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RESEARCH ARTICLE

Evaluation of Personal Radiation Exposure From Wireless Signals in Indoor and Outdoor Environments

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ABSTRACT With the development of wireless technology, the public is exposed to electromagnetic fields (EMF), which has led to concerns about the potential health effects of EMF exposures. This paper aims to evaluate personal EMF exposures from wireless signals in indoor and outdoor micro-environments in Malaysia. According to the influencing factors, four different types of micro-environments are selected. A radiation exposure meter called ExpoM-RF 4 is used to measure the electric field strength across these micro-environments. From the measurement campaigns, three machine learning (ML) techniques are simulated to model the Electric Field Strength in each micro-environment. The ML techniques are Fully connected neural network (FCNN), eXtreme Gradient Boosting (XG Boost), and Linear Regression (LR) to predict the RMS and Maximum radiation exposure. From the ML models, Total Emission Ratio (TER), Root Mean Square Error (RMSE) and Coefficient of Determination (R^2) are evaluated to measure the performance of ML. By comparison, it is found that LR performs well with single and simple data set, while XG Boost and FCNN demonstrate superior capabilities in handling multiple types of data sets. The FCNN model provides the most accurate predictions, particularly in urban and suburban areas where extreme values are observed. Finally, the measured data and the predicted radiation exposure levels are compared against public exposure limit by International Commission on Non-Ionizing Radiation Protection (ICNIRP), Malaysian Communications and Multimedia Commission (MCMC) and Federal Communications Commission (FCC). The results demonstrate that typically personal radiation exposure is lower than the exposure limit (61.4 V/m), which is similar to the most research results. However, in areas with dense population and numerous base stations, the maximum exposure can approach 56.7365 V/m (measured data), which is close to the exposure limit.

INDEX TERMS Electromagnetic fields (EMF), personal radiation exposure, micro-environments, ExpoM-RF 4, machine learning (ML), exposure limit, indoor and outdoor environment.

I. INTRODUCTION

With the rapid advancement of wireless networks, wireless technology has become an integral part of human daily life. The widespread deployment of wireless networks, the growing usage of mobile devices, and the expanding use of the Internet of Things (IoT) have significantly increased public exposure to electromagnetic fields (EMF) [1]. However, awareness and understanding of exposure to EMF remains limited. There are cases in some countries where some of the citizens seem to be apprehensive about radio frequency- electromagnetic fields (RF-EMF) exposures

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from telecommunication services that they actively oppose the installation of base stations. Furthermore, the potential health impacts of RF-EMF in sensitive environments such as kindergartens, hospitals, and other public spaces have been a topic of significant academic and public interest [2]. Therefore, it is essential to conduct a comprehensive and systematic assessment of RF-EMF exposure levels across various public environments.

EMF radiation is pervasive in everyday life, encompassing sources such as visible light, mobile phone and X- rays. While ionizing radiations such as X- rays and gamma rays has enough energy to break molecular bonds and ionize atoms, potentially causing skin burns and DNA damage at high intensities, non-ionizing radiations lacks sufficient energy to induce ionization. With the continuous advancement of broadcast and mobile telecommunication technologies worldwide [3], especially on introduction of 5G technology has raised concerns about the radiation safety. However, 5G operates within the radio frequency (RF) band of the non-ionizing electromagnetic spectrum. Organizations such as the International Commission on Non-Ionizing Radiation Protection (ICNIRP) have set strict exposure limits to prevent adverse health effects [4]. For example, in the high-frequency EMF (100 kHz–300 GHz), ICNIRP guidelines restrict temperature increase to 1 °C for the whole body, 2 °C for the head, and 5 °C for limbs, ensuring safe exposure levels [4], [5].

The International Agency for Research on Cancer classified RF-EMF as a possible human carcinogen in 2011 [6]. The World Health Organization (WHO) also classifies radio frequency radiation as a probable human carcinogen (Group 2B), indicating the need for further research into the long-term effects of low levels exposure from wireless devices. Since then, interest in human exposure to RF-EMF and its potential health effects has grown significantly [7]. During the COVID-19 pandemic, there have been a series of arson attacks on 5G base stations across the UK, which are believed to be linked to the spread of the virus. This extreme reaction highlights the lack of proper information. Increasing people's understanding of individual RF-EMF exposure levels can offer great help toward acceptance of technology, psychological prevention, and social stability. In a paper, people with more education on obtaining relevant EMF information are more confident in facing EMF radiation [8].

Mobile phones and base stations are the primary sources of RF radiation in outdoor environments [9]. When mobile phone is in use, it communicates with nearby base stations through RF signals. The level of exposure varies based on several factors, including the distance from the base station, the power output of the phones and base stations, and the frequency of the phone usage. In addition, base stations emit RF radiation to provide network coverage over a broad area, contributing to overall outdoor RF exposure. For indoor environment, the main source of RF radiation is Wi-Fi. Wi-Fi routers and connected devices emit RF signals to enable wireless internet access. The extent of Wi-Fi exposure depends on the distance from the router [10], the duration of exposure, and the router's power settings. Other common sources of RF radiation include Bluetooth devices, Frequency Modulation (FM) radio, Digital TV, Industrial, Scientific, and Medical (ISM) Bands. These signals propagate and get attenuated by the environments it propogates through, influencing overall exposure levels in the environments. Below is a list of customized frequency bands (with their central frequencies) in Malaysia [11], [12]:

TABLE 1. Frequency bands (with their central frequencies) in Malaysia.

Services to be Monitored	f_{min} [MHz]	f_{max} [MHz]	Fcentre [MHz]	Fdiff [MHz]	BW [MHz]
FM Radio	88	108	98	20	35
Digital TV (DTV) I	470	545	507.5	75	75
Digital TV (DTV) II	545	620	582.5	75	75
Digital TV (DTV) III	620	695	657.5	75	75
Mobile700TDD	758	798	778	40	35
Mobile800TDD	798	803	800.5	5	35
Mobile850UL	814	849	831.5	35	35
Mobile850DL	859	894	876.5	35	35
Mobile900UL	880	915	897.5	35	35
ISM1	902	928	915	26	35
Mobile900DL	925	960	942.5	35	35
Mobile1800UL	1710	1785	1747.5	75	75
Mobile1800DL	1805	1880	1842.5	75	75
DECT	1880	1890	1885	10	35
Mobile1900TDD	1900	1920	1910	20	35
Mobile2100UL	1920	1980	1950	60	75
Mobile 2100TDD	2010	2025	2017.5	15	35
Mobile2100DL	2110	2170	2140	60	75
Mobile 2300TDD	2300	2400	100	100	100
ISM2(WLAN1)	2400	2500	2450	100	100
Mobile 2600UL	2500	2570	2535	70	75
Mobile 2600TDD	2570	2620	2595	50	35
Mobile 2600DL	2620	2690	2655	70	75
Mobile TDD1	3525	3500	3462.5	75	75
Mobile TDD2	3500	3600	3550	100	100
Mobile TDD3	3600	3700	3650	100	100
WLAN2	5150	5250	5200	100	100
WLAN3	5250	5350	5300	100	100
WLAN4	5450	5550	5500	100	100
WLAN5	5550	5650	5600	100	100
WLAN6	5650	5750	5700	100	100
WLAN7	5750	5850	5800	100	100

All these signals are systematically measured and analyzed in this paper. Specifically, this list of 32 custom bands with their center frequencies are also registered into the ExpoM-RF4 device for measurement.

The main contributions of this paper are as follows:

1. Integrating field measurements with machine learning models to evaluate personal radiation exposure from wireless signals in indoor and outdoor environments in Malaysia. A total of 32 distinct signals were recorded, comprehensively considering various signal sources in the environment.
2. A comprehensive analytical formula was developed, incorporating electromagnetic field (EMF) parameters along with four related influencing factors, and was subsequently utilized within the machine learning framework.
3. Compare the measured data and the predicted value with public exposure limits. New discoveries have been made compared with previous studies. Typically personal radiation exposure is lower than the exposure limit, which is similar to the most research results. However, in areas with dense population and numerous base stations, the maximum exposure will be very close to the exposure limit.

II. RELATED WORK

International multiple studies have been conducted to monitor individual RF-EMF exposure with most findings indicating that human RF-EMF exposures remain well below the ICNIRP public exposure limits [2], [6], [13], [14], [16]. However, previous research often focuses on specific conditions in isolation or fails to account for non-detect values, which may affect the accuracy of their conclusions. In 2015, UK researchers Enver Hamiti et al. [13] choose five different types of micro-environments and obtained 122,944 measurement samples. The results obtained are compared with exposure limits given by ICNIRP. However, non-detect values were not analyzed in this phase of the study, so there is limitation on their methodology. Another study measured RF-EMF exposure across 94 participants in urban areas of eight European countries. Public transportation and city centers were consistently found to have the highest exposure levels, particularly due to downlink signals from mobile base stations [14]. However, individual activity patterns had an influence on the accuracy and variability of personal RF-EMF exposure measurements. These studies [13], [14] illustrate potential limitations of overlooking non-detect values in research of RF-EMF exposure. Therefore, comprehensive assessment that consider various factors within different micro-environments is crucial for obtaining reliable exposure data.

A paper presented five ML-based models for Uplink (UL) throughput prediction, comparing the performance of five different ML algorithms [15]. However, the geomagnetic measurements of this study are collected from the same environment, which may limit their general usage in different environments. Another Conducted RF-EMF measurements on electric buses in Samsun, Turkey. Highest RF-EMF observed was 6.01 V/m, much lower than ICNIRP public limits [16]. But this research scope is limited to two urban bus routes, and the conclusion may not be applicable to other vehicle types, such as subways or traditional buses. These studies [15], [16] show that full consideration of influencing factors and selection of appropriate environment have a great impact on the applicability of experimental results.

Integrating machine learning (ML) techniques into electromagnetic field research can improve modeling accuracy and computational efficiency. One study introduces a physics-informed ML approach using gradient-boosted decision trees to model radio frequency EMF exposure from 5G massive MIMO base stations, enabling the extrapolation of exposure levels at greater distances [17]. Another study proposed a deep residual convolutional neural network (DRCNN) to expedite full-wave electromagnetic simulations [18]. The DRCNN effectively captures complex electromagnetic behaviors while significantly reducing computation time compared to traditional methods. Other research has employed multiple ML models to analyze RF-EMF exposure and assess their predictive performance. For instance, a study on physical layer measurements of uplink and down link throughput compared five different ML algorithms to evaluate their performance [15]. Another study on RF-EMF exposure assessment for 5G base stations used three ML techniques to predict exposure levels, comparing the results with measured data for validation [19]. These studies highlight the advantages of using multiple ML models for analysis. Compared to relying on a single model, employing a diverse set of ML techniques improves data processing, enhances predictive accuracy, and leads to more robust and reliable conclusions.

The limitation of existing research on radio frequency electromagnetic field (RF-EMF) exposure can be summarized as follows:

These papers [13], [14], [15], [16] illustrate the critical importance of considering influencing factors and selecting appropriate environment to ensure reliability and applicability of experimental results. Therefore, achieving meaningful and generalizable findings requires not only strict adherence to international standards, but also to comprehensively consider the impact of various influencing factors when selecting the appropriate types of micro-environments.

The regulation of RF-EMF exposure is essential to safeguard public health amid the increasing prevalence of wireless technologies. International organizations such as the ICNIRP supported by the World Health Organization (WHO) [20] have developed comprehensive guidelines to regulate RF-EMF exposure. The ICNIRP guidelines, widely recognized and adopted globally, set limits on RF-EMF exposure based on detailed risk assessments. These guidelines consider both thermal and non-thermal effects [21], aiming to protect against known health risks.

Different countries have adopted and adapted international guidelines to fit their specific regulatory framework. For

TABLE 2. Related work and informative limits.

Article	Finding	Limitation
[13] Enver Hamiti et al 2015	Measured 122,944 measurement samples, found that exposure levels were lower than the reference values set by (ICNIRP).	Non-detectable values were not analyzed, which could affect the accuracy of the results.
[14] T. S. Joseph et al 2020	Measured RF-EMF exposure in eight European countries, results showed public transport and city centers had the highest exposure values.	Individual activity patterns had an influence on the accuracy and variability of personal RF-EMF exposure measurements.
[15] E. Eyceyurt et al 2022	Presented an ML-based Uplink (UL) throughput prediction model, which applies to 4G and possibly, 5G mobile networks.	Measurements are collected from the same environment, which may limit their general usage in different environments.
[16] Z. E. Albayrak et al 2024	Conducted RF-EMF measurements on electric buses in Samsun, Turkey and magnetic field exposure remained below ICNIRP public limits.	The research scope is limited to two urban bus routes, and the conclusion may not be applicable to other vehicle types.

example, Australia and Malaysia closely follow ICNIRP guidelines. The Australian Radiation Protection and Nuclear Safety Agency (ARPANSA) and Malaysian Communications and Multimedia Commission (MCMC) adopts the same exposure limits as ICNIRP 2020 guidelines [22], [23]. However, other countries, such as Italy and Switzerland, have implemented even stricter regulations due to public concern and precautionary principles. They set lower exposure limits in certain areas such as in residential zones and schools [24]. The FCC (Federal Communications Commission) in the United States set a maximum SAR limit of 1.6 W/kg averaged over 1 gram of tissue for public exposure [25], which is slightly more stringent than the ICNIRP standard.

The ICNIRP 's guidelines are based on a comprehensive evaluation of peer-reviewed scientific studies. The FCC 's guidelines are informed by the recommendations of expert panels, including the National Council on Radiation Protection and Measurements (NCRP), which reviews current research and provides guidance on safe exposure levels [26]. Therefore, this study adopts ICNIRP and FCC as the standard to assess human exposure to the magnetic field. Key metrics used to evaluate personal radiation exposure include electric field strength E (V/m), magnetic field strength H (A/m), and power density S (W/m^2). Since the data measured with ExpoM-RF 4 is the Root Mean Square (RMS) values of the signal electric field strength, electric field intensity E (V/m) is used to determine whether personal radiation exposure complies with the safety standards. RMS can be defined as follows:

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{1}$$

RMS: Root Mean Square, a measure that captures the overall energy or amplitude fluctuations of a signal.

N: Number of signals.

x_i: The electric field strength of each signal.

TABLE 3 and TABLE 4 shows public exposure limits for electromagnetic fields from ICNIRP and FCC guidelines respectively.

TABLE 3. ICNIRP guidelines 2020 [5].

Exposure scenario	Frequency range (Hz -GHz)	Electric field strength E (V/m)	Magnetic field Strength H (A/m)	Power Density S (W/m^2)
General public	0.1-30MHz	$300/f_M^{0.7}$	$2.2/f_M^{0.7}$	-
	30-400Mhz	27.7	0.073	2
	400-2000Mhz	$1.35f_M^{0.5}$	$0.0037f_M^{0.5}$	$f_M/200$
	2-300GHz	-	-	10

TABLE 4. FCC OET Bulletin 65 [21].

Exposure scenario	Frequency range MHz	Electric field strength E (V/m)	Magnetic field Strength H (A/m)	Power Density S (W/cm^2)
General public	30-300MHz	27.5	0.073	0.2
	300-1500Mhz	-	f/1500	2
	1500-100000Mhz	-	1.0	$f_M/200$

As presented in TABLE 3 and TABLE 4, for signals of different frequencies, the limit of electric field strength is calculated in different ways, including fixed values, given formulas, or calculated by power density. The relationship between power density and electric field strength can be calculated by the following formula:

$$S = \frac{E^2}{Z_0} \tag{2}$$

S: power density, W/m^2,

E: electric field strength, V/m,

Z_0: the impedance of free space, typically $Z_0 = 377\ \Omega$ [27]

The results of the ICNIRP and FCC standard electric field strength limits are shown as follows:

TABLE 5. Limits of electric field strength (ICNIRP).

Frequency range	Formula	Electric field strength E(V/m)
30 MHz - 400 MHz	-	27.7 V/m
400 MHz -2 GHz	$E = 1.35\ f_M^{0.5}$	27 V/m - 60.4 V/m
2 GHz - 6 GHz	$S = \frac{E^2}{Z_0} (S = 10\ \mathrm{W/m^2})$	61.4 V/m

Personal radiation exposure to EMF is influenced by various environmental and infrastructural factors. The building materials utilized in indoor environments significantly attenuate wireless signals from external sources, such as glass can cause significant insertion loss to wireless signals

TABLE 6. Limits of electric field strength (FCC).

Frequency range	Formula	Electric field strength E(V/m)
30 MHz - 400 MHz	-	27.7 V/m
400 MHz -2 GHz	$E=\sqrt{\frac{377}{150}f}$	27.5 V/m -61.4 V/m
2 GHz - 6 GHz	$S=\frac{E^2}{Z_0}(S=10\,W/m^2)$	61.4 V/m

passing through it [28]. The outdoor environment is relatively more complex due to the due to the multiple direct radiation sources such as base stations, dense buildings, moving vehicles, which contribute to signal reflection and scattering. Urban areas with tall and dense packed buildings can influence exposure levels by causing signal reflection and scattering. However, a study indicates that the building height has a limited effect on overall radiation exposure [29]. The number of base stations and population density also have significant effects on local electromagnetic exposure. The higher the population density, the higher the number of base stations is deployed to meet user needs, which may affect individual radiation exposure levels. However, increasing base station density can reduce the transmission power required for individual devices, potentially reducing individual radiation exposure levels [30]. The distance to base stations significantly affects exposure levels, as closer distances allow devices to operate at lower power, reducing overall exposure. In a paper which analyzes the downlink, uplink, and joint downlink and uplink exposure induced by the radiation from base stations and personal user equipment (UE) [31]. In a formula, it is provided to support this view that the strength of the electric field is inversely proportional to the square of the distance [32]. In another study, a formula is provided to support that different frequency bands have varying propagation characteristics. Related equation [4]:

$$S = \frac{4\pi\ \mathrm{Pr}}{\lambda^2 G} \tag{3}$$

$$\lambda = \frac{c}{f} \tag{4}$$

$$E = \sqrt{Z_0 \cdot S} \tag{5}$$

P_r is the received power (W), λ is the wavelength in free space,

G is the gain of the antenna, Z0 is the free space impedance.

After tidying up:

$$E = \frac{2}{c}\sqrt{Z_0 \cdot \frac{\pi\ \mathrm{Pr}}{G}} \cdot f \tag{6}$$

Vegetation can attenuate electromagnetic waves [33] and thus reduce field strength.

The relationship between Electric Field Strength and relevant influencing factors can be summarized as follows:

In the outdoor micro-environment, vegetation coverage, population density, building density and base station density are different in different occasions, which will affect the attenuation (reflection, scattering and absorption) and propagation of electromagnetic waves and then affect the radiation value. Therefore, different types of micro-environment should be divided according to the influencing factors.

TABLE 7. Influencing factors of electric field strength.

Article	Finding	Influencing factors
[29] Building and Environment, vol. 124, 2017.	Discuss the effects of buildings on scattering and reflection of electromagnetic fields.	It is pointed out that the building height has a limited effect on radiation exposure.
[30] G. Bianchi et al 2020	5G deployments will change the EMF exposure landscape but can be maintained within safe thresholds.	Increasing base station density can reduce the transmission power required for individual devices, potentially reducing individual radiation exposure levels.
[31] L. Chen et al 2023	Use a combination of simulation and theoretical analysis to jointly optimize system performance metrics and EMF exposure.	The equation between power density and Electric Field Strength.
[32] M. Gustafsson et al 2007	Present a framework for deriving physical limitations on antenna quality factor (Q), bandwidth, and other performance metrics.	The strength of the electric field is inversely proportional to the square of the distance, with equation is provided to support this view.
[33] J. Smith et al 2019	The study analysed the influence of urban vegetation on electromagnetic field attenuation	Vegetation can attenuate EMF waves and thus reduce field strength.

III. METHODOLOGY

The methodology of this work is outlined in Figure 1, including experimental measurement, statistical modeling, machine learning and comparative analysis.

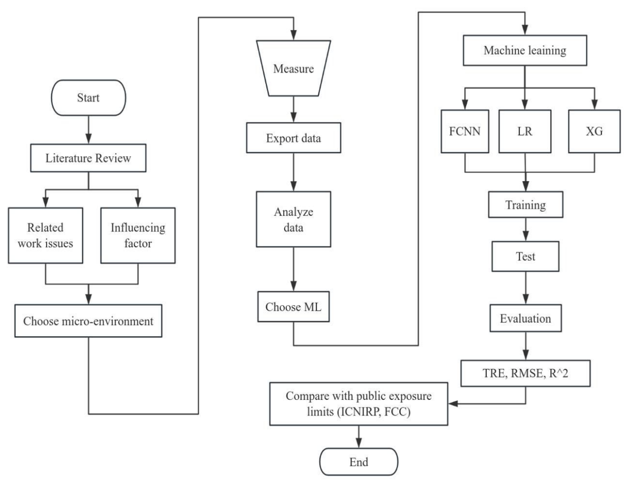

FIGURE 1. The flow chart of the methodology.

First, a comprehensive literature review is conducted to identify current research gaps and key influencing factors. Based on these findings, appropriate micro-environments are selected for this study. Next, data is collected in each micro-environment using the ExpoM-RF 4 radiation exposure meter. From the measurement campaign, the relationship between data and influencing factors are analyzed, such as frequency range and population density. For predictive modeling, three machine learning (ML) techniques are applied, namely FCNN, XG Boost and LR. Total Exposure Ration (TER), RMSE and R^2 are calculated to assess the performance of the model. Finally, the measured data and the predicted value are compared against public exposure limits set by ICNIRP and FCC. Further details on each step is described below.

A. MEASUREMENT EQUIPMENT

ExpoM-RF4 as shown in Figure 2 is used to measure RF-EMF in micro-environments. Compared to other measurement devices, it is compact and lightweight, making it convenient to carry in a waist pack. This device measures electric field strength (V/m) of EMF and can automatically record the peak value, the minimum value, and RMS value of each signal every six seconds. Additionally, its ability to configure custom frequency band lists from 50 MHz to 6 GHz provides exceptional flexibility, ensuring compatibility with future changes in frequency band allocations and regulations [34]. A total 32 custom frequency bands (with their central frequencies) in Malaysia have been recorded in the TABLE 1. These bands have been programmed into the ExpoM-RF4 for precise measurement and analysis.

FIGURE 2. ExpoM-RF4.

After measuring data, use the software ExpoM-RF4 Utility to connect the ExpoM-RF 4 device to the PC. The raw data, including Google Earth the KML files that visualizes measurement paths, are exported.

B. MEASUREMENT CAMPAIGN

The measurement campaign starts with selecting a suitable micro-environment. Based on the literature review, several factors influence radiation levels including population density, frequency, range, vegetation coverage, building height and base station density. Considering these influencing factors, four distinct micro-environments are selected which are urban (6 high population density areas in Kuala Lumpur), suburban (7 low population density areas in Cyberjaya), park (3 park areas) and one indoor micro-environment.

For indoor measurement, precautions are taken to minimize interference by avoiding the use of other electronic devices nearby during data collection. For outdoor micro-environments, predefined walking paths are established on a map to ensure consistency in measurement. These paths are defined as 1-2 km long and require a 20–30-minute walk to complete, which follow the ICNIRP stipulates. Google Maps is used to define the path length and walking area, with each micro-environment linked to a corresponding Google Maps route for reference. During data collection, the researcher follows the predetermined path while measuring RF-EMF exposure. The details of each micro-environment are provided in APPENDIX A.

To ensure accurate RF-EMF measurements while using Google Maps for navigation and minimizing interference from mobile phone radiation, each measurement campaign requires three team members. The first person used Google Maps to navigate the predefined walking path. The second person records environmental details including vegetation coverage, building features, number of base stations, and their proximity. To avoid interference, the third person carries only ExpoM-RF4 device in waist pact and is not allowed to bring any electronic equipment, mobile phone or Bluetooth-enabled equipment. This person follows the other two people while assisting in identifying any missing base stations. Those three should keep as much distance as possible to prevent interference from cell phone frequency. To account for the body-shielding effect during the measurements, the team walks to a designated point and then returns along the same path. This ensures that the ExpoM-RF4 device able to measure the RF-EMF exposure from both front and back direction.

C. MACHINE LEARNING (ML) MODELS

This study used machine learning to predict both maximum and RMS value of Electric Field Strength, considering various factors that influence EMF. Based on comprehensive literature review and recorded environmental characteristics, this study analyzed the influence factors on radiation value.

Figure 4 shows measured radiation exposure from 97.5 MHz to 5800 MHz.

As shown in Figure 3, the distribution of electric field intensity is shaped in a Gaussian distribution, with data mostly concentrated at the center and gradually decreasing to the sides.

TABLE 8 shows the calculated population density of each micro-environment along with the maximum RMS value and maximum electrical field strength. The population density is ranked from highest to lowest.

Figure 4 displays the maximum RMS value and maximum electric field strength against population density.

Electric field strength tends to be higher in densely populated areas and lower in sparsely populated regions.

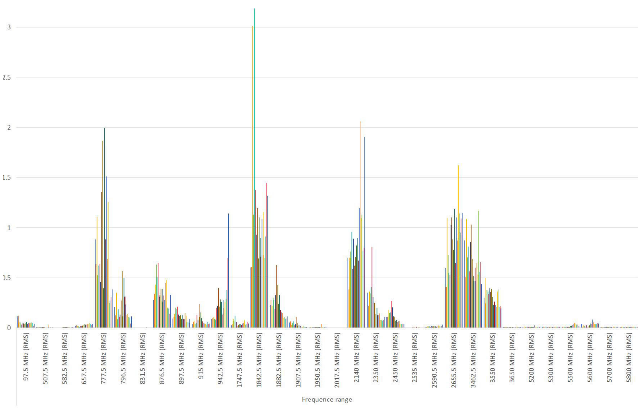

FIGURE 3. Measurement of electric field strength with respect to frequency range.

TABLE 8. The variation of electric field strength with population density.

Location Name	Population density {People/Km²}	Maximum RMS （V/m）	Max Value (V/m)
Jln Tun Razak	10541	7.961	56.737
KLCC area	6890	8.480	39.249
KLCC Park	6429	6.101	20.831
Hotel Geo	5739	6.026	32.096
Petaling Jaya (PJ)	5291	3.724	21.256
Bukit bintang	4790	10.427	30.455
Bukit Jalil Recreational Park	1541	0.499	2.603
Selangor Cyber Valley	1200	3.006	12.821
Cyberjaya City Centre	1074	1.576	15.624
Bangsar	1000	6.245	33.080
Cyberjaya Hospital	1000	4.504	27.234
Wisma Shell	987	3.556	16.477
Public Park	950	2.631	17.292
Dpulze Shopping Center	945	1.787	26.355
Cyber Heights Villa area	945	1.467	6.322
Putrajaya Wetlands Park	430	1.480	8.699

As can be observed from Figure 4, the distribution appears to follow a linear trend.

As for the average height of the building in the micro-environment, due to the complexity of the environment, it is challenging to obtain accurate value. Instead, the height range is estimated from the minimum to the maximum building height to minimize its impact on the analysis.

The number of base stations in the micro-environment is recorded, along with the shortest distance to the nearest base

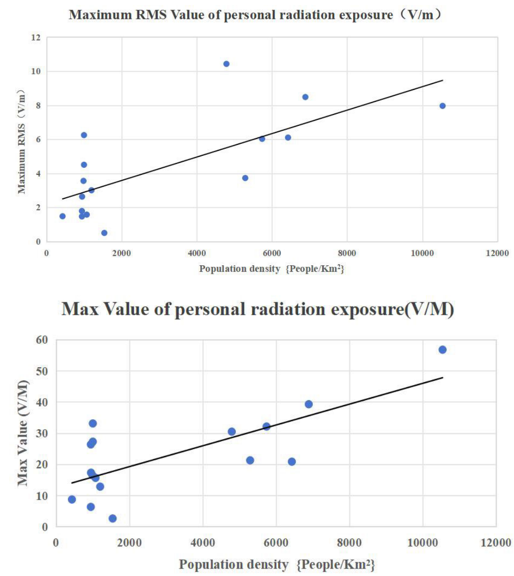

FIGURE 4. Trends with population density.

station. The maximum value of maximum personal radiation exposure is in Jln Tun Razak which reaches 56.7365 V/m. There are a total of four base stations in this area, and the nearest base station is only 0 meters away. The lowest value of maximum personal radiation exposure is in Bukit Jalil Recreational Park where has no base station in it, the value is just 2.6027 V/m. However, due to the different types of micro-environment, even when the number of base stations remains the same, the measured EF strength can differ significantly across different areas, this variability affects the EF strength from base station density. Since it has been found that the number of base stations has a significant impact on the radiation value. Additionally, vegetation coverage plays a crucial role in attenuating EM waves influencing the measured field strength. To account for these factors, machine learning models are trained separately for different environmental categories.

The combined formula method is applied in machine learning to analyze the data. Through a comprehensive analysis of the data, the relationship between electric field intensity and its influencing factors had been found, then create an equation for the electric field strength in relation to all relevant factors. In the measured dataset, the relationship between frequency range and electric field intensity follows a Gaussian distribution, whereas theoretical models indicate a linear relationship. To address this discrepancy, a logarithmic function is applied to smooth out rapid variation in features values, making the relationship more linear or near-linear while reducing the impact of extreme values. The equation is as follows:

$$\log(\mathrm{E}) = \log(\alpha+1)+\sum_{i=1}^{n}(\beta_{1i}\cdot\log(\mathrm{f_i}+1))+\beta_2\cdot\sigma_{\mathrm{F}}^{0.5} + \beta_3\cdot\log(\mathrm{P}+1)+\beta_4\cdot\mathrm{H}^{0.25}+\beta_5\cdot\mathrm{N}+\log(\varepsilon+1) \tag{7}$$

Adding 1 avoids undefined value is zero.

E: Personal radiation exposure in terms of electric field strength, V/m.

α : Constant term, representing baseline electric field strength.

$\log(f_i + 1)$: Each frequency will have its own transformed feature column in the dataset

$\sigma_F^{0.5}$: Square root of the standard deviation of frequency, reflecting the influence of frequency fluctuations on field strength.

$\log(P+1)$: Logarithm of population density, smoothing the impact of population density, P/km2.

$H^{0.25}$: Average building height raised to the power of 0.25, in order to reduce the influence of building height, m.

N: Number of base stations

ϵ : Error term, accounting for random or unmeasured factors influencing the electric field strength.

Some influencing factors follow Gaussian distribution, while others exhibit a linear relationship. While certain factors have well defined mathematical equations, others require data driven approaches to establish the relationship between electric field strength and influencing variables. Some micro-environments consist of multiple environmental types, while others are more uniform. Given that most features are numerical, Fully Connected Neural Networks (FCNN) and eXtreme Gradient Boosting (XGBoost) are chosen as the primary machine learning models for analysis. In addition, after applying a logarithmic transformation, the influencing factors exhibit a linear relationship with the electric field intensity. Then, linear regression (LR) is also selected to predict the radiation exposure.

LR is a statistical model that computes a linear weighted sum of the input features, mapping the result to a probability using the Sigmoid function. Additionally, XG Boost an ensemble learning algorithm based on gradient boosting, is employed for handling tabular data. It utilizes multiple decision trees to optimize the residuals of each iteration and gradually improve the model performance. In this study, the square error is used as the objective function, with a learning rate of 0.1. The model is trained using 100 decision tresses, each with a maximum depth of 5, to iteratively refine predictions and minimize loss.

FCNN is a type of feed forward neural network with hierarchical structure. As presented in FIGURE 5, the FCNN consists of three main components: the input layer, the hidden layer and the output layer. This study used machine learning to predict the RMS and maximum Electric field strength values. To achieve this, the model considered key influencing factors that affect EMF which are frequency range, population density, average height of building, number of base station and distance to base station. Therefore, the input layer has 5 input parameters, and the output layer has 2 predicted values. The FCNN designed in this study has 4 hidden layers, each layer applies nonlinear relationships using Rectified Linear Unit (ReLU) activation functions, while preventing overfitting through regularization.

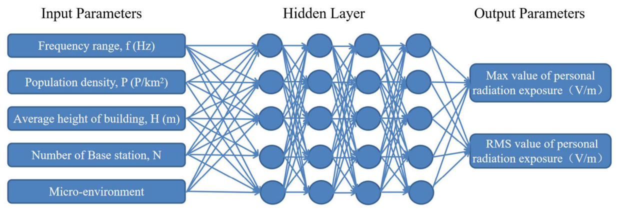

FIGURE 5. **The structure of FCNN.**

The first hidden layer is a fully connected dense layer comprising 256 neurons, employing the ReLU activation function. This layer serves as the initial projection of the input feature space into a higher-dimensional representation. To mitigate overfitting, L2 regularization (with a coefficient of 0.01) is applied to constrain the magnitude of the weights and encourage weight sparsity. The second layer continues the hierarchical abstraction of features, it retains 128 neurons to model meaningful intermediate representations. ReLU helps preserve non-linearity, while L2 regularization maintains model robustness. The third dense layer contains 64 neurons, continuing the progressive reduction in dimensionality. With ReLU activation and L2 regularization, this layer continues to compress the feature representation, distilling information into a more compact and abstract form, only the most important learned patterns are retained and passed forward. The final hidden layer consists of 32 neurons with ReLU activation. Unlike the preceding dense layers, this layer does not incorporate explicit regularization, thereby allowing the network to fully utilize these last representations without constraint, fine-tuning the output mapping.

In this study, 80% of the dataset are allocated for training and the remaining 20% for testing. Initially,the phenomenon of underfitting occurred when applied FCNN to simulate in the indoor environment and applied LR to simulate scenarios in urban and suburban areas. This is because when the data set is single, FCNN cannot learn the patterns in the data, so improved the learning from 0.001 to 0.01 to accelerate convergence and promote deeper feature learning. In contrast, the Logistic Regression (LR) model demonstrated greater robustness to extreme values, enabling it to handle outliers more effectively within the data. Therefore, an outlier mitigation step was first applied in urban and suburban samples, to reduce their impact on model training. After correction, the prediction results of all models are overfitting. Then using Rectified Linear Unit (ReLU) activation functions, while preventing overfitting through regularization. Finally, compared the predictive performance of the three models in different environmental scenarios.

D. METRICS FOR EVALUATION

Total Emission Ratio (TER) is calculated to assess RF-EMF exposure emission compliance in accordance with the limits specified in the ICNIRP/ FCC guidelines standards. It compares the actual measured RF-EMF levels to the allowed emission limits across a specified frequency range to the allowed emission limits across a specified frequency range.

$$\mathrm{TER} = \sum_{i \geq 97.5\mathrm{MHz}}^{5800\mathrm{MHz}} \left(\frac{\overline{E_i}}{E_{lim,i}} \right)^2 \leq 1 \tag{8}$$

E_i: The measured electric field strength at frequency i.

$E_{lim,i}$: The limit of electric field strength for compliance at frequency i.

Specific exposure limits from major standards organizations which have been calculated in Chapter 2:

ICNIRP: 27.7 V/m (frequency range 30 MHz -400 MHz)

27 V/m - 60.4 V/M (frequency range 400 MHz–2 GHz)

61.4 V/m (frequency range 2 GHz - 6 GHz)

FCC: 27.5 V/m (frequency range 30MHz -300MHz)

27.5 V/m -61.4 V/m (300MHz - 1.5 GHz)

61.4 V/m (frequency range 1.5 GHz - 6 GHz)

TER value should <= 1. If TER > 1, it means that the maximum exposure limit is exceeded, indicating non-compliance. The smaller the TER value, the lower the level of electromagnetic radiation, the more in line with international standards.

Compare the predicted value with the measured value. Root Mean Square Error (RMSE) is calculated to quantify the deviation between the predicted value and the real value, which reflects the size of the model prediction error.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i')^2} \tag{9}$$

y_i: The i th true value of the data.

y_i': The i th predicted value of the data.

The closer the value of RMSE is to 0, the higher the prediction accuracy of the model.

Coefficient of Determination (R^2) is determined to quantify the degree of variation of the independent variable to the dependent variable.

$$R^2 = 1 - \frac{\sum (y_i - y_i')^2}{\sum (y_i - \bar{y})^2} \tag{10}$$

y_i: The i th true value of the data.

y_i': The i th predicted value of the data. $\bar{y}$: The average of true value.

If $R^2 = 1$, it indicates the model perfectly explains the data.

If R^2 value is closer to 1, it indicates the model better explains the variation of the dependent variable, which means the better the model can fit the data.

If $R^2 = 0$, it indicates the model does not explain any variation in the data.

If $R^2 < 0$, it indicates the model performs worse than simply predicting the mean value for all observations, indicating a poor fit.

IV. RESULTS AND DISCUSSION

A. MEASURED RF-EMF EXPOSURES

The results of some outdoor and indoor environmental measurements are shown in Figure 6, where the walking paths are overlaid with measured electric field strength values along the route.

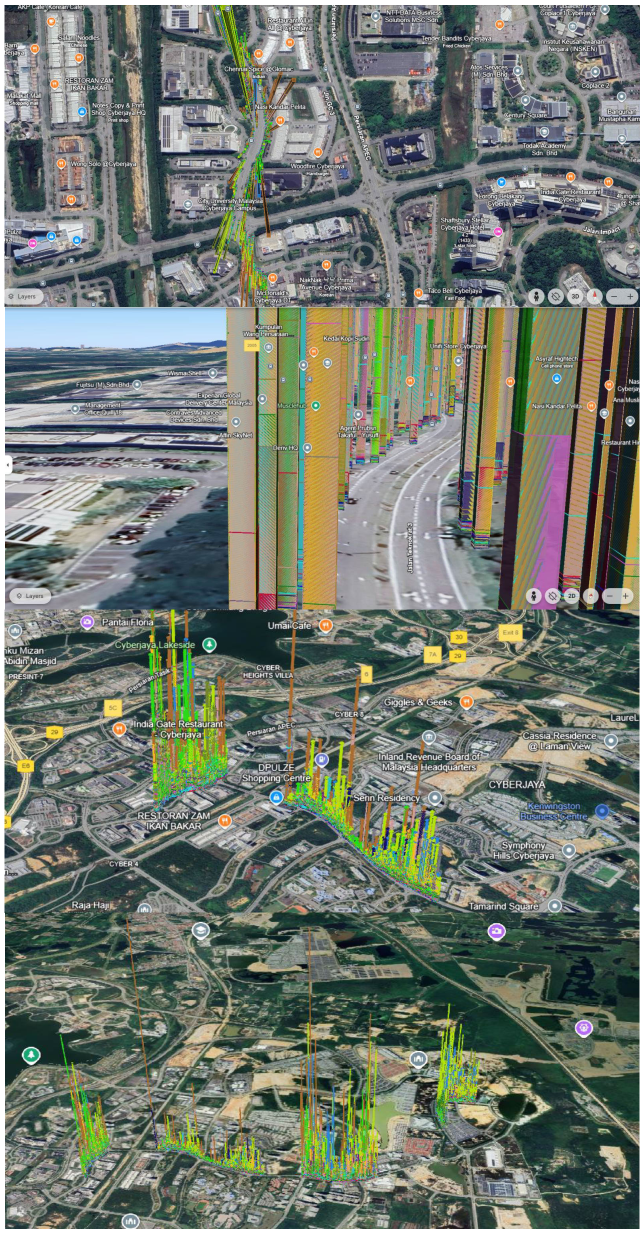

FIGURE 6. Measured data shown on map.

Display the maximum RMS of Electric Field Strength in each micro-environment. The results are presented in bar chart:

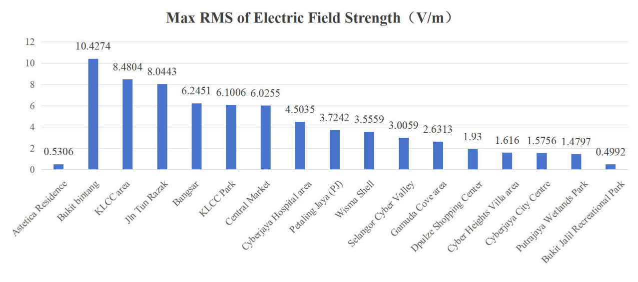

FIGURE 7. Max RMS value of electric field strength.

Display the maximum Electric Field Strength in each micro-environment. The results are presented in bar chart:

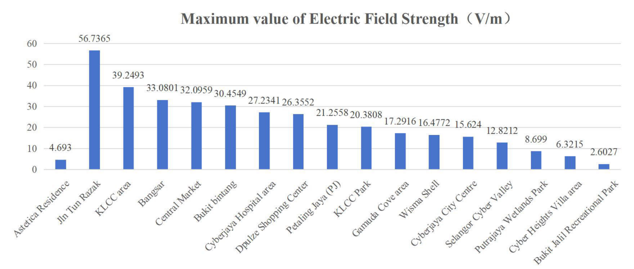

FIGURE 8. Maximum value of electric field strength.

As can be observed from Figure 7 and Figure 8, the measured data are all smaller than the ICNIRP and FCC 's public exposure limits. In addition, the Electric Field Strength of indoor micro-environment is much lower than that of indoor micro-environment.

B. PREDICTED RF-EMF EXPOSURES

The predicted RF-EMF exposure levels are discussed in accordance with each predication ML models below. The figures of predicted RF-EMF exposures results (Figure 9- Figure 20) are presented in APPENDIX B.

1) FULLY CONNECTED NEURAL NETWORK (FCNN)

The comparison between the true value and the predicted value in urban environment is shown in Figure 9. The maximum predicted RMS value of Electric Field Strength is 7.0917 V/m, the maximum predicted value of Electric Field Strength is 28.2077 V/m. The RMSE value of RMS is 0.1975, and the R^2 value of RMS is 0.9821. The RMSE value of MAX is 1.1863, and the R^2 value of MAX is 0.9521.

As can be observed from Figure 9, the RMS values of the electric field strength range from 0 to approximately 7 V/m, whereas the maximum values of the electric field strength range from 0 to approximately 28 V/m, exhibiting larger fluctuations, which explains why the RMSE of the maximum values is larger than that of the RMS values. The R^2 values exceeding 0.9 indicate that the model can explain more than 90% of the variance in the data. This suggests that the FCNN demonstrates strong predictive performance in estimating electric field strength in urban areas.

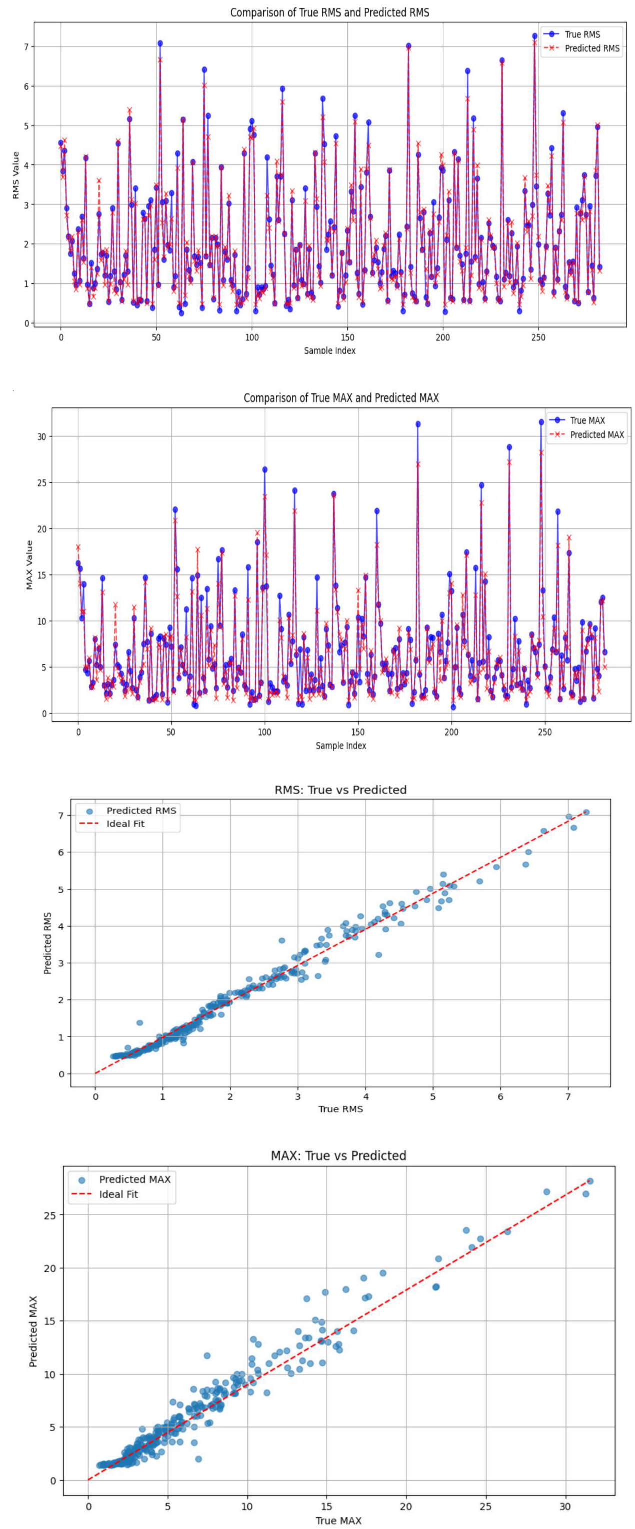

FIGURE 9. Comparison of true and predicted values of FCNN in urban environment.

For suburban environments (shown in Figure 10), the maximum predicted RMS value of Electric Field Strength is 4.5111 V/m, the maximum predicted value of Electric Field Strength is 23.2864 V/m. The RMSE value of RMS is 0.1054,

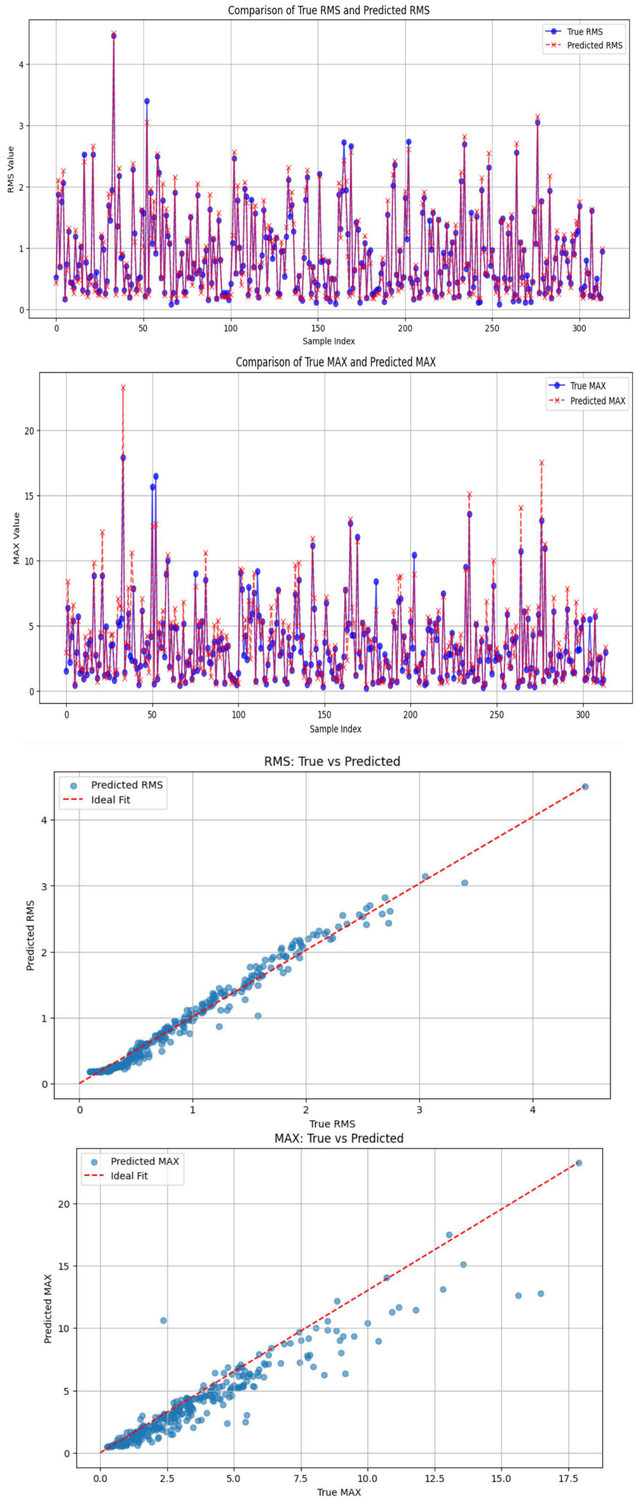

FIGURE 10. **Comparison of true and predicted values of FCNN in suburban environment.**

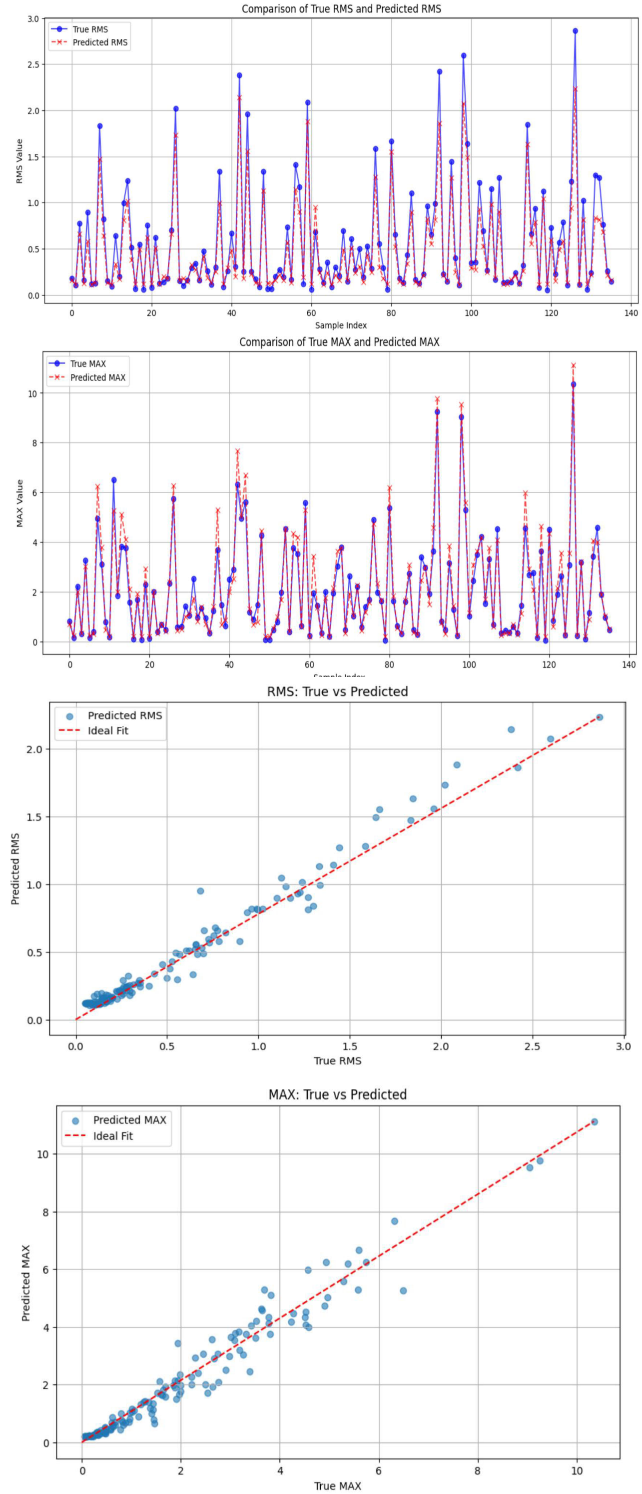

FIGURE 11. **Comparison of true and predicted values of FCNN in park environment.**

and the R^2 value of RMS is 0.9770. The RMSE value of MAX is 1.0473, and the R^2 value of MAX is 0.8659.

Compared with the urban area, the range of electric field strength is narrower, the overall error is reduced, leading to a lower RMSE value. The value of R^2 are 0.977 and 0.8659, indicating that FCNN also performs well in predicting the electric field strength in suburban areas.

For park environment (shown in Figure 11), the maximum predicted RMS value of Electric Field Strength is 2.2332 V/m, the maximum predicted value of Electric Field

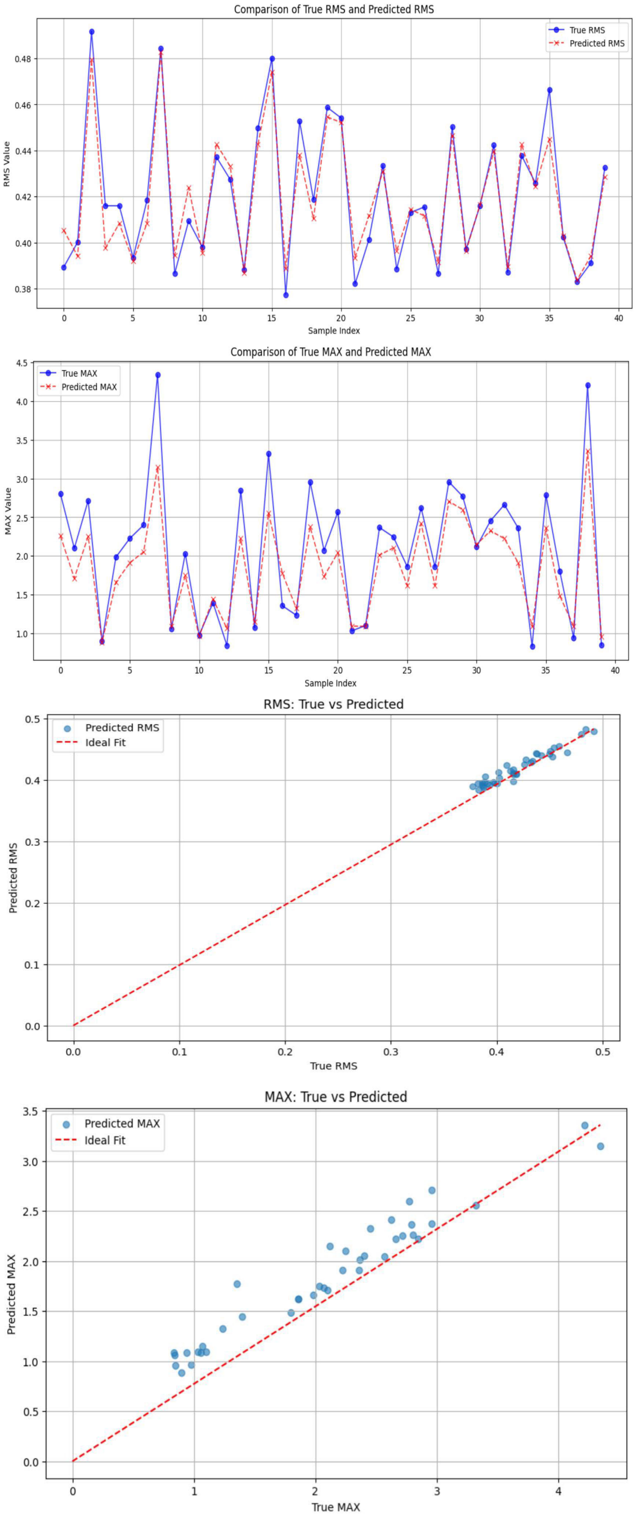

FIGURE 12. **Comparison of true and predicted values of FCNN in indoor environment.**

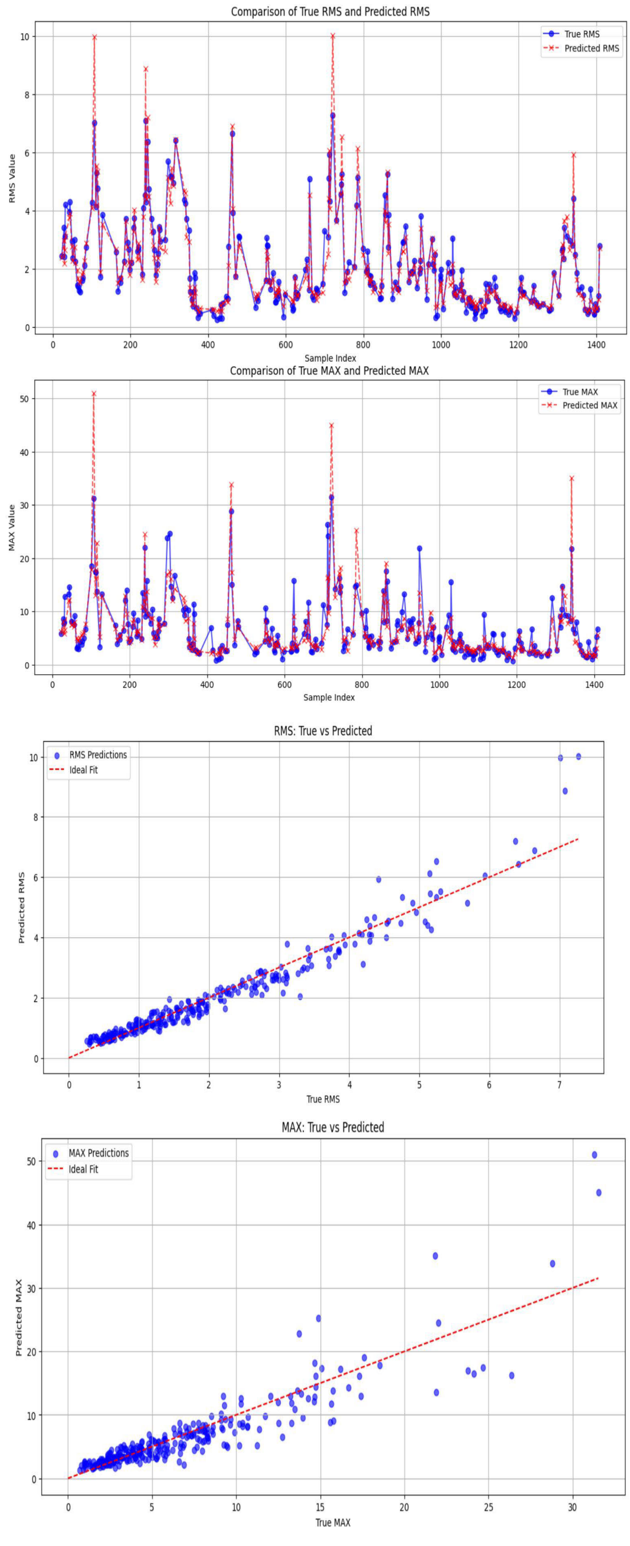

FIGURE 13. **Comparison of true and predicted values of LR in urban environment.**

Strength is 11.1278 V/m. The RMSE value of RMS is 0.1693, and the R^2 value of RMS is 0.9215. The RMSE value of MAX is 0.4748, and the R^2 value of MAX is 0.9418.

Compared with urban and suburban areas, in the park environment, electromagnetic sources are relatively sparse, and the area is expansive, resulting in fewer extreme values

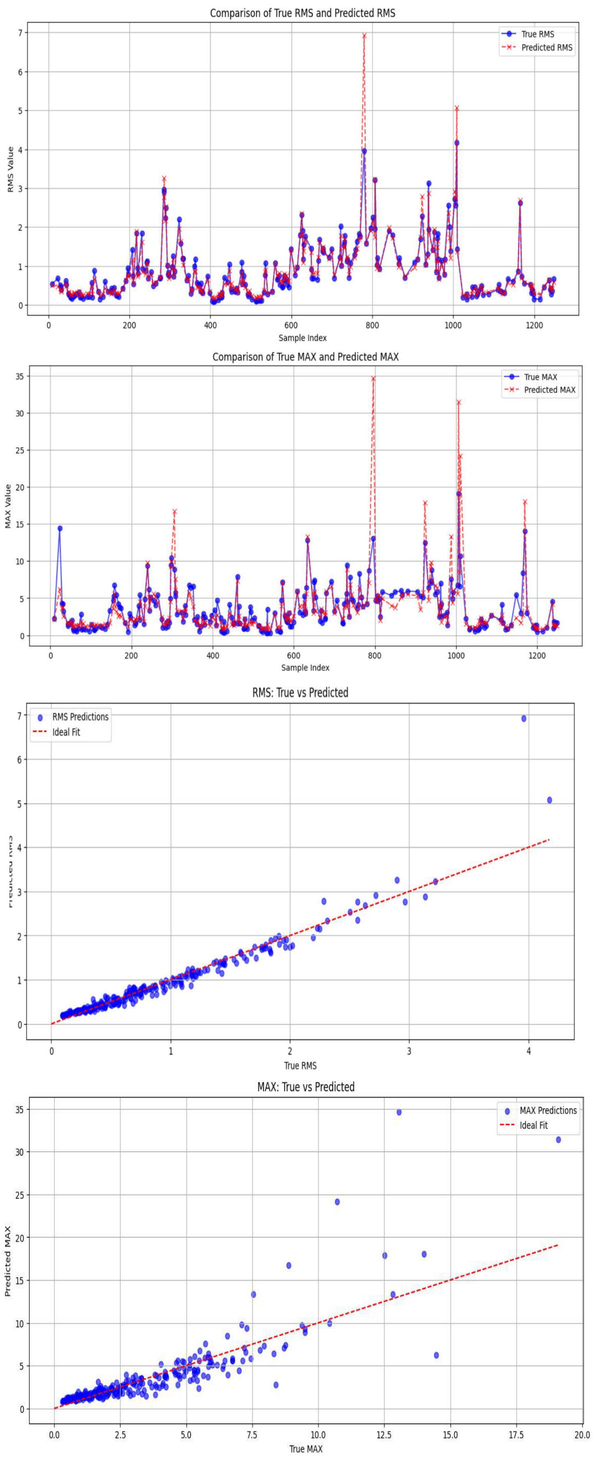

FIGURE 14. Comparison of true and predicted values of LR in suburban environment.

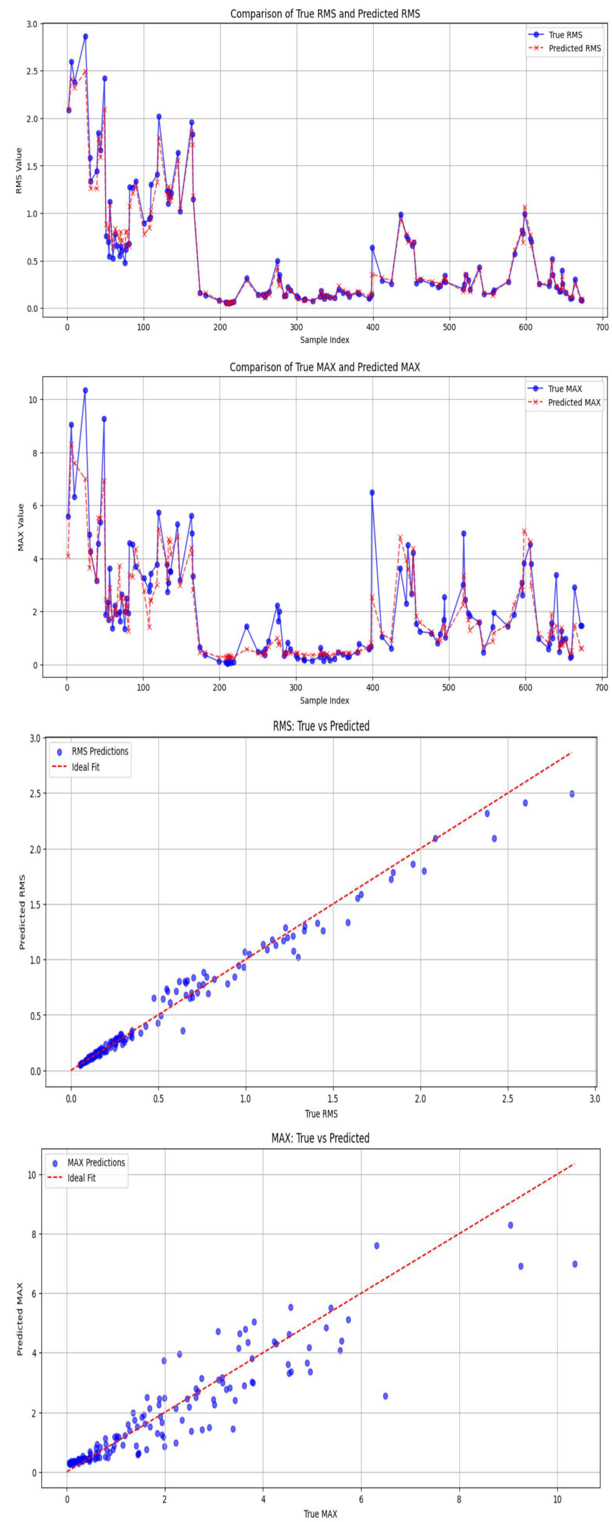

FIGURE 15. Comparison of true and predicted values of LR in park environment.

in the measured electric field strength. Consequently, the RMSE of the maximum values is comparatively lower, only 0.4787 V/m.

For indoor environment (shown in Figure 12), the maximum predicted RMS value of Electric Field Strength is 0.4161 V/m, the maximum predicted value of Electric Field Strength is 4.1045 V/m. The RMSE value of RMS is 0.0082, and the R^2 value of RMS is 0.9268. The RMSE value of MAX is 0.3986, and the R^2 value of MAX is 0.7956.

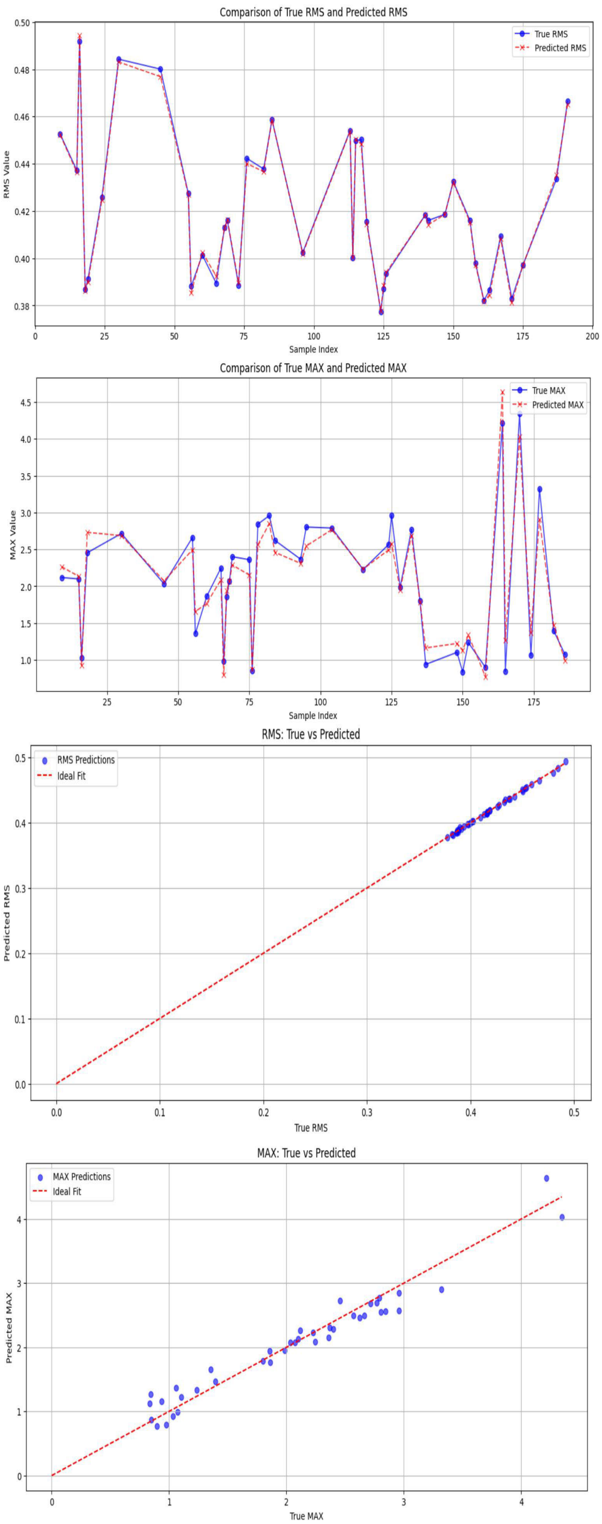

FIGURE 16. **Comparison of true and predicted values of LR in indoor environment.**

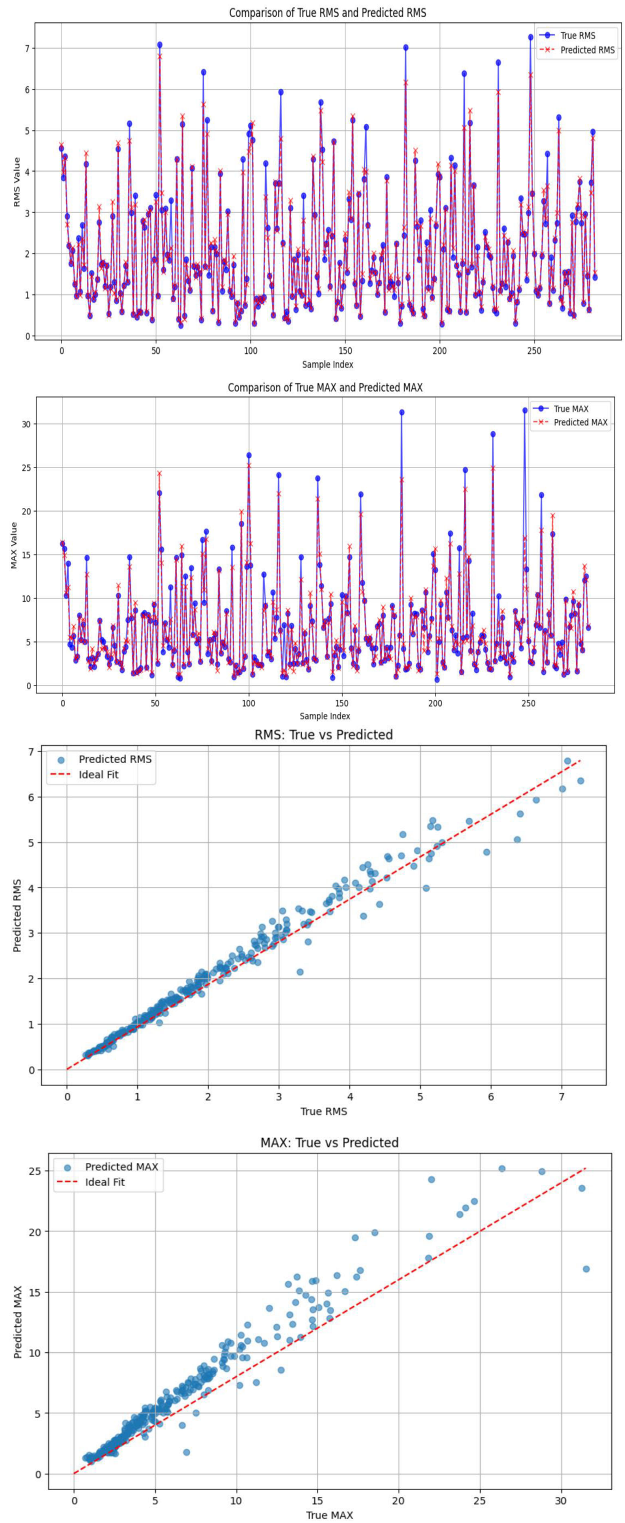

FIGURE 17. **Comparison of true and predicted values of XG Boost in urban environment.**

As can be observed from Figure 12, the electric field strength in the indoor micro-environment is more stable, the RMS values of the electric field strength range from 0.3 to 0.5 V/m, whereas the maximum values of the electric field strength range from 0.5 to 3.5 V/m. This results in a smaller RMSE value, particularly for the RMS values, where the RMSE is only 0.0082. In addition, the R^2 of maximum Electric Field Strength decreases to 0.7956, indicating that

FCNN is more suitable for analyzing multiple types of data sets.

2) LINEAR REGRESSION (LR)

For urban environment, the maximum predicted RMS value of Electric Field Strength is 10.0192 V/m, the maximum predicted value of Electric Field Strength is 51.0385V/m. The RMSE value of RMS is 0.4007, and the R^2 value of RMS is 0.9261. The RMSE value of MAX is 2.6968, and the R^2 value of MAX is 0.7522.

As can be observed from Figure 13, the RMS values of the electric field strength range from 0 to 10 V/m, whereas the maximum values of the electric field strength range from 0 to approximately 50 V/m. Since LR can not handle extreme values well, RMSE have particularly large values, twice that of FCNN. The R^2value also indicates that LR lacks the fitting capability exhibited by the FCNN with extreme values.

For suburban environments, the maximum predicted RMS value of Electric Field Strength is 6.8987 V/m, the maximum predicted value of Electric Field Strength is 34.6681 V/m. The RMSE value of RMS is 0.2208, and the R^2 value of RMS is 0.9044. The RMSE value of MAX is 2.2205, and the R^2 value of MAX is 0.4182.

As can be observed from Figure 14, the RMS values of the electric field strength range from 0 to 7 V/m, whereas the maximum values of the electric field strength range from 0 to approximately 35 V/m. And at the extreme value, the predicted value of LR is much greater than the actual value. This is because suburbs have seven different types of micro-environments, LR lacks the flexibility to effectively capture interaction and nonlinear patterns in these diverse micro-environments. This sensitivity to extreme values explains why the RMSE of LR is significantly higher than that of the FCNN. The R^2value of maximum Electric Field Strength is just 0.4182, indicating that LR lacks the fitting capability exhibited by the FCNN in handling multiple types of data sets with extreme values.

For park environment, the maximum predicted RMS value of Electric Field Strength is 2.4960 V/m, the maximum predicted value of Electric Field Strength is 8.2967 V/m. The RMSE value of RMS is 0.0868, and the R^2 value of RMS is 0.9793. The RMSE value of MAX is 0.7991, and the R^2 value of MAX is 0.8352.

As can be observed from Figure 15, the RMS values of the electric field strength range from 0 to 3 V/m, whereas the maximum values of the electric field strength range from 0 to 10 V/m. Due to the park's limited environmental variability, comprising only three distinct micro-environments with fewer extreme values, the RMSE and R^2 values of LR are close to those of FCNN.

For indoor environment, the maximum predicted RMS value of Electric Field Strength is 0.4945 V/m, the maximum predicted value of Electric Field Strength is 4.8734 V/m. The RMSE value of RMS is 0.0014, and the R^2 value of RMS is

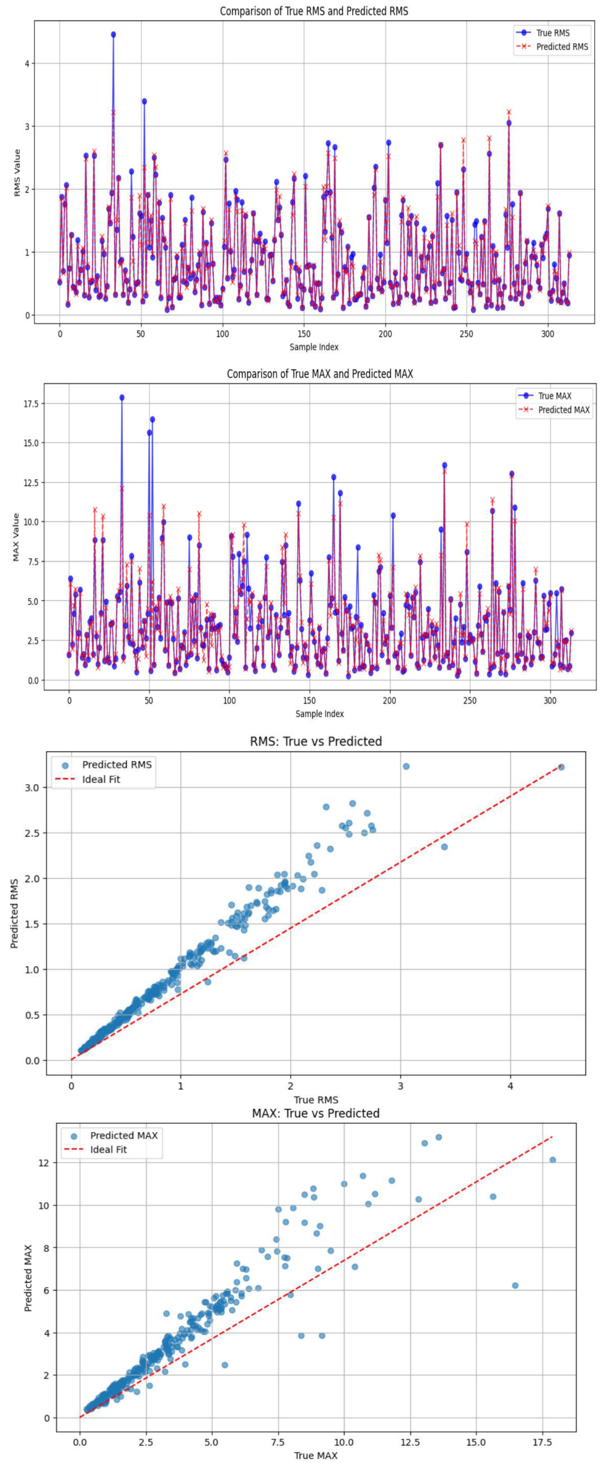

FIGURE 18. Comparison of true and predicted values of XG Boost in suburban environment.

0.9980. The RMSE value of MAX is 0.2016, and the R^2 value of MAX is 0.9477.

In the indoor environment, a single micro-environment is present, and the electric field strength is stable. The prediction performance of LR is inversely better than that of FCNN, indicating that LR is suitable for processing a single data set.

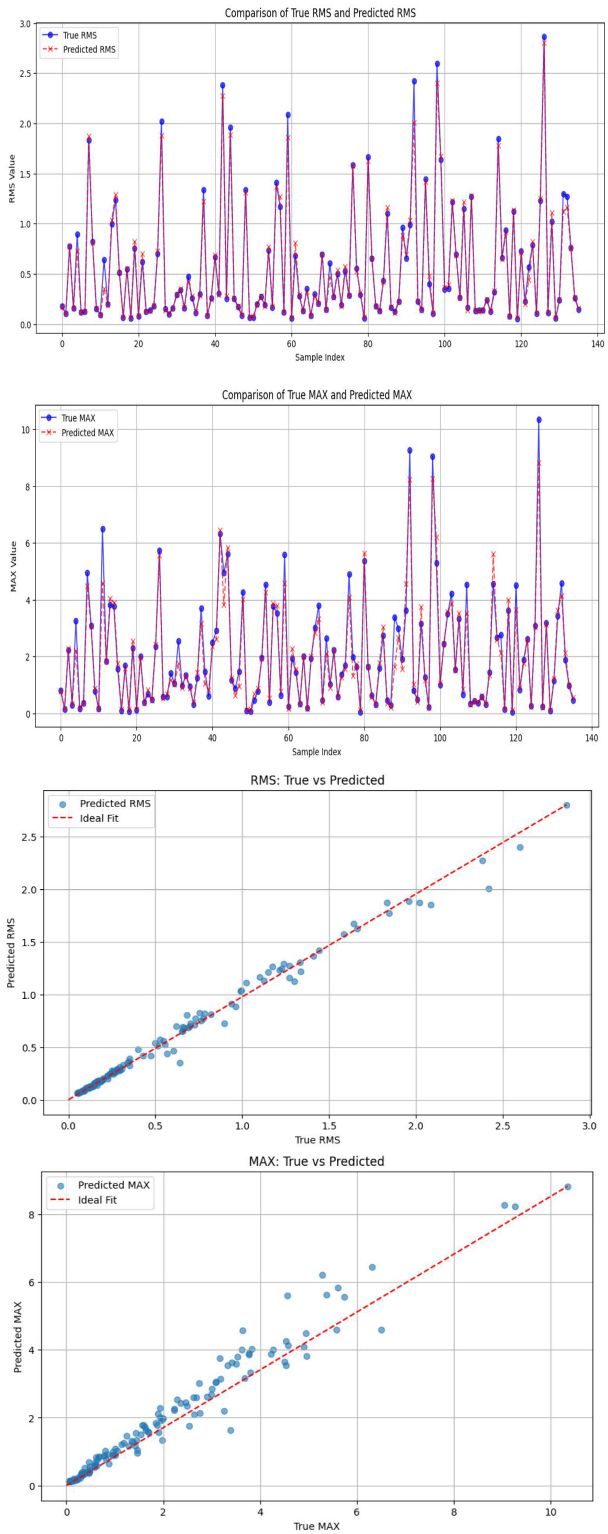

FIGURE 19. Comparison of true and predicted values of XG Boost in park environment.

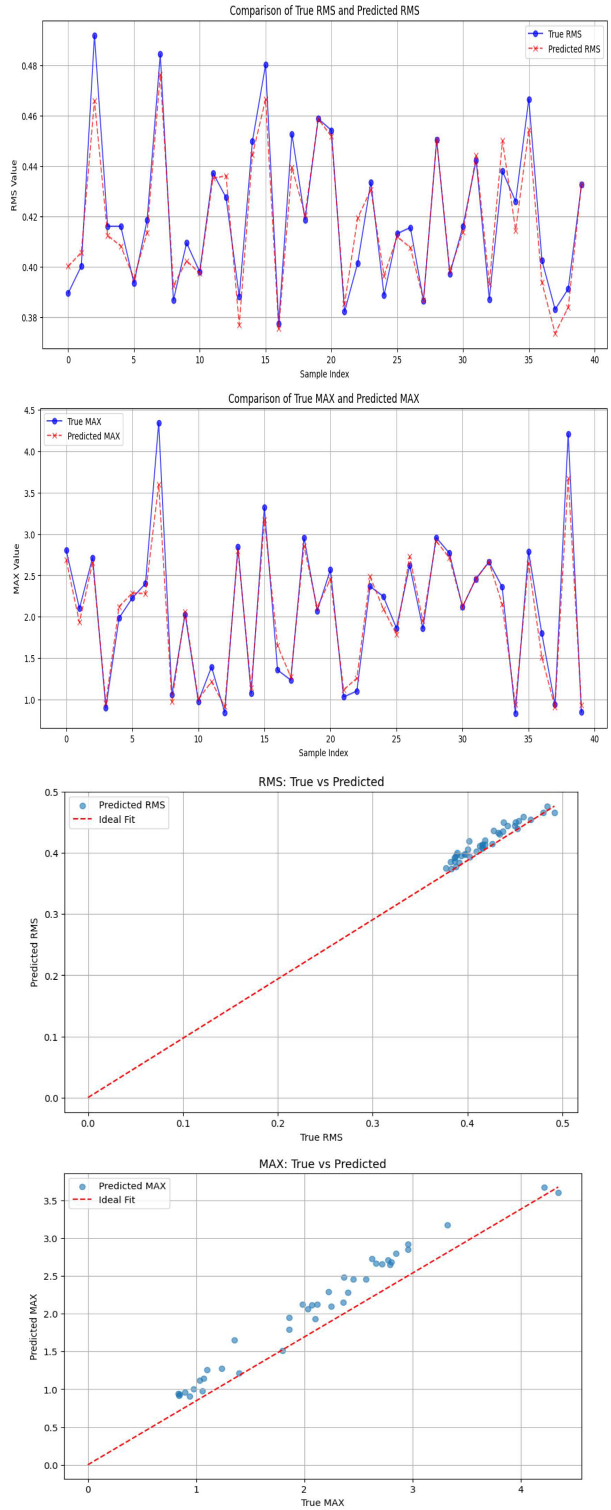

FIGURE 20. Comparison of true and predicted values of XG Boost in indoor environment.

3) EXTREME GRADIENT BOOSTING (XG Boost)

For urban environment (shown in Figure 17), the maximum predicted RMS value of Electric Field Strength is 6.7936 V/m, the maximum predicted value of Electric Field Strength is 25.2023 V/m. The RMSE value of RMS is 0.2239, and the R^2 value of RMS is 0.9769. The RMSE value of MAX is 1.3846, and the R^2 value of MAX is 0.9347.

As can be observed from figures, the range of RMS values of the electric field strength is similar to FCNN. But the RMSE of XG Boost is slightly higher than that of FCNN, which indicating a marginally larger prediction error. Likewise, the $R^2$of XG Boost is close to that of FCNN but slightly lower, suggesting a slightly weaker fit. Overall, the prediction performance of XG is comparable to FCNN, however, FCNN outperforms XG in handling extreme values.

For suburban environment (shown in Figure 18), the maximum predicted RMS value of Electric Field Strength is 3.2303 V/m, the maximum predicted value of Electric Field Strength is 13.2112 V/m. The RMSE value of RMS is 0.1246, and the R^2 value of RMS is 0.9678. The RMSE value of MAX is 0.9891, and the R^2 value of MAX is 0.8804.

The RMSE of RMS value of the XG Boost model is slightly higher than that of FCNN, the RMSE of maximum value of the XG Boost model is slightly lower than that of FCNN, the R^2 of RMS value of the XG Boost model is slightly lower than that of FCNN, The R^2 of maximum value of the XG Boost model is slightly higher than that of FCNN. This is because the extreme values in suburban areas are not as pronounced as those in urban areas, so the predictive performance of the two models is comparable.

For park environment (shown in Figure 19), the maximum predicted RMS value of Electric Field Strength is 2.8024 V/m, the maximum predicted value of Electric Field Strength is 8.8171 V/m. The RMSE value of RMS is 0.0673, and the R^2 value of RMS is 0.9876. The RMSE value of MAX is 0.4278, and the R^2 value of MAX is 0.9528.

The RMSE of XG Boost is similar to that of FCNN but slightly lower, indicating a marginally improved predictive accuracy. Similarly, the R^2valueof XG Boost is close to that of FCNN but slightly higher, suggesting that XG Boost captures variance in the data more effectively. This observation indicates that XG outperforms FCNN in the absence of extreme values.

For indoor environment (shown in Figure 20), the maximum predicted RMS value of Electric Field Strength is 0.4764 V/m, the maximum predicted value of Electric Field Strength is 3.6748 V/m. The RMSE value of RMS is 0.0084, and the R^2 value of RMS is 0.9228. The RMSE value of MAX is 0.1860, and the R^2 value of MAX is 0.9555.

In the indoor environment, the R^2value of LR is significantly higher than that of XG Boost. This can be attributed to the stability of the RMS values of the indoor electric field strength. As a result, LR is suitable for modeling a single, relatively simple data set, XG Boost is more robust and effective when dealing with multiple datasets that contain minimal or no extreme values, FCNN is best in handling multiple data sets with extreme values.

C. MODEL PERFORMANCE ANALYSIS

1) TOTAL EMISSION RATIO (TER)

The TER calculations of RMS are as follows.

The TER calculations of MAX are as follows.

TABLE 9. TER of RMS.

TER	RMS			
Micro environment	Measurement value	FCNN	LR	XG
Urban	1.847E-03	1.631E-03	1.758E-03	1.608E-03
Suburban	3.369E-04	3.560E-04	3.713E-04	3.223E-04
Park	2.384E-04	1.264E-04	1.696E-04	1.745E-04
Indoor	4.710E-05	4.593E-05	4.694E-05	4.651E-05

TABLE 10. TER of MAX.

TER	MAX			
Micro environment	Measurement value	FCNN	LR	XG
Urban	2.191E-02	1.737E-02	2.036E-02	1.746E-02
Suburban	5.395E-03	6.355E-03	8.437E-03	4.750E-03
Park	2.787E-03	2.517E-03	1.802E-03	1.942E-03
Indoor	1.354E-03	1.331E-03	1.361E-03	1.252E-03

All TER values are much less than 1, indicating that they are in line with international standards.

2) ROOT MEAN SQUARE ERROR (RMSE)

Then evaluate the performance of the model by analyzing the RMSE. The comparison of RMSE for different ML are as follows:

TABLE 11. RMSE of RMS.

RMSE	RMS		
Micro-environment	FCNN	LR	XG
Urban	0.198	0.401	0.224
Suburban	0.105	0.198	0.125
Park	0.169	0.087	0.067
Indoor	0.008	0.001	0.008

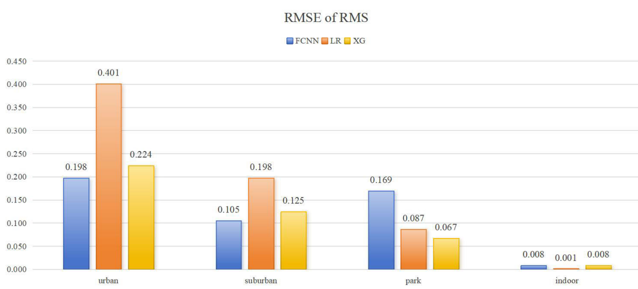

FIGURE 21. RMSE of RMS.

Since the MAX value of Electric Field Strength in outdoor environment is easily disturbed by external factors, the RMSE of these three models in urban and suburban areas are large.

By comparison, LR performs worse than other models in urban, suburban and park areas, because the RMSE of LR

TABLE 12. RMSE of MAX.

RMSE	MAX		
Micro-environment	FCNN	LR	XG
Urban	1.186	2.697	1.385
Suburban	1.047	2.933	0.989
Park	0.475	0.799	0.428
Indoor	0.399	0.202	0.186

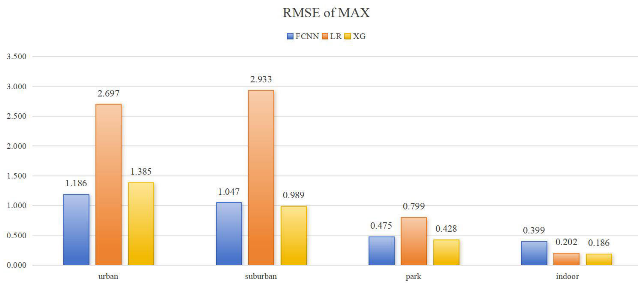

FIGURE 22. RMSE of MAX.

increases significantly to 2.6968 and 2.9325, respectively, and the error amplitude is more than double or triple that of other methods. The types of micro-environments and the samples are large in urban, suburban and park areas, while indoors just choose one micro-environment. This indicates that LR is suitable for analyzing a single type of data set. When analyzing multiple types of data sets, FCNN and XG Boost are more appropriate than LR.

In addition, while the performance of FCNN and XG Boost is close, FCNN performs better in both urban and suburban areas, possibly due to the presence of extreme values in urban and suburban areas. This indicates that FCNN can fit the extreme value data processing well.

In summary, LR has better prediction results under single and simple data sets, while XG Boost and FCNN have stronger analysis capabilities for multiple types of data sets. When the data is stable, XG Boost 's prediction is better than FCNN 's. However, when there are extreme values in the data, FCNN predicts better.

3) COEFFICIENT OF DETERMINATION (R^2)

Finally, evaluate the performance of the model by analyzing the R^2. The comparison of R^2 for different ML are as follows:

TABLE 13. R^2 of RMS.

R^2	RMS		
Micro-environment	FCNN	LR	XG
Urban	0.982	0.926	0.977
Suburban	0.977	0.919	0.968
Park	0.922	0.979	0.988
Indoor	0.927	0.998	0.923

TABLE 14. R^2 of MAX.

R^2	MAX		
Micro-environment	FCNN	LR	XG
urban	0.952	0.752	0.935
suburban	0.866	0.418	0.880
park	0.942	0.835	0.953
indoor	0.796	0.948	0.956

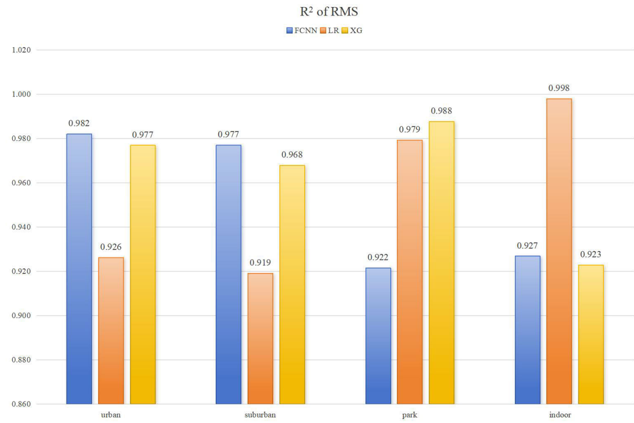

FIGURE 23. R^2 of RMS.

TABLE 15. Maximum MAX value of electric field strength.

Micro-environment	Max Value (V/m)			
	Measure ment	FCNN	LR	XG
urban	56.737	28.208	51.039	25.203
suburban	27.234	23.286	34.668	13.211
park	20.381	11.128	8.297	8.817
indoor	4.693	3.359	4.642	3.675

The results presented by R^2 are more intuitive, and the conclusions are the same as RMSE. LR predicts worse in the presence of extreme values and analyzing large and complex data. The predictive performance of FCNN and XG Boost is close, but FCNN 's prediction is better when have extreme values in the data.

D. DATA ANALYSIS

Since all three machine learning models achieve a high degree of fit across the four micro-environments, all the measured data and predicted value are selected for analysis. Select the TER of RMS value and MAX value of electric field strength in all environments for analysis.

The TER of RMS values of electric field strength are presented in Table 9. As shown in table, the electric field strength values in all types of micro-environments are much smaller than the ICNIRP and FCC 's public exposure limits.

According to the types of micro-environment analysis. The Electric Field Strength of indoor micro-environment is much

TABLE 16.

Micro-environment [n=17]			
Urban, n=6			
	Walking path	Google Map Link	Kml File Link
KLCC area	A 20-min walk from Kuala Lumpur Convention Center (via Jalan Pinang to Persiaran Petronas) to Petronas Twin Towers and back, 1.3 kms right hand sidewalk - see Map)	https://maps.app.goo.gl/YgfgbS1MQaEYoyYv6	https://drive.google.com/file/d/1n7jTLvMU0U1kLlnwuksF1GUxJc8DR4hi/view?usp=sharing
Bukit bintang	A 20-min walk from Bukit Bintang bus stop to Pavilion Kuala Lumpur, 168, Jln Bukit Bintang (via Jln Sultan Ismail->Jalan Raja Chulan) and back, 1.4 kms right hand sidewalk - see Map)	https://maps.app.goo.gl/4Rrw1W15z7aAr25h9	https://drive.google.com/file/d/1Z4b0J2R8DxVBIpr1bcb6Y0qqbBTmod6l/view?usp=sharing
Central Market (outdoor area/streets)	A 20-min from Hotel Geo bus stop (opposite of Central Market) up to Jalan Sultan parking (via see map) and back, 1.3 kms right hand sidewalk - see Map)	https://maps.app.goo.gl/xvphXkCpVrEafXH38	https://drive.google.com/file/d/19MMQtgsYB6yLiKhitU6euGK6WXnhUibB/view?usp=sharing
Jln Tun Razak	A 26-min walk from KL97 Wisma Selangor Dredging (Opp) to Jln Tun Razak road and back, 1.8 kms right hand sidewalk - see Map)	https://maps.app.goo.gl/BsDLT7ZTT2UEcXpG8	https://drive.google.com/file/d/1Jr0Ph__Rc05c3_B7-gvko-1Oo0fsXTfq/view?usp=sharing
Bangsar	A 24-min walk from Lrt Bangsar train station to KL1143 Bangsar Park (Selatan) bus station and back, 1.7 kms right hand sidewalk - see Map)	https://maps.app.goo.gl/TAoCA5U2AhWmHVAL6	https://drive.google.com/file/d/1Cd9k0j2qSpNDb24KWQ_XhKblO9u76OG_/view?usp=sharing
Petaling Jaya (PJ)	A 20-min walk from PJ Palms Sport Centre to PJ Sentral Tower (via Lorong Sultan->Persiaran Barat) and back, 1.5 kms right hand sidewalk - see Map)	https://maps.app.goo.gl/1NB5JUaJcQcbfBTi7	https://drive.google.com/file/d/15QBIVvGIkAr4nbXZudWiDFrgkj4OpdRh/view?usp=sharing

TABLE 16. ***(Continued.)***

Micro-environment [n=17]			
Park, n=3			
	Walking path	Google Map Link	Kml File Link
KLCC Park	A 20-min walk through KLCC park from KLCC Tnl end (start of the park) to the other end of the park using the given path and back, 1.4 kms right hand sidewalk - see Map)	https://maps.app.goo.gl/kt3EKaDd1ZHmLsqb9	https://drive.google.com/file/d/15SFf-FpU0X0JyDYm58EWnQKzoZ0Goa6_/view?usp=sharing
Bukit Jalil Recreational Park	A 22-min walk starting from Bukit Jalil Recreational Park North Entrance to the other side of the (big) lake and back 1.2 kms right hand sidewalk - see Map)	https://maps.app.goo.gl/9NQv9Pc32mwDJvJw6	https://drive.google.com/file/d/1XLHIngr2N8vTVMP5CCyA37_G7EckIFvb/view?usp=sharing
Putrajaya Wetlands Park	A 26-min walk from the Lookout Tower to DEWAN SEMINAR PEJABAT NURSERI TAMAN WETLAND PUTRAJAYA (Government office) and back, 2.2 km right hand sidewalk - see Map)	https://maps.app.goo.gl/a2Qjmm1yPXaSJUz87	https://drive.google.com/file/d/1q2sqrqhNAb9glRxhVETt70CeeYsscX5-/view?usp=sharing
Indoor, n=1			
	Walking path	Google Map Link	Kml File Link
Astetica Residence	Astetica Residence	https://maps.app.goo.gl/dhQv4L9Cv3eLXdgQ9?g_st=com.google.maps.preview.copy	https://drive.google.com/file/d/120XaM0u6A8df1KwklpEMjhkLo8H3aEEQ/view?usp=sharing

lower than that of indoor micro-environment. This is because indoor environmental materials use concrete, brick and metal, which can absorb or deflect electromagnetic waves, shielding external electromagnetic sources effectively [28]. Moreover, indoor electromagnetic fields have limited sources and are usually limited to electronic devices, such as Wi-Fi routers, computers, cell phones, and other household appliances. In contrast, outdoor areas especially in urban environments, are often located near high-power sources. In addition, the Electric Field Strength is particularly strong in more prosperous areas such as KLCC area. In remote areas, especially those with only three to five floors of buildings such as PJ Palms Sport Centre, the Electric Field Strength value is weak. For the park environment, with no buildings but very dense vegetation, the Electric Field Strength value is even lower. This is because the height and density of the building affect the propagation and reflection of electromagnetic waves [29]. Vegetation density

TABLE 16. ***(Continued.)***

Micro-environment [n=17]			
Suburban, n=7			
	Walking path	Google Map Link	Kml File Link
Cyberjaya City Centre	A 22-min walk from MRT Cyberjaya City Centre (PY40) to PRPN (Persiaran APEC) and back, 1.7 kms right hand sidewalk - see Map)	https://maps.app.goo.gl/nyCVGSx9fh8jkCvB9	https://drive.google.com/file/d/1XhrCATZjaNm7yYK5hzb0k5loir-2Z7Ax/view?usp=sharing
Wisma Shell	A 22-min walk starting from in front of McDonald's Cyber 5 DT to Wisma Shell Bus stop and back, 1.5 kms right hand sidewalk	https://maps.app.goo.gl/6xDVYcRsJCN726X86	https://drive.google.com/file/d/1ggCdx5Di53RkAGd1-x4owixb0MEwVTtp/view?usp=sharing
Dpulze Shopping Center	A 24-min walk starting from Cyberjaya Transport Terminal (Stop ID: SP75)/ front of DPULZE Shopping Centre to MMU Entrance B (Stop ID: SP86) and back, 1. kms right hand sidewalk - see Map)	https://maps.app.goo.gl/YMXu3AmveuEEe1TQ7	https://drive.google.com/file/d/1qYqkcDsEC0CNADS3B_5Xhh-OtZPufofd/view?usp=sharing
Selangor Cyber Valley	A 26-min walk starting from in front of RSKU residence Idaman Selangorku to Brainy Bunch International School and back, 1.9 kms right hand sidewalk - see Map)	https://maps.app.goo.gl/jDx3WBHf87FTrXLD9	https://drive.google.com/file/d/1Ex8FoX8_whnOJwaPREkHrutjzwHhw73f/view?usp=sharing
Cyberjaya Hospital area	A 24-min walk from Cyberjaya Hospital bus stop to SK Cyberjaya 1 Bus stop (opposite of Tamarind Square) and back, 1.6 kms right hand sidewalk - see Map)	https://maps.app.goo.gl/SGtydU5mtr3bfEpS6	https://drive.google.com/file/d/1U1GmrM4jf9eh05v0oRYvk1PcqLfRpiry/view?usp=sharing
Cyber Heights Villa area	Start from Seri Puteri School Bus stop to Jalan Cyber Sutera and go back.	https://www.google.com/maps/dir/2.909802,101.6650104/2.9077097,101.6626193/@2.9092498,101.6617772,494m/data=!3m1!1e3!4m9!4m8!1m5!3m4!1m2!1d101.6629088!2d2.9091299!3s0x31cdb7a9b5d5bea5:0x315a8e5bd7b60a1a!1m0!3e2?entry=ttu	https://drive.google.com/file/d/1uFKYeMamMfUTSLVRl0cF_qgxchDwiUxH/view?usp=sharing
Gamuda Cove area	A 20-min walk from the start of Gamunda Covet to he round about on Persiaran Cove Utama (via Persiaran Cove Utama past Gamuda Cove Experience Gallery) and back, 1.8 kms right hand sidewalk - see Map)	https://www.google.com/maps/dir/2.8870409,101.6181665/2.88659,101.6102672/@2.887069,101.6097645,1608m/data=!3m1!1e3!4m2!4m1!3e2?hl=en&entry=ttu	https://drive.google.com/file/d/10JDVSxa30bh7jaHgaj4xMRQzvyGdF3pq/view?usp=sharing

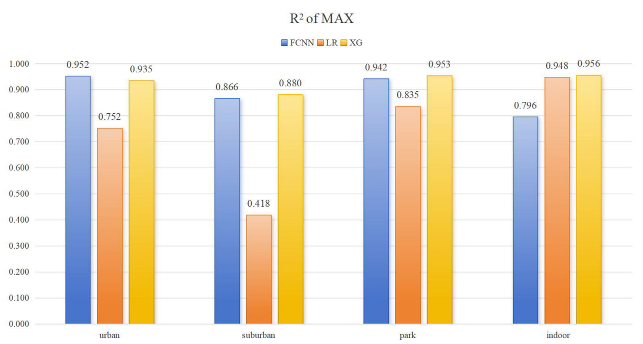

FIGURE 24. R^2 **of MAX.**

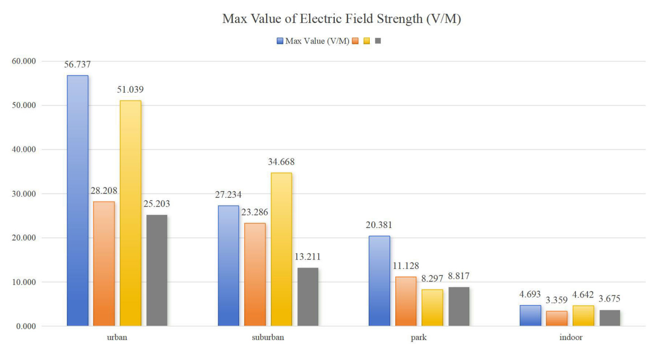

FIGURE 25. **Maximum MAX value of electric field strength.**

will attenuate electromagnetic waves and thus affect field strength [33].

Displaying the measured data and predicted values of the maximum MAX values of Electric Field Strength in different types of micro-environments, the comparison results are presented in the bar chart.

The measured data and predicted values are all less than 61.4 V/m, but the maximum exposure in urban areas with dense population and numerous base stations is very close to the exposure limit.

V. CONCLUSION

LR has better prediction results under single and simple data sets, while XG Boost and FCNN have stronger analysis capabilities for multiple types of data sets. In addition, FCNN predicts best in the presence of extreme values and analyzing large and complex data.

By comparing and analyzing the measured data and predicted values across different micro-environments, it is observed that the highest levels of personal radiation exposure typically occur in outdoor urban areas, which is characterized by high population density, high concentration of base stations, and close proximity to these stations. In contrast, park areas with dense vegetation exhibit significantly lower personal radiation exposure. The dense trees act as natural attenuators, absorbing and scattering the electromagnetic waves, which reduces their intensity. Indoor environments generally exhibit lower electromagnetic field strengths compared to outdoor environments. This can be attributed to structural shielding provided by building materials and fewer high-power sources.

Typically, Electric Field Strength is much lower than the international exposure limits, which is similar to the most research results [2], [6], [13], [14], [16]. However, in areas with dense population and base stations, the maximum value of Electric Field Strength would increase at some point, even close to the exposure limit.

Future work entails comprehensive analysis based on road GPS data and signal sources. Especially in the outdoor environment, with multiple signal sources, and the changing distance from the signal sources when moving, complicating the assessment of radiation exposure to EMF. Furthermore, since all the micro-environments for the measurement are selected in common environments in daily life. Future work can choose the site of special cases, such as workplaces that need to handle or come into contact with electromagnetic field equipment, or at concerts where there are large crowds and communication delays.

APPENDIX A
DETAILS OF MICRO-ENVIRONMENTS

See Table 16.

APPENDIX B
PREDICTED RF-EMF EXPOSURES RESULTS

A. FULLY CONNECTED NEURAL NETWORK (FCNN)

See Figs. 9-12.

B. LINEAR REGRESSION (LR)

See Figs. 13-16.

C. EXTREME GRADIENT BOOSTING (XG Boost)

See Figs. 17-20.

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