# An IoT-Device Based on K-Nearest Neighbors for Heatstroke Illness Prevention

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## Abstract

This study utilizes Internet of Things (IoT) technology integrated with a private cloud infrastructure to investigate heatstroke mechanisms in individuals exposed to outdoor environments, particularly under dehydration or impaired thermoregulation conditions. The objectives are to develop an automated real-time heat monitoring and warning system and to evaluate its accuracy and user satisfaction in preventing heat-related illnesses. Field trials were conducted with 50 participants, including students in outdoor classes, athletes in training, and workshop attendees exposed to direct sunlight. A prototype system was designed to autonomously collect environmental data—temperature, humidity, and air pressure—via external sensors. A mean fusion technique was applied to combine sensor data with meteorological information obtained from the open weather map API, enhancing data reliability and prediction accuracy. The fused dataset was analyzed using the K-Nearest Neighbor (KNN) algorithm to estimate heatstroke risk. The optimal configuration (k = 3) achieved an accuracy of 86.67% in identifying high-risk heat conditions. Experimental results showed that when ambient temperatures increased continuously from 35°C to 37°C, the system issued real-time heat warnings. Under these conditions, physiological responses indicated that core body temperature could rise to approximately 40°C, a critical threshold associated with heatstroke and potentially life-threatening outcomes if intervention is delayed. The system effectively delivered automated alerts to support timely preventive actions.user evaluation demonstrated high satisfaction, with an overall average score of 4.37 out of 5.00 (87.44%), while device control functionality received a higher rating of 4.54 (90.80%). These results suggest that the proposed system is a reliable, cost-effective, and scalable solution for localized temperature monitoring and heatstroke risk mitigation, particularly suitable for educational and outdoor environments requiring proactive heat risk management.

**Keywords:** Realtime processing, Heat stroke, Private cloud, KNN, IoT technology

## Introduction

      The body cannot control and discharge heat when its core temperature climbs above a particular degree. This condition can lead to various health issues and may even result in death. Many things can affect this illness, but the environment is the most important. For example, being in places with high humidity and poor ventilation, or being in extreme heat, especially during heatwaves, can make it harder for sweat to evaporate and cool down. Doing outside activities for a long time without protection like umbrellas or fans makes things a lot more dangerous. People who are very young, extremely elderly, or already unwell are more likely to get sick because their bodies can't keep their temperature stable. This list covers those who have cardiovascular, pulmonary, cerebrovascular, or Parkinson's disease, as well as overweight people, which makes it harder for their bodies to dissipate heat and circulate blood. Heat stroke is more likely in those unaccustomed to hot weather or sleep-deprived. Risk is higher when you do things like severe outdoor exercise, wear clothes that don't breathe, get dehydrated, or drink too much alcohol or caffeine. Some prescription drugs (like diuretics, antihypertensives, vasoconstrictors, and psychiatric drugs) and illegal drugs (like cocaine and amphetamines) can make it harder for the body to control its temperature. Such substances can cause the body to lose more fluids or make it harder to get rid of heat. So, to lower the number and severity of heat strokes, it's important to know about these different risk factors and take the right steps to avoid them.

      Outdoor activities are a significant contributor to heatstroke. This research aims to enhance student learning while simultaneously implementing a warning and monitoring system, particularly for outdoor activities conducted in low-humidity, high-temperature environments. Examples include curricula emphasizing open-air learning, such as military training, scouting activities, practical learning through volunteer development camps, and recreational events within educational institutions. These activities not only promote physical health but also cultivate desirable characteristics like discipline, responsibility, teamwork, and adaptability to diverse environments. However, the environmental conditions during outdoor activities, especially in open areas and during periods of high temperatures, significantly impact participant safety. A common and potentially life-threatening issue is heatstroke, a condition where the body's thermoregulation fails, leading to systemic organ failure, notably affecting the nervous and circulatory systems.

      According to a 2024 report by the World Health Organization, the past three years have demonstrated a persistent global increase in the number of days with ambient temperatures exceeding 35 °C, accompanied by an estimated annual rise of 30–40% in heatwave occurrences across multiple regions compared with the pre-2020 period. This accelerating trend substantially elevates the incidence of heat-related illnesses, particularly heat stroke, during outdoor activities

and occupational exposure (World Health Organization, 2024; Lugo-Amador et al., 2004). The onset of heat stroke is not solely attributable to elevated ambient temperature; rather, it emerges from a multifactorial interaction among environmental conditions, physiological responses, and individual characteristics. Excessive perspiration without sufficient replacement of fluids and electrolytes, inappropriate clothing such as tight-fitting or poorly ventilated garments, and prolonged exposure to high humidity significantly impair the body's thermoregulatory mechanisms. Furthermore, individual vulnerability is exacerbated by predisposing factors including chronic dehydration and underlying health conditions such as cardiovascular disease or diabetes, which reduce tolerance to thermal stress (Lugo-Amador et al., 2004). Given these complexities, accurate and continuous monitoring of environmental conditions—particularly air temperature and relative humidity—using reliable sensors and standardized measurement methodologies is essential for effective heat stress assessment and prevention. Advances in sensor networks, microcontroller-based systems, and Internet of Things (IoT) architectures have enabled real-time environmental data acquisition and processing, supporting proactive health risk management in outdoor and industrial settings (Addoddorn, 2012; Yoddumnern et al., 2018; Rghioui et al., 2021). When combined with machine learning techniques, such systems can further enhance predictive accuracy and early warning capabilities for hazardous weather and health-related events (Abhishek et al., 2012; Mahesh, 2018; Sharma et al., 2014). Among the established indices for environmental heat assessment, the Wet Bulb Globe Temperature (WBGT) is widely recognized as a comprehensive indicator of heat stress. WBGT integrates key determinants of thermal load, including air temperature, relative humidity, radiant heat, and air movement, and is expressed in degrees Celsius or Fahrenheit. Importantly, this index accounts for both internal heat generation arising from metabolic activity during physical work and external heat gain from the surrounding environment, making it particularly suitable for evaluating heat exposure in outdoor activities and occupational contexts (ISO 7243; NIOSH). Environmental heat is transferred to the human body through three primary mechanisms: conduction, convection, and thermal radiation. In addition, workload intensity plays a critical role, as metabolic heat production increases proportionally with physical exertion. Individuals performing heavy workloads generate significantly greater internal heat compared to those engaged in light tasks, thereby increasing the risk of heat accumulation and heat-related illness. Consequently, international heat exposure standards explicitly incorporate workload as a key parameter when defining permissible heat exposure limits and risk thresholds, reinforcing the necessity of integrating environmental monitoring, workload assessment, and physiological considerations in heat risk management frameworks (Shigley & Mischke, 1989; Krutz et al., 1984).

The integration of WBGT-based environmental monitoring with validated sensor systems and intelligent data processing therefore provides a scientifically robust foundation for heat stroke risk

assessment, early warning, and preventive decision-making. Such an approach is increasingly aligned with modern smart monitoring systems that leverage IoT and embedded machine learning on resource-constrained devices, enabling timely and effective interventions in outdoor activity management and public health protection (Sudharsan et al., 2021; Wang et al., 2022).

**Table 1**: Summary of Factors Contributing to Heatstroke illness

| Aspect Considered | Details of Risk Factors |
|---|---|
| 1. Physical condition and personal behavior | - Infants and elderly individuals have immature or deteriorated thermoregulatory systems.<br>- Individuals with underlying health conditions such as cardiovascular disease, pulmonary disease, Parkinson's disease, stroke, or obesity.<br>- Individuals unacclimated to hot climates, e.g., those migrating from cooler regions.<br>- Individuals with insufficient rest, affecting recovery and internal temperature regulation.<br>- Those engaging in strenuous physical activity under direct sunlight, such as athletes, military personnel, or laborers.<br>- Wearing thick or poorly ventilated clothing.<br>- Inadequate fluid intake leading to dehydration.<br>- Excessive consumption of alcohol or caffeine.<br>- Use of certain medications such as diuretics, beta-blockers, psychiatric drugs, antihistamines, and stimulants like amphetamines or cocaine, which can impair the body's thermoregulatory function. |
| 2. Environmental conditions: humidity and temperature | - Exposure to heat waves where temperatures may exceed 35°C for extended periods.<br>- High relative humidity in certain areas impeding sweat evaporation and heat dissipation.<br>- Enclosed or poorly ventilated spaces, such as indoor areas with stagnant air.<br>- Outdoor activities without access to shade or cooling aids.<br>- According to WHO (2024), the number of extreme heat days has increased by an average of 30–40% annually since 2020.<br>- Sharma et al. (2014) confirmed that even in moderately high temperatures, heat stroke can still occur if the body loses sweat without adequate replenishment of water and electrolytes. |

Following Table 1, the research primarily aims to address the threat of heatstroke by first conducting an in-depth investigation into the various factors contributing to its occurrence among individuals engaging in outdoor activities. The knowledge gained from this analysis will then inform the development of an automated device capable of effectively monitoring and alerting users to hazardous heat conditions in open areas. This device is intended to serve as a proactive measure for early prevention. Ultimately, the study will focus on evaluating the effectiveness of the developed surveillance system to ensure its capability in genuinely preventing heatstroke incidents, thereby enhancing safety for individuals participating in outdoor activities.
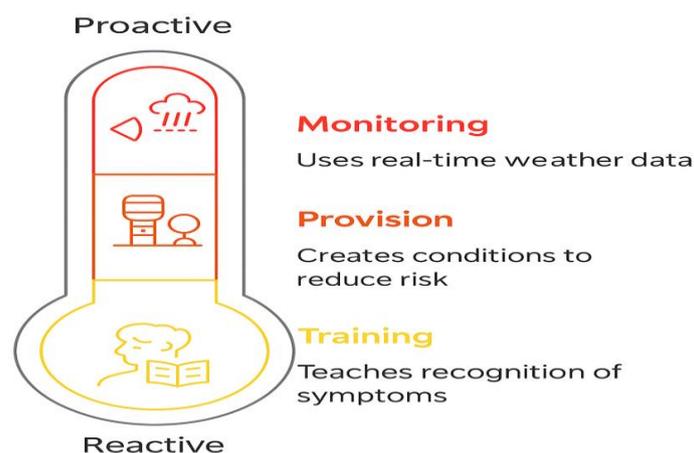
## Methodology



**Figure 1**  Guidelines for preventing heatstroke (Source: Researcher, 2025)

Figure 1 demonstrates heat stress management options, ranging from reactive to proactive. At the reactive level, training focuses on teaching people to recognize heat stress indicators so that individuals are prepared when problems emerge. Moving upward toward proactive solutions, provision focuses on generating risk-reducing settings, such as assuring access to cooling and drinking. At its most proactive, monitoring entails analyzing real-time weather data to anticipate and mitigate problems before they materialize. These layers emphasize the significance of transitioning from reactive to proactive actions in effectively decreasing heat stress.

### 1. IoT for Heatstroke Prevention

The integration of these three approaches can effectively reduce the risk of heatstroke during outdoor activities and enhance participant safety. Heatstroke is a medical emergency caused by the body's inability to regulate internal temperature, which can result in severe symptoms and even death, particularly among vulnerable populations exposed to extreme heat, such as young children, the elderly, and outdoor laborers. Young children are at higher risk due to their immature

thermoregulatory systems, and outdoor play during hot weather may limit physical activity and increase health risks. Providing education to parents and installing supportive infrastructure—such as sunshades, shaded rest areas, and automated drinking water dispensers in public spaces—are proactive measures that should be encouraged. Elderly individuals often experience a diminished ability to regulate body temperature and may have underlying health conditions that increase their susceptibility to heatstroke. Climate change-induced temperature rises further intensify these risks, which can be mitigated by offering shaded rest areas and weather-related information. Outdoor workers, including construction workers, farmers, and sanitation staff, face heightened heatstroke risks due to prolonged exposure to high temperatures and physically demanding tasks. Key preventive measures include education on heatstroke prevention, access to drinking water, and appropriate work scheduling (Lugo-Amador et al., 2004). From a technological innovation perspective, leveraging information technology can enhance the design and development of a Smart Outdoor Safety System (SOSS) aimed at preventing and managing heatstroke in public areas, integrating intelligent safety measures into outdoor environments (Abhishek K et al. 2012).

- Temperature and humidity sensors are installed in playgrounds or outdoor training areas to monitor weather conditions in real time.

- A smartphone-based alert application is provided for teachers, parents, or activity supervisors to receive timely weather updates and recommendations for adjusting activities accordingly.

- A real-time risk dashboard displays heat-related risk levels and suggests appropriate mitigation measures, such as rescheduling activities to early morning or late afternoon, or reducing the duration of physically demanding tasks.

The integration of Internet of Things (IoT) technology with a private cloud infrastructure (IP: 61.19.33.12), combined with cloud services from OpenWeatherMap and the development of a mobile application, can effectively reduce the risk of heatstroke among vulnerable populations and enhance public safety in open areas.

Following Fig 2, the conceptual framework diagram presents an end-to-end system for detecting and mitigating heatstroke risk by connecting users, sensing devices, local interfaces, an edge processing module, and a private cloud platform. Mobile phones and laptops, operated by users or trainers, collect contextual inputs and interact with wearable or environmental sensors that continuously measure physiological and ambient parameters, such as body temperature, heart rate, humidity, and solar exposure. Those data are streamed to a central edge unit illustrated at the center, where preprocessing, real-time visualization, and preliminary decision rules convert raw measurements into actionable indicators. Aggregated summaries are securely sent to a private cloud for advanced analysis, detection of historical trends, and ongoing model updates that improve risk thresholds over time. When increased risk is detected, the system triggers alerts indicated by the

dashed path to users and trainers, allowing quick intervention and behavioral adjustment modification. The loop of sensing, edge processing, cloud analytics, and human oversight emphasizes speed, privacy, and scalability, while the graphical emphasis on heat-stroke outcomes underscores the system's public-health purpose. Overall, the framework balances automated detection with human-in-the-loop notification to reduce heat-related harm in field scenarios. It is designed for deployment in outdoor activities, occupational settings, and mass events.
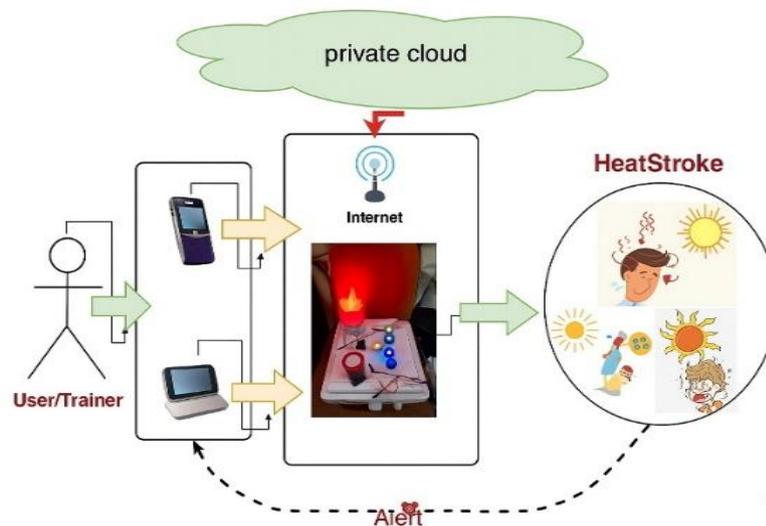


**Figure 2** Conceptual Framework (Source: Researcher, 2025)

## 2. Smart Device and Cooperation

This study involved experimental trials with university students and athletes undergoing training programs, most of which were conducted in open outdoor settings. It was found that heatstroke poses a silent but severe threat in environments with abnormally high temperatures or excessive humidity—particularly in the context of outdoor activities. This condition not only affects the health of outdoor workers but also endangers the general public, especially under the increasingly volatile climate conditions witnessed in recent years. Proactive surveillance and timely warning systems are thus essential in mitigating the incidence of heatstroke (World Health Organization, 2024). The system developed in this research was designed as a Smart Monitoring System to assess real-time heatstroke risk by integrating digital devices, private cloud processing, and multimodal alert mechanisms. The system targets general users—including field workers, caregivers, the elderly, and the public in open spaces—through portable devices such as smartphones or tablets that receive continuous updates and alerts. At the core of the system are environmental sensors deployed in high-risk locations such as playgrounds, construction sites, and outdoor rest areas. These sensors collect environmental data—temperature, humidity, and the Wet-Bulb Globe Temperature (WBGT) index, a standard indicator for physical heat stress risk. The data are transmitted to a private cloud platform that functions as a central processing hub, dynamically evaluating

environmental risk using machine learning techniques to analyze cumulative heat exposure and forecast critical heatstroke thresholds. When the system detects risk levels exceeding the safety threshold, it immediately issues alerts to users via text, sound, and visual indicators from local sensors, such as red flashing lights or audible sirens (Sharma A et al. 2014). A key feature of the system is its real-time responsiveness and automated functionality, eliminating the need for initial human intervention. This makes it particularly suitable for deployment in densely populated or high-risk areas, especially in Thailand, where average temperatures have significantly increased due to climate change over the past decade. This research represents a critical advancement in integrating digital technology with proactive health promotion, offering not only an alert mechanism but also fostering public awareness of extreme heat hazards, thereby encouraging behavioral adjustments such as seeking shade, staying hydrated, and avoiding outdoor activities during peak temperature periods.
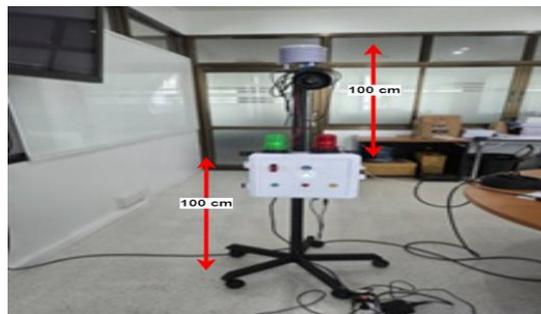


**Figure 3.1** Smart Box Circuit          **Figure 3.2** Installation

**Figure 3**  Hardware architecture of the IoT-based heatstroke monitoring device

(Source: Researcher, 2025)

Following Figure 3, the smart device operates using a microcontroller unit (MCU) integrated with multiple weather sensors (Addoddorn, 2012). These sensors collect real-time environmental data such as temperature, humidity, and possibly light intensity. The data is then processed locally by the MCU before being transmitted securely to a private cloud platform for further analysis (Yoddumnern et al., 2018). The cloud system performs co-processing tasks such as data filtering, classification, and decision-making based on predefined models—likely using algorithms such as K-Nearest Neighbors (KNN)—to determine environmental conditions and potential risks, such as heatstroke. After cloud-based analysis, the processed results are sent back to the device to activate output components, including indicator lamps and a speaker (Jay, 1981). The green lamp signifies safe or normal environmental conditions, while the red lamp and speaker alarm indicate high-risk or abnormal conditions that require immediate attention. This system ensures real-time visual and auditory alerts to users in critical situations. Additionally, the device connects to a mobile or web application that allows users to monitor environmental status, receive alerts, and review historical

data remotely. By integrating MCU control, cloud-based computation, and intelligent output signaling, the device demonstrates an efficient IoT-based solution for smart weather monitoring and responsive environmental safety management (Sharma A et al. 2014).

The K-Nearest Neighbour (K-NN) algorithm is a classification method that determines the most appropriate class for a new instance by examining a predefined number of the closest existing cases or conditions. This technique involves identifying the most similar or nearest neighbors and counting the frequency of each class among these neighbors. The new condition is then assigned to the class with the highest occurrence among the nearest neighbors. In this context, environmental parameters are obtained from both local sensor nodes and the public cloud service OpenWeather-API (see Fig. 4). These parameters are used in a combined calibration process to enhance accuracy and consistency, employing the Euclidean distance equation to ensure proper alignment of the new condition with the most similar class. From Fig.4, the weather data in the image indicates current and forecasted conditions in Chiang Rai, which are useful for heat and environmental risk prediction. Key points for prediction: high humidity and perceived temperature (heat index) indicate potential heat stress conditions despite moderate actual temperatures. Continuous rainfall with high UV suggests fluctuating thermal comfort levels, increasing risk when rain stops and direct sun returns. Stable high temperatures over several days can accumulate heat exposure, raising the likelihood of heat-related illnesses. These data support the need for real-time monitoring and heat alert systems to anticipate and mitigate heatstroke risks during outdoor activities. Although the temperature appears moderate, the high humidity, UV index, and persistent heat pattern make this an important period for proactive heat risk prediction and early warnings (Lugo-Amador NM et al. 2004).
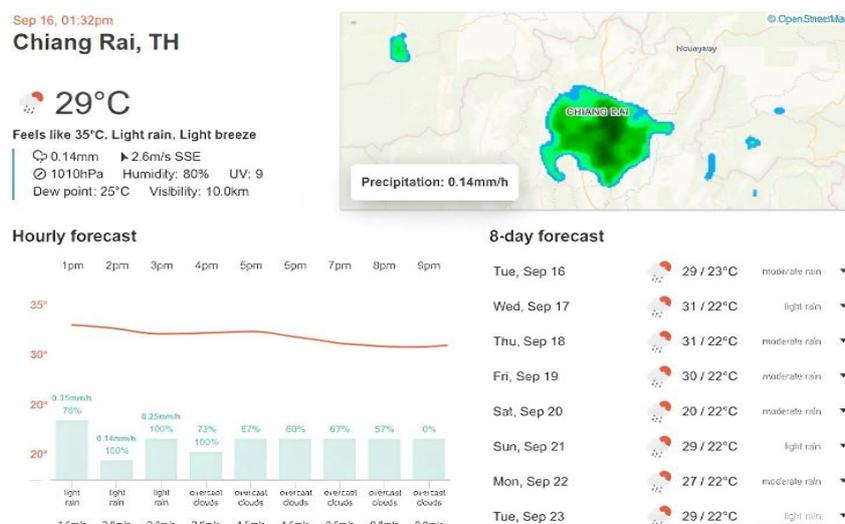


**Figure 4** Public Cloud Service-API (Source: https://openweathermap.org/api)

## Results

The data values transmitted to the cloud system, which have undergone a calibration process to enhance accuracy, are presented in Table 2. This table displays the results obtained after the data have been processed and adjusted for precision.

**Table 2** After Calibrating data on private cloud (IP:61.19.33.12)

| Time stamp | temp | prespresure | humid | Clouds | Wind |
| --- | --- | --- | --- | --- | --- |
| Col1 | Col2 | Col3 | Col4 | Col5 | Col6 |
| 1546300800 | 29.10 | 1034.88 | 78.61 | 6 | 2.96 |
| 1546311600 | 32.40 | 1034.33 | 88.80 | 66 | 3.28 |
| 1546322400 | 33.40 | 1034.54 | 89.50 | 33 | 3.58 |
| 1546333200 | 30.70 | 1034.82 | 89.70 | 4 | 3.81 |
| 1546344000 | 25.80 | 1035.27 | 82.00 | 2 | 4.25 |
| 1546354800 | 29.50 | 1036.04 | 79.60 | 52 | 3.80 |
| 1546365600 | 31.50 | 1037.77 | 80.30 | 54 | 3.26 |
| 1546376400 | 29.50 | 1040.03 | 77.30 | 0 | 3.66 |
| 1546387200 | 28.00 | 1041.78 | 73.49 | 0 | 3.28 |
| 1546408800 | 25.70 | 1043.48 | 77.37 | 9 | 2.98 |
| 1546419600 | 25.90 | 1044.58 | 78.30 | 11 | 2.57 |
| 1546430400 | 25.50 | 1044.82 | 68.80 | 5 | 2.38 |
| 1546441200 | 28.40 | 1044.15 | 70.30 | 0 | 2.15 |
| 1546452000 | 30.30 | 1044.43 | 79.60 | 4 | 1.98 |
| 1546462800 | 29.50 | 1044.23 | 82.01 | 19 | 1.90 |
| 1546473600 | 27.50 | 1043.73 | 83.19 | 24 | 1.73 |
| 1546495200 | 31.50 | 1043.09 | 83.04 | 0 | 1.61 |
| 1546506000 | 28.50 | 1043.53 | 80.68 | 0 | 1.52 |

## 1. Prediction based on KNN

Weather forecasting using the K-Nearest Neighbors (KNN) method is a machine learning technique that relies on historical data to predict future weather conditions. The process begins with the collection of meteorological data such as temperature, humidity, wind speed, and geographical information. These data are then cleaned and normalized to a common scale to enhance the accuracy of distance calculations. Subsequently, the user selects the parameter K, representing the number of nearest neighbors considered for prediction. Distance metrics, such as Euclidean distance,

are employed to measure the similarity between new data points and historical records, enabling the model to generate weather forecasts based on the closest analogous observations.

When the nearest neighbor data points are identified, the system processes them to predict the target value, such as the temperature for the following day or the type of weather condition. For numerical values, the prediction is calculated by averaging the neighbors' values, whereas for categorical data, a majority voting approach is employed. The performance evaluation of the KNN algorithm typically utilizes metrics such as accuracy or Root Mean Square Error (RMSE) to assess effectiveness. This method is characterized by its simplicity and strong applicability to well-recorded datasets; however, it requires significant computational resources, especially with large or dispersed datasets, which may impact accuracy in certain scenarios. The distance calculation is based on the Euclidean Distance formula, a geometric measure of the straight-line distance between two points in a two-dimensional (2D) space, mathematically expressed as follows:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

The example of k-NN grouping in term of 3-NN and 5-NN. Following Fig. 5, the KNN relies on local patterns rather than global assumptions. For k = 3, the algorithm makes a robust prediction by considering the majority among the closest three neighbors, reducing noise and improving classification reliability compared to using just one nearest neighbor. In heatstroke prediction, for example, this method could classify a current weather condition as "high-risk" or "low-risk" based on its similarity to past labeled environmental data.
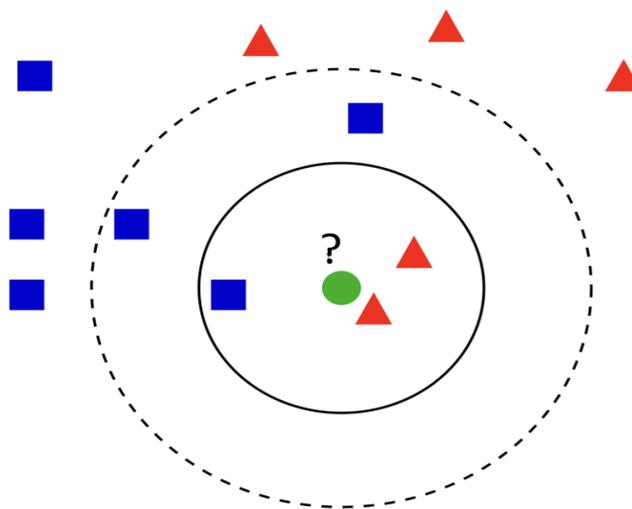


**Figure 5** The data setting of k-value (Source: Researcher, 2025)

In the KNN algorithm, the Euclidean distance formula is utilized to calculate the distance between a new data point and existing historical data points in order to identify the nearest

neighbors. These closest points play a critical role in determining the output values, such as predicting temperature or classifying weather conditions.

**Euclidean Distance Equation:**

$d=\sqrt{(T_1-T_2)^2+(H_1-H_2)^2}$

d = \sqrt{(T_{1} - T_{2})^2 + (H_{1} - H_{2})^2}

Current data value: T1=37, H1=32

Euclidean Distance Methodology:

- Setting 1: $(37-38)^2+(32-30)^2=1+4$ =sqrt(5)≈2.24
- Setting 2: $(37-37)^2+(32-35)^2=0+9$ =sqrt(9)=3.00
- Setting 3: $(37-35)^2+(32-40)^2=4+64$ =sqrt(68)=8.25
- Setting 4: $(37-36)^2+(32-33)^2=1+1$ =sqrt(2)≈1.41

Following Table 3, the dataset includes temperature, humidity, and risk labels for heat conditions. Higher temperatures (37–38 °C) with lower humidity (30–35%) indicate risk, while moderate temperatures (35 °C) with higher humidity (40%) are normal. This pattern helps train a KNN model to predict heatstroke risk based on environmental similarity.

**Table 3**  Training data set

| Temp (°C) | Humidity (%) | Label |
|:---:|:---:|:---:|
| 38 | 30 | 1 (risk) |
| 37 | 35 | 1 (risk) |
| 35 | 40 | 0 (normal) |
| 36 | 33 | 1 (risk) |

Following Fig.6, shows how 3-NN groups data based on the nearest three neighbors. The red circle marks the neighborhood, containing the closest points that influence classification. The green line suggests a decision boundary separating classes, while the distant point outside the circle has no effect. The algorithm assigns the new point's label based on the majority class of these three neighbors, making the classification locally accurate and less affected by outliers (Sharma A et al. 2014).
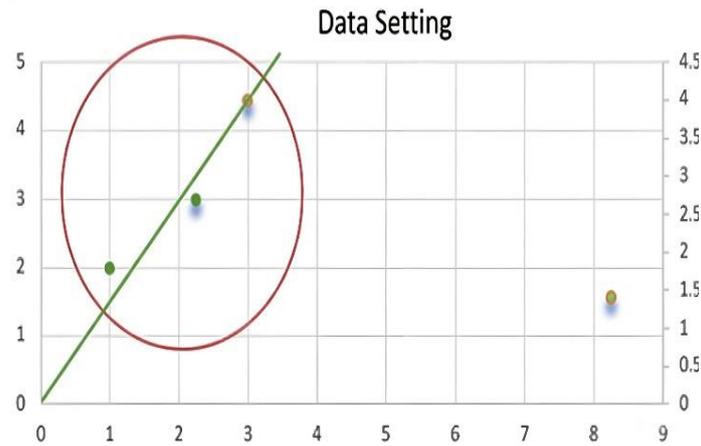
**Figure 6** Group of data set

Have Selected 3 Nearest Neighbors (k = 3): The setting point 4, 1, 2 Having Label = 1

Result: High risk, have been heatstroke.

## 2. Algorithm of the prediction

Following Figure 7, The diagram illustrates the KNN prediction process in seven steps. Step 1 collects environmental data, and Step 2 splits it into training and test sets. Step 3 initializes the KNN model, followed by Step 4, where the model is trained using labeled data. Step 5 predicts outcomes and evaluates accuracy, while Step 6 forecasts new weather conditions based on similar past patterns. Finally, Step 7 triggers a real-time alert, supporting timely heatstroke risk prevention and decision-making.
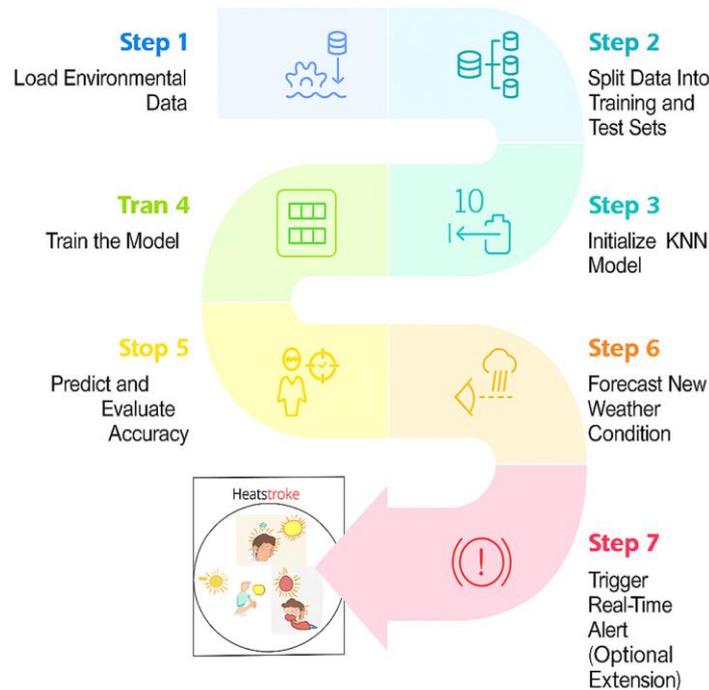


**Figure 7** Prediction Process (Source: Researcher, 2025)

The proposed process begins with the acquisition of relevant environmental data, particularly ambient temperature and relative humidity, which are recognized as critical risk factors associated with heat-related illnesses and heat stroke (World Health Organization, 2024; Lugo-Amador et al., 2004). These data are collected through sensor-based monitoring systems integrated with microcontroller platforms, enabling continuous and reliable environmental observation suitable for outdoor and occupational settings (Addoddorn, 2012; Yoddumnern et al., 2018). Subsequently, the acquired dataset is preprocessed and partitioned into training and testing subsets, a fundamental step in machine learning model development and performance evaluation (Mahesh, 2018). A Deep Neural Network (DNN) model is then initialized and configured, followed by a supervised training phase in which the model learns complex, nonlinear relationships between environmental variables and heat stroke risk outcomes. Similar data-driven approaches have been successfully applied in weather forecasting and environmental prediction tasks, demonstrating the effectiveness of neural network-based models in capturing intricate patterns within meteorological data (Abhishek et al., 2012). During the training phase, the model iteratively optimizes its parameters to improve predictive accuracy, enabling it to identify latent risk patterns that may not be evident through conventional threshold-based methods. Upon completion of training, the model is evaluated using the test dataset to assess its predictive performance and generalization capability. The trained model is subsequently deployed to forecast unseen environmental conditions and to assess heat stroke risk in real-world scenarios, thereby supporting proactive health risk management (Mahesh, 2018; World Health Organization, 2024). In addition to the DNN-based predictive framework, the system incorporates a k-nearest neighbors (KNN) approach as an interpretable and computationally efficient method for classification and risk estimation, particularly in scenarios with limited data or resource-constrained environments. KNN has been widely applied in weather condition prediction and environmental classification tasks, demonstrating reliable performance in identifying similar historical patterns for risk assessment (Sharma et al., 2014). The combination of DNN and KNN methodologies enhances both predictive accuracy and system robustness. Furthermore, in cases where elevated heat stroke risk is detected, the system supports an optional real-time alert mechanism to disseminate warnings promptly to users or relevant authorities. Such alert-driven architectures align with modern IoT-based health monitoring systems, enabling timely preventive actions and reducing response latency (Rghioui et al., 2021; Sudharsan et al., 2021). Recent advances in embedded machine learning and microcontroller-based intelligence further support the feasibility of deploying such predictive models on edge devices for real-time operation (Wang et al., 2022).

Overall, the proposed framework constitutes an intelligent heat stroke risk prediction and prevention system that integrates environmental sensing, machine learning algorithms, and real-time alerting mechanisms. By leveraging both DNN and KNN techniques, the system provides effective

forecasting, interpretable risk assessment, and proactive intervention capabilities, contributing to improved safety and public health outcomes in outdoor activity management.

**- KNN Processing.**

```
BEGIN

Step 1: Load Environmental Data

        LOAD weather_data.csv INTO dataset

        EXTRACT features: temperature, humidity, pressure ⟶ X

        EXTRACT labels: weather_condition ⟶ y

Step 2: Split Data into Training and Test Sets

        SPLIT X, y INTO X_train, X_test, y_train, y_test

        USING ratio 80% training, 20% testing

Step 3: Initialize KNN Model

        SET k ⟵ 3

        INITIALIZE KNN model WITH n_neighbors = k

Step 4: Train the Model

        FIT KNN model WITH X_train AND y_train

Step 5: Predict and Evaluate Accuracy

        PREDICT y_pred USING KNN model ON X_test

        CALCULATE accuracy = MATCH(y_pred, y_test) / TOTAL(y_test)

        DISPLAY "Model Accuracy: ", accuracy × 100, "%"

Step 6: Forecast New Weather Condition

        INPUT new_data ⟵ [temperature, humidity, pressure]

        PREDICT predicted_condition ⟵ KNN.predict(new_data)

        DISPLAY "Predicted Weather Condition: ", predicted_condition

Step 7: Trigger Real-Time Alert (Optional Extension)

        IF predicted_condition IS "High Heat Risk" THEN

          ACTIVATE voice_alert_system

          LOG alert_event TO cloud_storage

        ENDIF

END
```

**Table 4** Testing Set

| Test Case | Temperature (°C) | Humidity (%) | Observed Weather Condition |
|-----------|------------------|--------------|----------------------------|
| Test Set 1 | 34.00 | 22 | Clear sky / Very hot |
| Test Set 2 | 26.20 | 60 | Rainfall |
| Test Set 3 | 38.70 | 56 | Rainfall |
| Test Set 4 | 22.30 | 32 | Clear sky |
| Test Set 5 | 32.00 | 47 | Clear sky / Moderately hot |

Following Table 4, the data based on the results of the five test sets, it was found that the observed weather conditions were clearly correlated with relative humidity. In particular, when the humidity exceeded 50%, such as in Test Set 2 (60%) and Test Set 3 (56%), rainfall was recorded despite the significant difference in temperatures (26.20°C and 38.70°C, respectively). This indicates that humidity plays a more critical role in predicting rainfall than temperature alone. Conversely, in Test Sets 1, 4, and 5—where humidity levels were below 50%—the weather conditions were predominantly clear, regardless of whether the temperature was high (e.g., 34.00°C) or moderate. Furthermore, it was observed that high temperatures combined with low humidity, as in Test Set 1, often resulted in extremely hot and dry weather, whereas low temperatures with low humidity, as in Test Set 4, led to cooler conditions with clear skies. Therefore, it can be concluded that humidity is a primary factor influencing the occurrence of rainfall, while temperature mainly affects thermal perception. Both parameters should be considered together to improve the accuracy of weather forecasting.

**Table 5** Testing Set Evaluation Results

| Test Set | Data Characteristics | k-NN Prediction | Actual Result | Evaluation Result |
|----------|----------------------|-----------------|---------------|-------------------|
| 1 | Extremely hot / Low humidity | Clear sky /Very hot | Very hot | ✓ Matched |
| 2 | Moderate temperature /High humidity | Rainy | Rainy | ✓ Matched |
| 3 | Very hot / High humidity | Rainy or Thunderstorm | Rainy | ✓ Matched |
| 4 | Cold / Low humidity | Clear | Clear | ✓ Matched |
| 5 | Warm / Moderate humidity | Clear / Rather hot | Rather hot | ✓ Matched |

Table 5, the testing table compares five cases—from extremely hot/low humidity to cold/low humidity—listing k-NN predictions, actual outcomes, and evaluation. In every case, the 3-NN prediction matched the observed result, indicating consistent, reliable classification across varied weather conditions and supporting the model's robustness for practical heat-risk detection in these test scenarios.

The results from testing five data sets indicate that weather prediction using the k-Nearest Neighbors (k-NN) method achieved complete agreement with the actual outcomes. Specifically, the model accurately predicted "extremely hot" conditions under low humidity, "rainy" conditions under moderate temperature and high humidity, "rainy or thunderstorm" conditions under very hot and high humidity, "clear sky" under cold and low humidity, and "rather hot" under warm and moderate humidity. These findings demonstrate that the k-NN model exhibits high accuracy and effectiveness in forecasting weather based on the given data characteristics.

**Table 6** Percentage Accuracy of Event Classification Evaluation

| Test Case | Actual Data (Data Set) | Classification Result (K=3) | Classification Result (K=5) | Classification Result (K=7) |
|---|---|---|---|---|
| Test Set 1 | Rainy | Clear Sky | Clear Sky | Clear Sky /Very Hot |
| Test Set 2 | Rainy | Rainy | Rainy | Rainy |
| Test Set 3 | Rainy | Rainy | Rainy | Rainy |
| Test Set 4 | Clear Sky | Clear Sky | Clear Sky | Clear Sky |
| Test Set 5 | Clear Sky | Clear Sky | Clear Sky | Clear Sky /Rather Hot |
| Accuracy (%) | | 86.67 | 60.00 | 28.57 |

In summary following Table 6, the table compares classification outcomes for k = 3, 5, and 7 across five test sets, showing overall accuracies of 86.67%, 60.00%, and 28.57%, respectively. k = 3 produces the most consistent correct labels; increasing k introduces conflicting labels by incorporating more distant neighbors, degrading performance. This indicates the dataset benefits from a small k where local similarity is most predictive.

### 3. The Heatstroke- IoT Application

This study aims to develop a cost-effective weather forecasting station that collects only two environmental parameters—air temperature and relative humidity—using low-cost sensors. To enhance data accuracy, the system integrates wireless communication capabilities, allowing it to

access weather data from the OpenWeatherMap API ([https://openweathermap.org/api] (https://openweathermap.org/api)) for comparison and averaging. This hybrid approach improves the reliability of the local sensor readings. The device is designed for outdoor use, making it a suitable prototype for deployment in various locations. The real-time operation of the application is illustrated in Fig 8. Heatstroke Application with multi-platform.
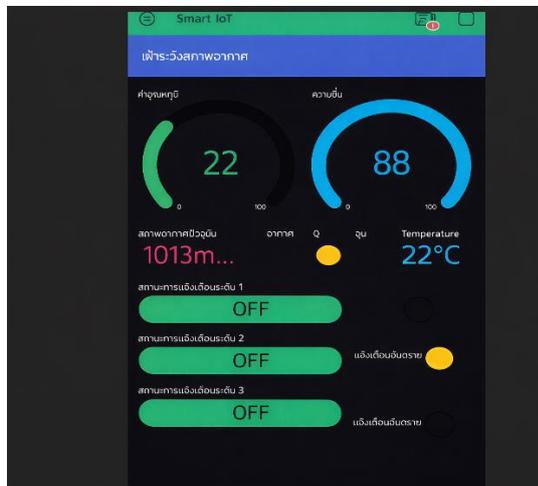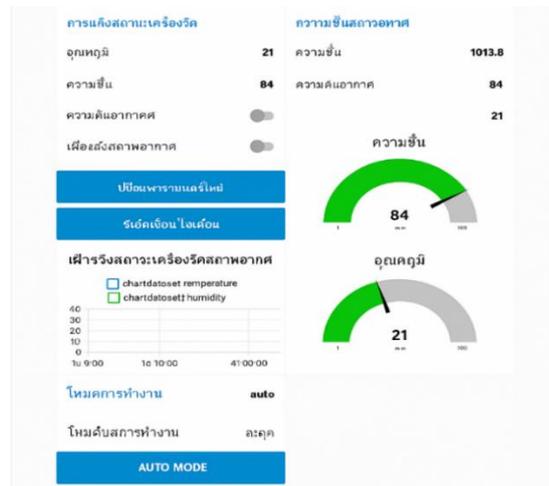


Figure 8.1 Mobile Application.          Figure 8.2 Web Application.

**Figure 8** Heatstroke Application multi-platform (Source: Researcher, 2025)

## 4. Efficiency Project

The processing efficiency of the proposed surveillance system was evaluated based on five key performance factors, incorporating data collected from experimental participants, including students, athletes, and construction workers. These participants engaged in a range of outdoor activities conducted under direct sunlight in open environments, as summarized in Table 7. In addition to the technical performance evaluation, user satisfaction with the system was assessed through a structured questionnaire administered to a sample group of 50 participants. The questionnaire employed a five-level Likert scale to measure participants' perceptions regarding system usability, accuracy, responsiveness, and overall satisfaction. The combined analysis of system performance metrics and user satisfaction data provides a comprehensive assessment of both the operational effectiveness and practical applicability of the proposed surveillance system in real-world outdoor scenarios.

**Table 7** Efficiency of Device Utilization

| No. | Item | Mean | Percentage (%) | S.D. | Evaluation Criteria |
|---|---|---|---|---|---|
| 1 | Design of circuit box and material utilization | 4.24 | 84.80 | 0.88 | High |
| 2 | Capability in designing the application for control and operation | 4.24 | 84.80 | 0.76 | High |
| 3 | Result reporting via automatic configuration | 4.46 | 89.20 | 0.81 | High |
| 4 | Device control operation | 4.54 | 90.80 | 0.81 | Very High |
| 5 | Appropriateness for practical use | 4.38 | 87.60 | 0.75 | High |
| | **Overall** | **4.37** | **87.44** | **0.80** | **High** |

The study found that among the 50 participants who tested and controlled the devices. Following Table 7 shows high device-utilization efficiency across five criteria: circuit-box design/materials (mean 4.24, 84.80%, SD 0.88, High), application design for control/operation (mean 4.24, 84.80%, SD 0.76, High), automatic result reporting (mean 4.46, 89.20%, SD 0.81, High), device control operation (mean 4.54, 90.80%, SD 0.81, Very High), and appropriateness for practical use (mean 4.38, 87.60%, SD 0.75, High). The overall mean is 4.37 (87.44%, SD 0.80), indicating strong, reliable performance with device control rated best.

## Discussions

Heat stroke is a life-threatening condition resulting from the body's inability to regulate internal temperature effectively. Several risk factors contribute to its onset, which can be categorized by levels of severity. The primary risk factor is extreme heat or heat waves, which significantly elevate core body temperature beyond safe limits. This is followed by strenuous physical Vulnerable populations requiring special attention include young children and the elderly, whose thermoregulatory systems are underdeveloped or declining, as well as individuals with chronic conditions such as cardiovascular disease, pulmonary disorders, or obesity, which impair blood circulation and heat dissipation. Additional, albeit lower-level, risk factors include the use of certain medications and stimulants—such as diuretics, antihypertensives, psychiatric drugs, and illicit substances like amphetamines and cocaine—that disrupt the body's thermal control. High relative humidity, inappropriate clothing that limits ventilation, insufficient rest, and a lack of acclimatization

to hot climates (e.g., due to relocation or travel) may also contribute. Although these latter factors may pose lower risk individually, their combination with other stressors can trigger heat stroke. Therefore, awareness and avoidance of these contributing elements are crucial for the effective prevention of heat stroke.

The developed heatstroke prediction and alert system integrates Internet of Things (IoT) technology with private cloud-based data processing to support the analysis and monitoring of heat-related health risks during outdoor activities. The system employs a smart circuit box equipped with environmental sensors to measure temperature, humidity, and atmospheric pressure. These data are transmitted in real-time via WiFi to a private cloud server with IP address 61.19.33.12. To enhance accuracy, the system also retrieves continuously updated weather data from the Open Weather Map API, incorporating local environmental variables such as temperature, humidity, and pressure. These values are averaged with sensor readings from the actual deployment site to produce more reliable data inputs. The integrated dataset is then divided into training and testing sets at an 80:20 ratio and used in a K-Nearest Neighbors (KNN) algorithm with k = 3. Experimental results showed that the system achieved a prediction accuracy of 86.67% for identifying heatstroke risks. The model is trained on the training set and validated with the test set to evaluate its performance. When new weather data are classified as "High Heat Risk" the system issues a real-time voice alert and logs the event automatically. This mechanism enables timely, accurate, and reliable preventive health surveillance in outdoor environments.

The evaluation of the heatstroke surveillance system's effectiveness, conducted with a sample group comprising territorial defense students, their supervisors, and training instructors operating in both regular and field training areas under the curriculum of the Territorial Defense Command, indicated that the system demonstrated a high level of efficiency based on six core assessment criteria. The design and material quality of the circuit enclosure received an average score of 4.24 (84.80%), categorized as high, matching the average score for the application's design and usability. The system's automated reporting function—crucial for issuing risk alerts—scored an average of 4.46 (89.20%), also at a high level of satisfaction. The control command for operating devices received the highest average score at 4.54 (90.80%), indicating the system's strong responsiveness and control capabilities. Practical applicability scored 4.38 (87.60%), resulting in an overall system performance rating of 4.37 (87.44%), classified as high. Overall, the findings highlight the system's strong potential for effective deployment in outdoor activities at risk of heatstroke.

## Conclusion and Suggestions

The promotion of outdoor activities in conjunction with effective surveillance and prevention of heat stroke constitutes a shared responsibility among educational institutions, local authorities, and community stakeholders. The integration of public health knowledge with technological innovation and systematic management frameworks is essential to ensure that outdoor activities are conducted safely, efficiently, and sustainably, while also supporting the holistic physical and cognitive development of participants. In this study, the k-nearest neighbors (k-NN) algorithm is employed as a computationally efficient and interpretable machine learning approach for forecasting heat stroke risk and providing early warning notifications. By leveraging historical meteorological data and identifying patterns from similar environmental conditions in past events, the k-NN model enables accurate risk classification and timely prediction of heat-related health threats.

Nevertheless, the operational performance of the proposed system is subject to an important limitation. Specifically, the system requires continuous Internet connectivity to support real-time data acquisition, online processing, and dynamic model inference. The reliance on online infrastructure may constrain system availability in areas with limited network coverage or unstable connectivity. Despite this limitation, the proposed Internet-dependent architecture enhances the responsiveness and preparedness of public health agencies, educational institutions, and community members by facilitating prompt decision-making and effective preventive interventions against heat stroke incidents.

This system can be further developed into a cost-effective and practical wireless weather forecasting station suitable for deployment in households, educational institutions, and general organizations. By enabling continuous monitoring of environmental conditions and heat-related risk factors, the system has the potential to generate positive societal impacts, particularly at the community and local levels. Specifically, the implementation of such a system can contribute to reducing health risks among vulnerable populations, including students, athletes, and construction workers, by supporting informed decision-making and timely preventive actions. Moreover, the availability of real-time environmental information and risk alerts enhances safety during outdoor activities and promotes greater awareness of heatwave-related hazards, thereby fostering a culture of health consciousness and risk prevention within communities.

In addition to its immediate practical benefits, the system may be integrated with advanced Artificial Intelligence (AI) technologies, such as Large Language Models (LLMs) or Agentic AI, to further enhance the accuracy, adaptability, and interpretability of weather prediction and heat risk assessment. Such integration can enable intelligent data interpretation, contextualized recommendations, and adaptive decision support, thereby improving the overall precision and usefulness of the system for end users and decision-makers. From a policy perspective, it is

recommended that educational institutions, local authorities, and government agencies consider adopting this system as part of standardized safety management frameworks for outdoor activities. Incorporating the system into institutional guidelines and operational protocols can support systematic risk monitoring, early warning dissemination, and evidence-based policy implementation. Furthermore, the promotion of such technology at the policy level may encourage wider adoption of smart environmental monitoring systems, strengthen community resilience to extreme heat events, and support long-term public health and climate adaptation strategies.

## Acknowledgement

## References

Abhishek, K., Singh, M. P., Ghosh, S., & Anand, A. (2012). *Weather forecasting model using artificial neural network. Procedia Technology, 4*, 311–318. https://doi.org/10.1016/j.protcy.2012.05.047

Addoddorn, C. (2012). The design and construction of wireless spray weeds robot controlled by microcontroller. *Engineering and Applied Science Research*, *37*(1), 19–27. https://ph01.tci-thaijo.org/index.php/easr/article/view/1686

Jay, C. (1981). *Small engine operation and service*. American Technical Publishers.

Krutz, G., Thomson, L., & Claar, P. (1984). *Design of agricultural machinery*. John Wiley & Sons.

Lugo-Amador, N. M., Rothenhaus, T., & Moyer, P. (2004). Heat-related illness. *Emergency Medicine Clinics of North America, 22*(2), 315–327. https://doi.org/10.1016/j.emc.2004.01.004

Mahesh, B. (2018). Machine learning algorithms: A review. *International Journal of Science and Research (IJSR), 7*(8), 381–386. https://doi.org/10.21275/ART20203995

Rghioui, A., Naja, A., Mauri, J. L., & Oumnad, A. (2021). An IoT-based diabetic patient monitoring system using machine learning and NodeMCU. *Journal of Physics: Conference Series, 1743*(1), 012035. https://doi.org/10.1088/1742-6596/1743/1/012035

Sharma, A., Chaturvedi, S., & Gour, B. (2014). A semi-supervised technique for weather condition prediction using DBSCAN and KNN. *International Journal of Computer Applications, 95*(10), 21–26. https://doi.org/10.5120/16631-6500

Shigley, J. E., & Mischke, C. R. (1989). *Mechanical engineering design*. (5th ed.). McGraw-Hill.

Sudharsan, B., Breslin, J. G., & Ali, M. I. (2021). ML-MCU: A framework to train ML classifiers on MCU-based IoT edge devices. *IEEE Internet of Things Journal, 9*(16), 15007–15017. https://ieeexplore.ieee.org/document/9490288

Wang, T., Fang, K., Wei, W., Tian, J., Pan, Y., & Li, J. (2022). Microcontroller unit chip temperature fingerprint informed machine learning for IIoT intrusion detection. *IEEE Transactions on Industrial Informatics, 19*(2), 2219–2227. https://ieeexplore.ieee.org/document/9847023

World Health Organization. (2024). *Heat claims more than 175,000 lives annually in the WHO European Region, with numbers set to soar.* https://www.who.int/europe/news/item/01-08-2024-statement--heat-claims-more-than-175-000-lives-annually-in-the-who-european-region--with-numbers-set-to-soar

Yoddumnern, A., Chaisricharoen, R., & Yooyativong, T. (2018). A smart WiFi multi-sensor node for fire detection mechanism based on social network. *International Journal of Online and Biomedical Engineering, 14*(10), 4–20. https://doi.org/10.3991/ijoe.v14i10.8488