A Low-Cost Portable IoT System for Real-Time Environmental and UV Radiation Monitoring

Abstract—**Urban microclimates show a lot of variation in the environment. This makes regional weather forecasts inadequate for determining personal ultraviolet (UV) radiation exposure. To tackle this issue, this paper discusses the design, implementation, and validation of a portable, low-cost Internet of Things (IoT) system for real-time environmental monitoring. The prototype includes a dual-mode feedback system. It gives immediate on-site data through an integrated LCD and allows for remote, long-term analysis using the ThingSpeak cloud platform. We conducted a month-long data collection campaign by deploying five units in different locations within the Dhaka division. This created a detailed dataset that captures data over time and space. The main contribution of this work is a quantitative analysis of this data. It confirms that while meteorological conditions are strong predictors (sunny: +0.39, rainy: -0.40), local micro-environmental features significantly influence personal safety. Importantly, we measure the protective effect of urban tree shade, which has a notable negative correlation (-0.21) with the UV index. The analysis also shows that cloudy weather does not reliably reduce UV radiation. It presents a weak positive correlation (+0.14), suggesting the influence of scattering effects like the broken cloud phenomenon. This is important for public health awareness. This study validates a practical solution for personal environmental monitoring and provides a solid dataset for developing future predictive models based on machine learning.**

Index Terms—**Internet of Things (IoT), Environmental Monitoring, UV Radiation, Low-Cost Sensors, Correlation Analysis, broken cloud, Public Health**

I. Introduction

The rise of Internet of Things (IoT) technologies has changed how we collect data in many fields, particularly in environmental monitoring [1] [2]. In crowded cities like Dhaka, microclimates can vary greatly from one location to another, leading to a need for detailed, real-time data. A key concern is exposure to ultraviolet (UV) radiation, which is a known environmental carcinogen linked to higher risks of skin cancer and other health problems. Having immediate access to local environmental conditions can greatly boost public awareness and personal safety. Recent advancements in IoT have led to significant research in environmental monitoring, especially focusing on UV radiation. This research can be divided into three areas: new sensor development, system implementation and communication, and data calibration techniques.

A key area of research has been the creation of wearable and flexible UV sensors. Innovations include nanomaterial-based sensors connected to smartphones [3], flexible IGZO sensors on paper substrates [4], nanozyme-based dosimeters with color feedback [5], and hydrochromic paper dosimeters [6]. These methods focus on low-cost, disposable, and wearable designs. Clinical trials have shown that wearable dosimeters can change user behavior and lower UV exposure [7]. More advanced devices, like flexible CuO/ZnO nanowire photodetectors [8] and wearable spectroradiometers [9], offer greater sensitivity and precision but often struggle with scalability, durability, and cost for widespread public use.

In system-level design, researchers have looked into different communication protocols and structures. LoRaWAN is a popular choice for its low power and long-range capabilities, as seen in platforms for remote UV monitoring [10] and discussed in systematic reviews of environmental IoT networks [11]. However, these systems are usually built for fixed installations and have duty-cycle limitations. Other methods have used Wi-Fi-based microcontrollers like the ESP32, sometimes paired with mechanical systems like dual-axis sun trackers to enhance accuracy. This does add complexity and power consumption [12]. A major challenge in deploying these low-cost sensor networks is making sure the data is reliable. To tackle this issue, researchers have examined calibration and bias-correction methods using machine learning algorithms, such as Random Forests, to greatly improve sensor accuracy compared to reference-grade instruments [13] [14].

Despite these advancements, a significant gap remains between the broad data provided by national weather services and the specific information people need for their daily decisions. While meteorological agencies offer reliable regional forecasts, they often do not capture local changes in temperature, humidity, and, most importantly, UV index. Although much research has focused on developing new sensor materials and improving specific communication methods, there is still a need for integrated systems that are portable, affordable, and give immediate, useful feedback. Our work tackles this issue by creating a complete system that uses easily accessible, low-cost components with a dual feedback mechanism: a local LCD for immediate readings and a cloud-based dashboard for remote logging and analysis. This approach offers a practical and repeatable solution for personal environmental safety.

The main contributions of this work are as follows:

- The collection of a new, month-long environmental dataset that includes temperature, humidity, and UV index readings from five different cities in the Dhaka Division.
- A thorough analysis of the gathered data, with visualizations showing the relationship between UV index and important local factors like weather type and tree shade.
- A comparison of UV exposure patterns over space and time, highlighting monthly changes across all monitored locations and variations by time of day (morning, noon, and afternoon).

II. System Architecture and Methodology

Both the physical hardware prototype and the cloud-based monitoring backend of the suggested IoT system were used to validate it, guaranteeing reliable local and remote access to environmental data.

1) Hardware Architecture: The ESP32, AM2320, and GY-8511 sensors, along with a 16x2 LCD, make up the assembled prototype, which is displayed in Figure 1. For portability and ease of modification, every component is integrated on a breadboard Figure 2. As the main local display, the LCD continuously displays the calculated UV index, temperature (T), and relative humidity (H) in real time. In field applications, where users might not have internet access but still need quick, actionable data, this feature is especially helpful.

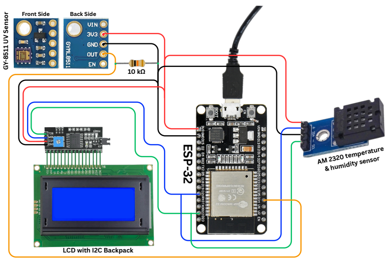

Fig. 1: Schematic diagram

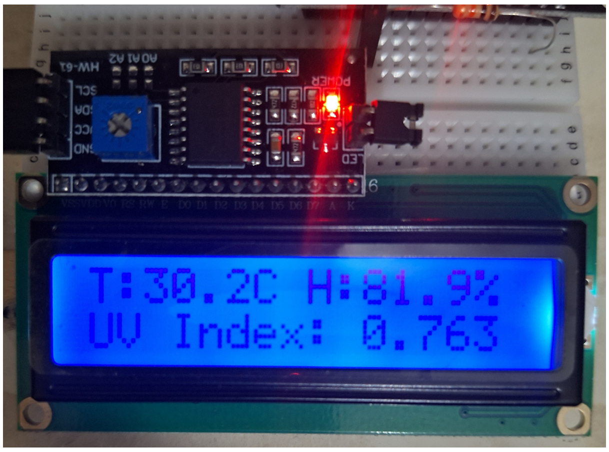

Fig. 2: Assembled prototype showing real-time environmental readings (temperature, humidity, UV index) on the 16x2 LCD.

2) System Workflow and Cost-Effectiveness: At the same time, the system sends data wirelessly to the ThingSpeak IoT platform, which acts as the cloud backend. Interactive tools for historical and real-time analysis are available on the ThingSpeak dashboard:

- **Charts:** Time-series plots visualize (Figure 3) historical trends in temperature, humidity, and UV index, enabling long-term monitoring and pattern recognition.
- **Gauges:** Real-time gauges (Figure 4) offer quick insights into current conditions.
- **Alerts:** Threshold-based notifications can be configured to trigger when parameters, such as the UV index, exceed safe limits.

This entire operational sequence is visually summarized in the workflow diagram shown in Figure 5. In this loop, the microcontroller polls the sensors to get current temperature, humidity, and raw UV voltage data. The system processes this information immediately and displays it on the local LCD, updating every five seconds for real-time feedback. At the same time, the firmware converts the raw UV voltage into a standard UV index and checks it against a safety threshold. For example, a UV Index from 0 to 3 is safe, from 3 to 6 is moderately risky, from 6 to 10 is high risk, and above 11 is extremely risky [15]. If the threshold is exceeded, the onboard LED lights up, and a "UV ALERT" message appears on the LCD. Additionally, the system collects sensor data and sends it to a ThingSpeak cloud channel. This dual-mode operation provides immediate data access on-site and reliable data logging remotely. A key objective of this research was to ensure the developed system is not only functional but also low-cost and easily replicable. All components were sourced from the local electronics market in Dhaka, demonstrating their widespread availability. The total cost for a single monitoring unit is approximately 1,230 BDT (about $10.50 USD), as detailed in Table I, confirming the affordability of the prototype for widespread deployment in educational, community, or personal settings.

TABLE I: Cost Breakdown of a Single Monitoring Unit

Product	**Price (BDT)**
ESP32 (30-pin) microcontroller	380
GY-8511 UV Sensor	220
AM2320 Temperature & Humidity Sensor	220
16x2 LCD with I2C Module	240
Jumper Wires (30 pcs set)	60
Breadboard (830 tie-points)	110
Total	**1,230**

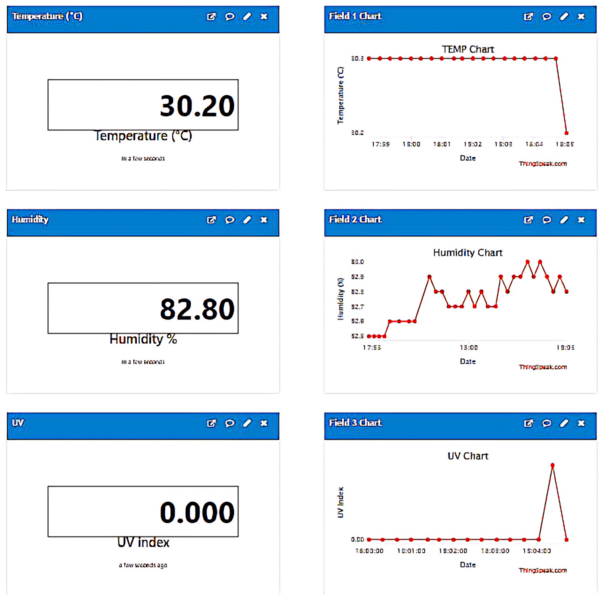

Fig. 3: ThingSpeak dashboard showing real-time data visualization and historical time-series charts.

III. Experimental Setup and Data Analysis

A. Data Acquisition and Dataset Description

To study micro-environmental variations and evaluate the system, we collected a detailed dataset over one month. We deployed five identical IoT monitoring devices across five cities in the Dhaka Division: Dhaka, Tangail, Gazipur, Faridpur, and Narayanganj. To capture a wide range of conditions, we placed

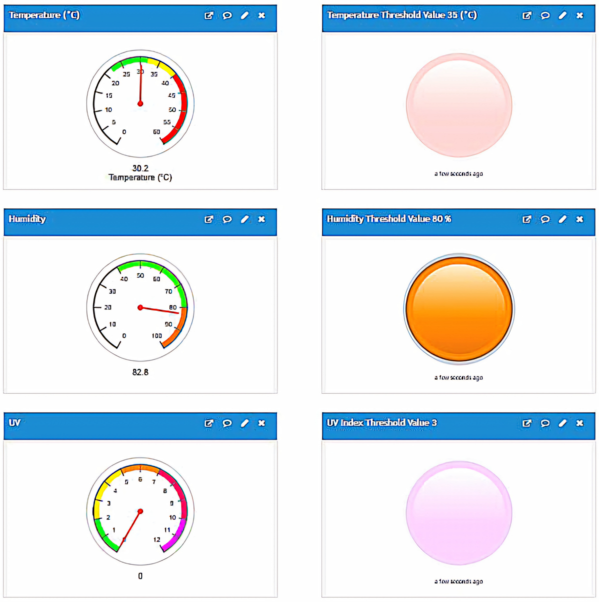

Fig. 4: ThingSpeak dashboard gauges and threshold alert indicators for monitoring safety limits.

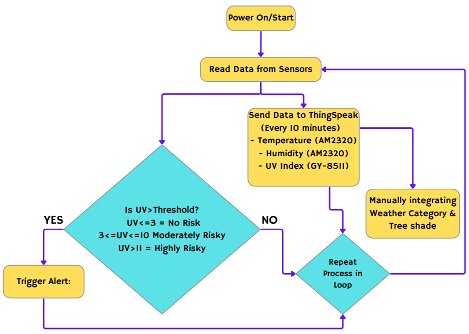

Fig. 5: The system's operational workflow, from initialization and sensor reading to the conditional logic for UV alerts and periodic data transmission to the cloud.

devices in each city in various micro-environments, including open areas with direct sunlight and spots under tree shade.

We acquired data daily during three specific times: morning (9:00 AM to 10:30 AM), noon (12:00 PM to 1:30 PM), and afternoon (3:00 PM to 4:30 PM). To ensure data quality and reduce transient sensor noise, we aggregated raw readings into single data points by calculating the average value over a 10-minute interval. We filtered out any unusual readings, like zero or erratic low values, during this pre-processing stage.

Along with automated sensor readings, we also recorded manual notes for important context. This included classifying the weather as 'Sunny,' 'Cloudy,' or 'Rainy,' and noting whether there was tree cover using a binary `is_under_shade` feature (1 for shaded, 0 for not shaded). The final curated dataset has about 4500 data points. Each entry is time-stamped and includes the following attributes: `date`, `place time`, `temperature (°C)`, `humidity (%)`, `uv_index`, `weather_category`, and `is_under_shade` (Figure 6).

	B	C	D	E	F	G	H	I
1	Date	Place	Time	Temperature (°C)	Humidity (%)	UV Index	Weather Category	Tree
2	2025-08-01	Dhaka	9:00	29.3	82	3.2	Cloudy	0
3	2025-08-01	Dhaka	9:10	27.6	87.4	3.6	Cloudy	0
4	2025-08-01	Dhaka	9:20	30.5	81.7	3	Cloudy	1
5	2025-08-01	Dhaka	9:30	30	90.9	3	Cloudy	1
6	2025-08-01	Dhaka	9:40	28.2	82.5	3.3	Cloudy	0
7	2025-08-01	Dhaka	9:50	31.4	85.2	3.9	Cloudy	0
8	2025-08-01	Dhaka	10:00	28.7	84.3	4.2	Cloudy	0
9	2025-08-01	Dhaka	10:10	29.7	87.4	3.9	Cloudy	0
10	2025-08-01	Dhaka	10:20	28.8	84.8	3.2	Cloudy	0
11	2025-08-01	Dhaka	10:30	28.8	85.2	3.3	Cloudy	0
12	2025-08-01	Dhaka	12:00	32	82	2.7	Cloudy	0
13	2025-08-01	Dhaka	12:10	32.7	75	2.1	Cloudy	1

Fig. 6: A small part of the structured dataset shows the recorded parameters for each timestamp. The columns include date, location, time, sensor readings, the environmental context, Tree shade condition.

B. *Data Visualization and Analysis*

This section presents a systematic analysis of the collected dataset. The visualizations are organized to first provide a high-level overview of UV exposure patterns, followed by a detailed examination of the factors influencing these patterns, and concluding with an analysis of inter-variable correlations.

1) Overall UV Exposure Patterns: The analysis begins with an overview of the aggregated UV data. Figure 7 illustrates the daily variations in the average UV index across the five monitored cities. Gazipur had the highest average UV index. This is due to its open industrial landscape, which has fewer trees and not many tall buildings. These factors allow for more direct sunlight. In contrast, Dhaka and Narayanganj have dense urban areas and high pollution, which often limit UV exposure. We collected our data using a monitoring device in Gazipur's industrial zone. This area features wide open spaces and little shading. The environmental conditions, combined with local weather factors like cloud cover, likely led to the higher UV levels recorded in Gazipur. To summarize these spatial differences, Figure 8 presents the average UV index for each city throughout the entire monitoring period. This confirms that Gazipur had the highest average UV exposure. The daily pattern of UV radiation is clearly shown in Figure 9, which plots the average UV index against the hour of the day, peaking around 13:00. Finally, Figure 10 shows that the overall UV index readings follow a right-skewed distribution, indicating that moderate exposure was common.

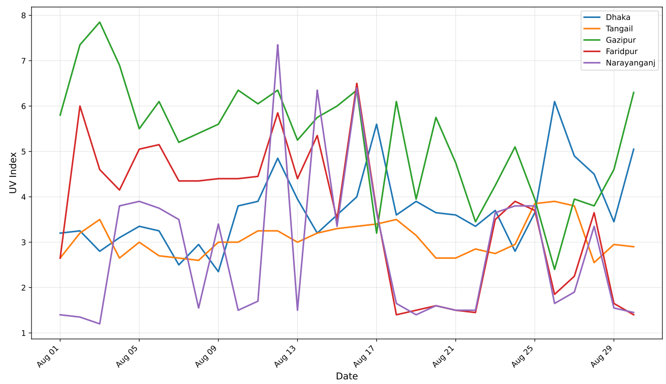

Fig. 7: Daily mean UV Index fluctuations across the five monitored cities during the month of August.

2) Analysis of Influencing Factors: To understand the main factors affecting UV variation, we looked at the data based on specific time and environmental elements, as shown in Figure 11. The analysis of time of day supports the daily pattern, with the median UV index reaching its highest point around noon. Weather conditions play a key role as well. Sunny

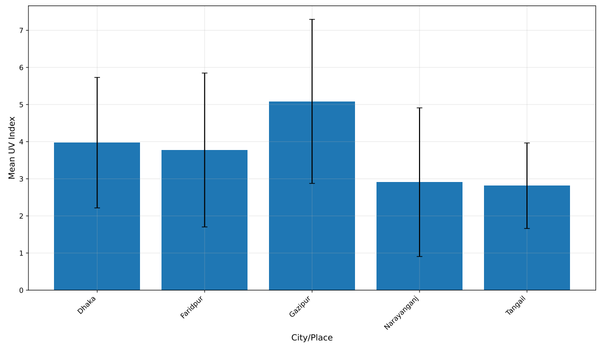

Fig. 8: Mean UV Index per city over the entire study period. Error bars represent the standard deviation.

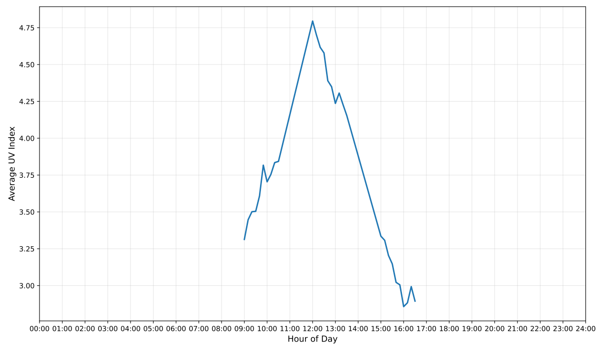

Fig. 9: Average UV Index by hour of the day, illustrating the diurnal cycle of UV radiation.

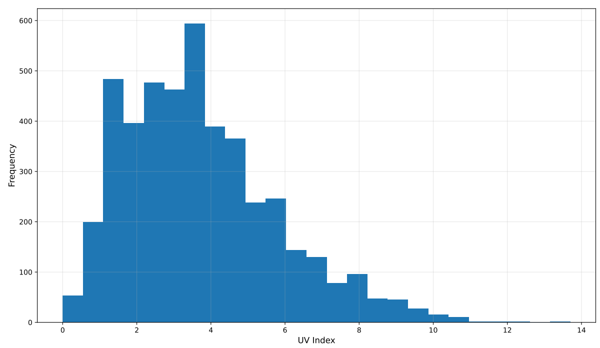

Fig. 10: Overall distribution of UV Index readings from the entire dataset, showing the frequency of each recorded value.

days show a much higher median and a wider range of UV values than cloudy or rainy days. In addition, having tree cover noticeably lowers the median UV index by about 1.5 points.

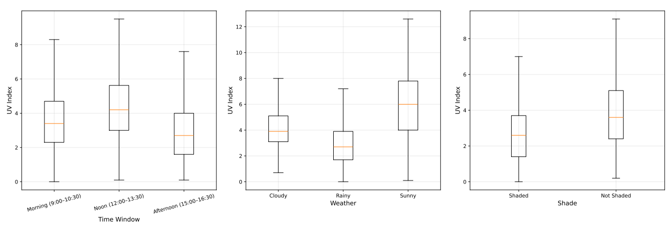

Fig. 11: Comparative box plot analysis of UV Index distribution based on temporal, meteorological, and environmental shading factors.

3) Inter-Variable Relationships: Finally, we investigated the correlations between the continuous environmental variables (Figure 12). The correlation matrix indicates a weak positive correlation between temperature and UV index (0.16) and a weak negative correlation between humidity and UV index (-0.15). The hexbin density plots provide a more granular view, showing that the highest density of UV readings occurs when temperatures are between 30°C and 32.5°C and humidity is between 80% and 95%.

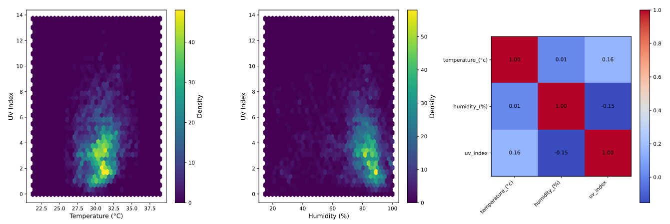

Fig. 12: Correlation analysis of continuous environmental variables, showing a Pearson correlation heatmap and hexbin density plots for UV Index vs. Temperature and Humidity.

4) Quantitative Correlation Analysis of Environmental Determinants: To measure how environmental conditions affect UV exposure, we conducted a Pearson correlation analysis, as shown in Figure 13. We one-hot encoded the categorical variables for weather (Sunny, Cloudy, Rainy) and tree shade. This approach enabled a direct comparison of their influence on the UV index. The resulting correlation matrix shows clear evidence that both large-scale weather conditions and small-scale environmental features significantly affect personal UV exposure.

The strongest relationships are tied to weather patterns. There is a strong positive correlation between the UV index and sunny conditions, with a Pearson coefficient of +0.39. This shows that direct sunlight during clear skies is the main reason for higher UV readings. In contrast, rainy weather has a strong negative correlation of –0.40, demonstrating how heavy clouds and rain significantly reduce UV radiation. Interestingly, cloudy conditions show a weak positive correlation of +0.14. This relates to the broken-cloud effect, where scattered or partial cloud cover lets direct sunlight pass through gaps. It also increases UV exposure through scattering and reflection by nearby cloud edges. Studies confirm that nearly 3% of UVB readings taken over a full year are actually boosted by broken clouds, not reduced [16] [15]. This insight has important implications for public health messaging. People should not think that cloudy skies provide full protection from UV exposure, as significant and even high levels of UV can still reach the ground on overcast days.

A key contribution of this study is measuring the impact of micro-environments. The presence of tree shade has a statistically significant negative correlation of -0.21 with the UV index. Although this value is lower than that of weather conditions, it remains an important finding. It provides clear evidence of the protective benefits of urban green infrastructure. This result highlights the importance of local environmental features in creating areas with lower UV exposure within a larger, uniformly irradiated zone. For individuals, seeking shade is a simple and effective way to protect themselves, and this analysis supports such recommendations. In summary, the

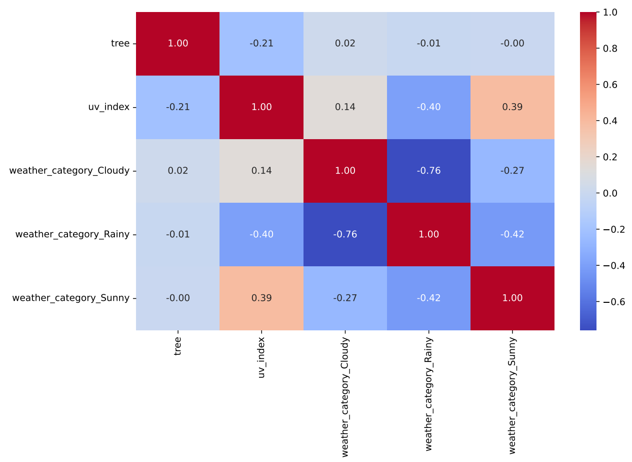

Fig. 13: Pearson correlation matrix illustrating the relationships between the UV index and key environmental factors. Weather categories and tree shade are one-hot encoded for quantitative analysis.

correlation analysis shows that while broad weather patterns influence the overall UV environment, local elements like tree canopies significantly affect personal UV radiation levels.

IV. Future Work

We are building upon the basic data presented in this paper. Future work will focus on two main areas. First, we are going to keep collecting data at the five places we mentioned. We will do this for a whole year. Having this data over time will let us see how things change with the seasons. It will also give us a stronger base for making predictions. Second, with more data, we can build and teach machine learning models. These models will forecast the UV index for each specific location. This will make the system more helpful for public health and safety.

V. Conclusion

In this paper, we outlined the successful design, implementation, and validation of a portable, low-cost IoT system for real-time environmental and UV radiation monitoring. The developed prototype has a dual-mode feedback system. It provides immediate on-site data through an LCD and allows long-term remote analysis via a ThingSpeak cloud backend. During a month-long deployment across five different locations in the Dhaka division, we demonstrated the system's ability to capture detailed spatiotemporal environmental data, bridging the gap between regional forecasts and local exposure levels.

The main contribution of this work is the quantitative analysis of the collected dataset. Our findings confirm that while broad meteorological conditions mainly drive UV exposure, local micro-environmental features significantly influence personal risk. We established a strong positive correlation between sunny weather and UV index (+0.39) and a strong negative correlation with rainy conditions (-0.40). More importantly, we measured the protective effect of urban green infrastructure, revealing a significant negative correlation between tree shade and UV index (-0.21). This validates the importance of localized environmental features for personal safety. Moreover, our analysis showed that cloudy weather is an unreliable reducer of UV radiation (+0.14), which is crucial information for public health awareness.

While the current system is effective, its dependence on existing Wi-Fi infrastructure and a manual power source limits its use in remote or off-grid areas. Future work will focus on two main areas. First, we plan to extend the data collection campaign to a full year to capture seasonal variations and create a larger dataset. Second, this long-term dataset will serve as the basis for developing and training machine learning models. The ultimate goal is to use this data to create a reliable predictive system that can forecast localized UV index levels, turning a real-time monitoring tool into a proactive public health and safety application.

Data Availability

To help with future research in this area, people who are interested can get the source code and dataset by sending a request through email.

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