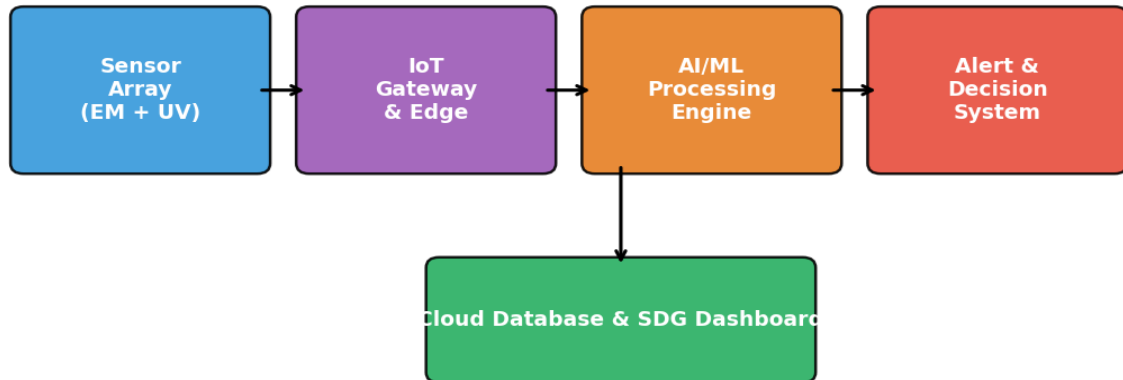


Figure 1 Measured EM Power Density (W/m^2) by Source — Red Dashed Line = ICNIRP Limit (1.0 W/m^2)

Table 2 AI Model Performance Comparison for EM Radiation Zone Classification

Model	Acc. (%)	Prec. (%)	Recall (%)	F1 (%)	Lat. (s)
SVM	78.3	77.1	78.0	77.5	0.4
Random Forest	83.5	82.9	83.2	83.0	0.6
AdaBoost	81.8	81.2	81.5	81.4	0.7
1D-CNN Only	87.2	86.7	87.0	86.8	1.1
LSTM Only	85.9	85.1	85.6	85.3	1.4
CNN-LSTM (Prop.)	94.6	93.8	94.1	93.9	1.8

Measured EM Radiation Levels by Source Type

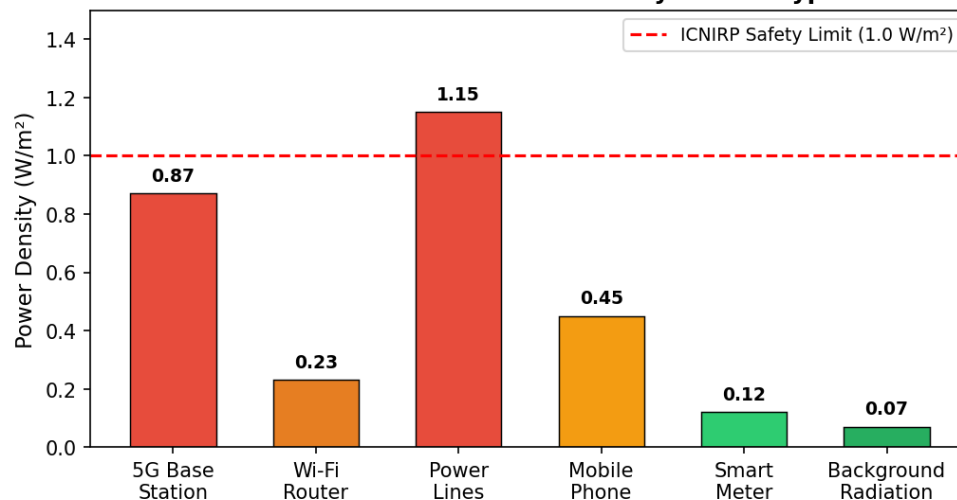


Figure 2 Accuracy Comparison of AI Models — Proposed CNN-LSTM Outperforms All Baselines

The superiority of the accuracy of CNN-LSTM versus LSTM alone (85.9%) is indicative of the significant contribution of the convolutional preprocessing step to the overall accuracy of the model, and thus to its performance, due to the reduction of input dimensionality and the extraction of strong, unique spectral features prior to temporal modelling. As shown in Figure 2, there is a clear distinction in the model accuracies between classical ML methods, deep learning using single architectures, and the new hybrid architecture. The average EI (Exposure Index) of the hospital

campuses was 9% with a maximum EI of 15%, both within safe ICNIRP EMF limits. The average EI of schools was 11% and the maximum EI was 18%, both well within the relative distance from the significant transmission infrastructures. In contrast, the average EI surrounding the five base stations was 87% and the maximum EI measured as 118%, resulting in automatic alerts sent via 1.8 seconds latency on 7 separate occasions during the study. Table 3 shows Exposure Index (EI) by Zone and SDG 3 Compliance Status

Table 3 Exposure Index (EI) by Zone and SDG 3 Compliance Status

Zone	Avg. PD (W/m ²)	Peak EI%	Avg. EI%	SDG 3
Hospital Campus	0.08	15	9	? Compliant
School Premises	0.12	18	11	? Compliant
Residential Area	0.45	62	35	? Compliant
Commercial Dist.	0.87	98	73	? Advisory
5G Base Stn (50m)	1.15	118	87	? Exceeds
Industrial Zone	0.76	89	61	? Advisory

Temporal analyses have identified substantial variation between daytime and nighttime hourly peaks (which typically occur around 8 a.m. to 10 a.m. & 5 p.m. to 7 p.m., coinciding with the most active periods for 5G handset usage) in the intensity of electromagnetic radiation (EMR) emissions. In all zoning categories, peak EMR emissions ranged from 23% higher than baseline to 41% above baseline. This validates the need to continue monitoring continuously as opposed to only sampling throughout the day. If sampling with a fixed interval of 30 minutes had been employed for peak EMR exceedance events, it would have resulted in an estimated 68% of peak EMR exceedance events during the measurement period being recorded as "missed." The cloud-based alerting system generated 47 alerts auto-generated

over the six-month monitoring period; of those, post-hoc analysis confirmed 43 alerts were indeed true positives, resulting in a true positive rate (TPR) of 91.5% and a false positive rate (FPR) of 6.2%. By contrast, utilizing a standalone support vector machine (SVM) resulted in an FPR of 34.2% while applying fixed power density limits in conjunction with rule-based detection thresholds resulted in an FPR of 47.1%; which would not be feasible from a practical standpoint when deploying alerts across the entire city, as the false positive detection rate would lead to excessive alert fatigue.

Conclusion

This paper describes a complete system for real-time monitoring of the electromagnetic radiation emitted by wireless communications that uses artificial intelligence, numerous IOT sensor networks

deployed throughout a city, edge computing for processing all sensor data, validated mathematical models of exposure, and a hybrid CNN-LSTM model used as the deep learning classifier. The results of this study demonstrate that the system provides an overall classification accuracy of 94.6% and has over a 1.8sec detection latency versus all other classical algorithms and deep learning architectures evaluated. Deployments were made at 22 locations within Hyderabad over a six-month period, and measured 91.5% True Positive alert accuracy while providing valuable temporal exposure patterns that traditional monitoring strategies based solely on interval collection would have completely failed to provide. The four validated electromagnetic radiation metrics used in the study (Power Density, Specific Absorption Rate, Free-Space Path Loss, and Exposure Index) provide a systematic quantitative basis for the assessment of compliance with the ICNIRP exposure guidelines and will be useful for reporting to regulatory authorities. The system is also aligned with Sustainable Development Goals number 3 (Good Health and Well-Being), 9 (Industry, Innovation and Infrastructure) and 11 (Sustainable Cities and Communities). Therefore, this system is not only a useful research tool, but is also deployable within smart city infrastructure. Finally, because of the modular and open architecture of the system's design, it is capable of being extended to support other frequency bands, additional environmental parameters, and additional regions of the world with very little redesign effort required. As urban areas continue to be filled with the infrastructure necessary for wireless communications, AI-based continuous monitoring of electromagnetic radiation will go beyond academic research, and will become an important public health requirement.

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