Internet of things heatstroke detection device

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ABSTRACT

The increasing frequency and intensity of heat waves due to climate change underscore the critical need for proactive measures to prevent heat stroke, a life-threatening condition affecting individuals of all demographics, with vulnerability among the elderly and outdoor workers. In response to this pressing public health challenge, we present the internet of things (IoT) based heat stroke prevention device, a comprehensive solution leveraging a suite of sensors including temperature, atmospheric, pulse rate, blood pressure, and gyroscope sensors, seamlessly integrated with an ESP32 microcontroller and Firebase's real-time database. Central to the device's functionality is a random forest classifier machine learning model, trained on historical data and user-specific parameters, to accurately predict the likelihood of heat stroke onset in real-time. Rigorous testing and validation procedures demonstrate the device's high accuracy and reliability in sensor measurements, data transmission, and model performance. The accompanying web-based dashboard provides users with intuitive access to their current health metrics, including temperature, humidity, blood pressure, pulse rate, and personalized predictions for heat stroke risk. This innovative device serves as a versatile tool for public health agencies, occupational safety programs, and individuals seeking to safeguard their well-being in the face of escalating temperatures and climate uncertainties.

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1. INTRODUCTION

It is critical to take preventative action to avoid heat-related diseases, especially heat stroke, in areas where rising temperatures and unstable weather patterns are major concerns [1]. Heatwave frequency and intensity are increasing due to climate change, which emphasizes the urgent need for preventative health monitoring and mitigating measures [2], [3]. In addition to having an adverse effect on people of all ages and health conditions, heat-related issues also have a major negative economic impact, especially on outdoor workers like farmers and construction workers who are essential to the growth of the national economy [4], [5]. Traditional preventive techniques frequently fall short in terms of offering prompt insights and thorough risk assessments [6], [7]. To solve these complex issues, creative solutions utilizing cutting-edge technology like cloud-based platforms, sensor integration, machine learning (ML), and internet of things (IoT) are required [1], [4], [8]. To meet this need, this endeavor will create and implement an IoT-based heat stroke prevention device that combines cutting-edge technology for real-time monitoring, predictive analytics, and customized treatments [1], [7]–[9]. The device's data collecting mechanism is based on sensor integration, making it possible to continuously gather important health indicators that point to concerns associated with heat. In tandem with the collection of sensor data, the project leverages machine learning algorithms to instantly analyze and comprehend the vast amounts of sensor data streams. A random forest classifier model, which is well respected for its resilience and adaptability, is utilized. Moreover, a complex online application that makes use of the React framework has been created to give users easy access to their health data and predictive insights [10], [11]. The user interface is this online application, which provides a visually appealing dashboard with real-time health parameters including temperature, humidity, blood pressure, and pulse rate together with individualized forecasts of the risk of heat stroke. The online application makes use of Firebase's real-time database to provide smooth data synchronization and cloud storage, guaranteeing dependability and accessibility on a variety of devices and systems [12].

Considering climate change, the IoT-based heat stroke prevention device offers a comprehensive way to reduce the risks of heat-related diseases, marking a turning point in proactive health monitoring and heat stroke prevention. Its innovative design incorporates state-of-the-art technologies like machine learning, IoT, sensor integration, ReactJS, and Firebase to solve urgent public health issues in a brilliant and innovative way. With persistent research, development, and cooperation, the goal is to make a significant contribution to global health and safety, protecting people's health in a world where climate change is unpredictable [13].

The literature covers wearable technology with sensors to monitor vital signs like body temperature, heart rate, and sweat rate for heat stroke detection [14], [15] IoT-based systems track physiological and environmental data, forecast heat stroke risk, and provide alerts [8], [16]. Advanced data analysis methods like personalized risk models and anomaly detection algorithms are used for early symptom detection [1], [5]. Infrared cameras and thermal imaging detect high body temperatures [10]. The importance of temperature control and efficient cooling techniques in heatstroke management is emphasized [5]. Specific applications include systems for vehicles, workplaces, elderly, and active individuals [4], [5]. Combining physiological and environmental data, including dynamic heat maps, is crucial for accurate risk assessment and prevention [12], [17]–[19]. Other notable works include a flexible patch for heat stress monitoring [12], studying environmental factors and stroke risk [16], [20], and a smartwatch-based system [21], [22].

2. METHOD

A methodical strategy is used in the creation of the IoT-based heat stroke prevention device, combining state-of-the-art technology, extensive testing, and iterative improvement. Sensors for measuring body temperature (normal range: 36.5 °C to 37.5 °C), blood pressure (usual values: systolic 90-120 mmHg, diastolic 60-80 mmHg) [23], pulse rate (normal range: 60-100 beats per minute), humidity, and ambient temperature are all integrated into this systematic procedure [1], [24]. It is critical to comprehend the risks associated with heat-related disorders. The risk of heat stroke, a serious illness marked by a body temperature of 40 °C or greater, increases as body temperature rises above 40 °C and enters the dangerous zone [11]. Extreme heat events increase the risk of heat-related health problems since ambient temperatures can rise over 45 °C [16]. People may notice an increase in heart rate and blood pressure during heat waves as their bodies try to adjust to the extreme heat [7]. The heat stroke prevention device regularly checks various physiological factors in order to solve these issues [13]. By utilizing machine learning techniques, the gadget evaluates the gathered information to forecast the likelihood of heat stroke [6]. By means of iterative training on heterogeneous datasets that span a range of physiological profiles and environmental situations, these algorithms gradually improve their prediction accuracy [9]. To summarize, the all-encompassing structure incorporates innovative approaches, cross-disciplinary cooperation, and meticulous verification procedures. The heat stroke prevention device provides an effective way to reduce the hazards associated with rising temperatures in a warming environment by utilizing IoT technology and sophisticated sensors [25].

2.1. Sensor interfacing

To effectively monitor and prevent heat-related diseases, our IoT-based heat stroke prevention device requires a wide range of health metrics, which require careful design and development during the sensor interface phase. The choice of sensors was carefully examined, considering aspects like precision, dependability, sensitivity, and alignment with the project's goals. To ensure that the gadget could offer thorough insights into a person's health status and environmental factors, each sensor was selected with a specific purpose in mind.

Figure 1 depicts the workflow of the heat stroke detection process. First the body temperature and blood pressure are monitored using temperature and BP sensor. ESP32 provides data to Firebase for further processing. Our sensor suite's central component, the ESP32 microcontroller, was chosen for its adaptability, processing power, and wide range of connection options. As the primary hub for integrating and aggregating data from several sensors, the ESP32's numerous general-purpose input/output (GPIO ports) and integrated Wi-Fi enabled smooth connectivity and data transfer to Firebase for additional analysis and visualization. We chose the DS18B20 temperature sensor because of its remarkable accuracy and digital output capabilities for body temperature monitoring. To interface this sensor with the ESP32 microcontroller and ensure accurate temperature readings that are essential for the early identification of heat stroke-related hazards, the one wire protocol must be implemented. In addition to monitoring body temperature, assessing surrounding temperature and humidity levels to contextualize an individual's environment was also vital. To this end, the DHT11 sensor was incorporated into the device, providing supplementary data that could help evaluate the impact of environmental factors on heat stress susceptibility [4]. Figure 2 clearly shows the prototype of the system which consists of different sensors used to measure body parameters. The sensor input is processed by the processing board and the result will be displayed on display board.

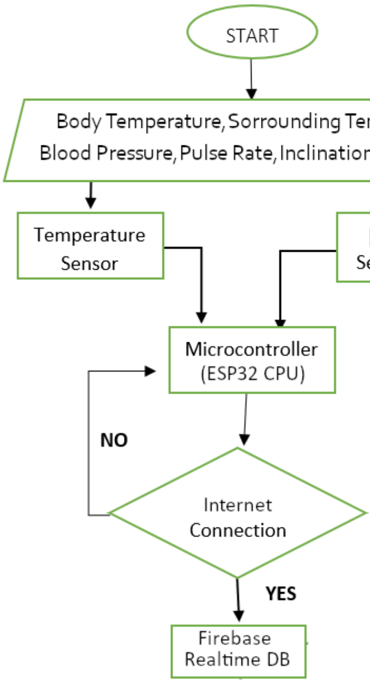

Figure 1. Sensor workflow

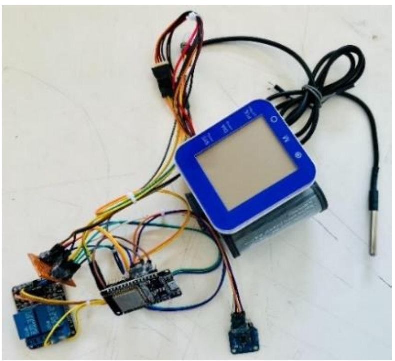

Figure 2. Breakdown of the sensors used and interfaced

To comprehensively monitor cardiovascular parameters, including systolic and diastolic blood pressure along with pulse rate, we integrated a specialized blood pressure sensor renowned for its accuracy and reliability. Furthermore, understanding the criticality of detecting falls, a common consequence of heat stroke and related health emergencies, we integrated the ADXL335 accelerometer into our device. This sensor plays a pivotal role in detecting sudden changes in motion and orientation, indicative of a fall event. Interfacing this sensor required meticulous signal conditioning and calibration processes to ensure accurate detection of falls and minimize false alarms. Each sensor underwent thorough initialization, calibration, and configuration to optimize performance and maintain data integrity [13], [15]. Additionally, robust error handling mechanisms were implemented to address any potential issues and ensure seamless operation throughout the data acquisition process [16], [26]. Once sensor data was acquired, it underwent processing, formatting, and transmission to Firebase's Realtime database using the Firebase Arduino library. This involved establishing secure connections, implementing data transmission protocols, and ensuring compliance with Firebase's API requirements to facilitate seamless synchronization and storage of real-time health data [8], [21]. Through Firebase, sensor data was securely stored and made readily accessible for analysis and visualization through our web application interface. Consequently, the IoT-based heat stroke prevention device's sensor interfacing process was painstakingly planned and carried out project that included a wide range of sensors, complex calibration and programming steps, and a smooth integration with Firebase for real-time data synchronization and storage [3], [26]. The device guaranteed dependability, and functionality in proactive health monitoring and heat stroke prevention by using our methodical methodology [27].

The system architecture for a heatstroke detection and monitoring device for the IoT that uses a machine learning model is shown in Figure 3. The system is design to gather information from personal and environmental sensors, use a machine learning algorithm to interpret it, and then show the results on an online dashboard. Figure 4 shows the dashboard of results obtained after testing the device. The device shows location, weather information with various parameters value such as bmp 82, blood pressure 140 and 84, clearly gives the possibility of percentage of heat stroke. The UV index 12.07 indicates strong sun exposure which indicates major heatstroke risk.

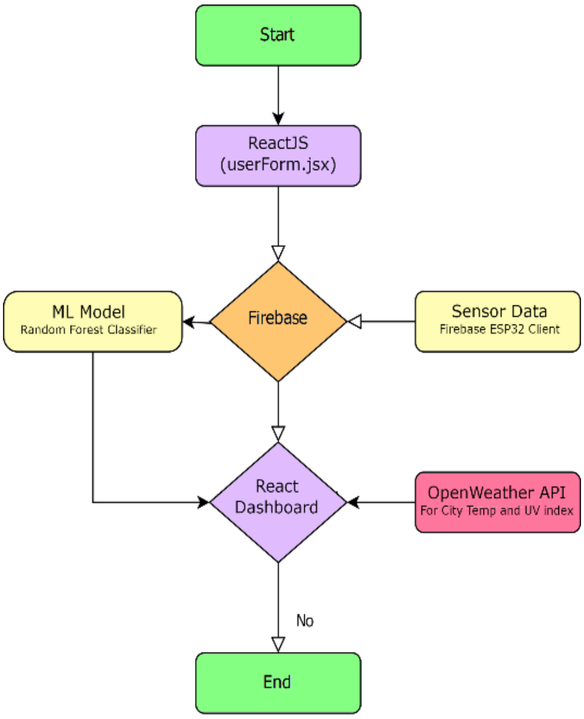

Figure 3. Complete workflow

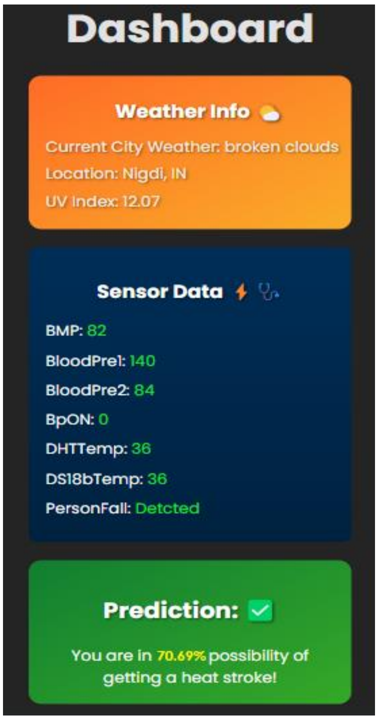

Figure 4. React web application UI

2.2. API and Firebase-React connection

An important step forward in the fight against heat stroke and preventive health monitoring was the integration of Firebase with the React web application. This complex procedure, which was supported by an advanced combination of front-end development, real-time data synchronization, and predictive analytics, embodied the coming together of state-of-the-art technology to protect personal health. React, a JavaScript toolkit well-known for its declarative syntax and component-based design, was in the vanguard of technology. Using the modular design principles of React, a set of components was created with great care, each specifically designed to address different aspects of data visualization and user interaction. React was the cornerstone of the web application's design, providing smooth scalability and code maintainability in everything from the slick and user-friendly user interface to the dynamic presentation of real-time health information.

A crucial aspect of the project included gathering user data, which was made easier with React forms designed to record a wide range of demographic and health-related information. With the help of Reacts form handling features, a carefully planned symphony of radio buttons, dropdown menus, and input fields was created to elicit detailed and accurate user replies. The data moved smoothly to Firebase's real-time database, a powerful cloud storage and synchronization platform as soon as the user entered their information. Firebase's scalable architecture and powerful APIs provided user data with a haven where it could be accessed and used for additional processing and analysis. Unmatched data accessibility and integrity were made possible with Firebase acting as the backend framework, which was crucial for the smooth coordination of the predictive analytics pipeline. Simultaneously, the React web application was packed with a variety of elements meant to provide users with immediate feedback and actionable information. For example, the weather component used external APIs to retrieve UV index and temperature data particular to a certain region, providing a clear picture of how environmental factors influence the risk of heat stroke. In the meanwhile, the sensor data component provided a dashboard of health measurements retrieved in real time from the internet of things sensor suite, acting as a window into the user's physiological domain. But the probability section of the web app, where the wonders of predictive modeling were shown, could have been its crowning achievement. This part determined the likelihood of heat stroke starting with surgical accuracy thanks to machine learning algorithms that were trained on a multitude of historical data and user-specific characteristics. All the predictions, which demonstrate the effectiveness of data-driven decision-making, were sent back to Firebase's real-time database to complete the feedback loop and provide users with individual risk assessments. To put it simply, the way Firebase was integrated with the React web application was a perfect marriage of technological wizardry and user-centered design. A digital environment where data flowed smoothly, insights abound, and lives were protected from the devastation of heat-related diseases was created through painstaking attention to detail and unrelenting innovation.

2.3. ML model and prediction

The IoT-based heat stroke prevention device's predictive modeling component exemplified an intensive procedure including challenging data collecting, preprocessing, and algorithmic selection. The data is collected for female and male using the random forest classifier as shown in Figure 5, which is well-known for being flexible and resilient when working with imbalanced data, the objective was to accurately and consistently predict the likelihood that a heat stroke would occur while overcoming obstacles like a lack of data and a class imbalance. The journey began with the challenging task of gathering data, wherein the lack of easily accessible datasets required human compilation and selection of pertinent data points. Using a variety of sources, including sensor readings, user demographics, and medical history, a heterogeneous dataset was painstakingly assembled to capture the complex nature of heat-related dangers. The data's relevance and integrity were guaranteed by this human curation procedure, which established a strong basis for further attempts at predictive modeling.

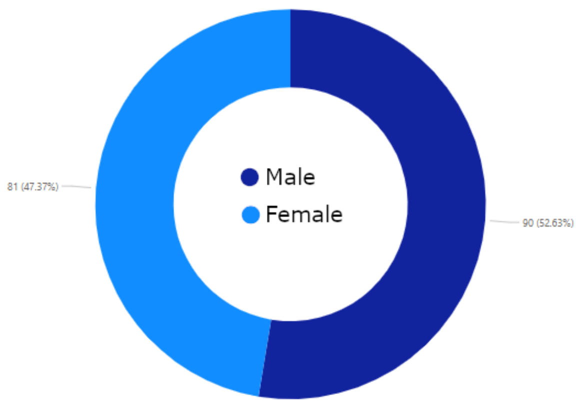

Figure 5. Data visualization of gender of people in training dataset

Following the compilation of the dataset, a thorough data preparation stage was initiated, which involved the use of methodical cleaning, transformation, and augmentation procedures. To develop a unified and standardized dataset that is suitable for predictive modeling, efforts were undertaken to address problems including missing values, categorical encoding, and feature normalization. Notably, to reduce class imbalance and support model generalization, oversampling and under sampling strategies had to be used due to the unbalanced nature of the dataset, which included a larger incidence of non-heat stroke cases. After the dataset was ready for modeling, a rigorous algorithmic selection process was used to assess a variety of machine learning classifiers for their accuracy in predicting heat stroke. Various alternatives, including support vector machines (SVM) and decision trees, were examined; each having advantages and disadvantages when it comes to performing categorization jobs. Following careful consideration, the random forest classifier was declared the best option due to its reputation for managing intricate datasets with nonlinear connections and reducing overfitting.

Extensive cross-validation tests were carried out, examining a wide range of classification metrics across multiple validation folds, to evaluate the prediction performance of the random forest model. Metrics including accuracy, precision, recall, and F1-Score provide thorough insights into the model's dependability and accuracy in identifying heat stroke risks. A thorough comparative analysis demonstrated how well the random forest classifier handled the complexities of the dataset when compared to other classifiers. Support vector machines performed admirably while handling high-dimensional data, but in the restricted training data regime, they presented difficulties because of their computational complexity and overfitting vulnerability. Random forest provided the resilience and generalization qualities that decision trees did not, notwithstanding their simplicity and interpretability.

To sum up, the incorporation of the random forest classifier into the predictive modeling pipeline demonstrated a data-driven strategy for early illness detection and proactive health monitoring. The development of a strong predictive model that can accurately and consistently identify heat-related risks was made possible by rigorous data curation, preprocessing, and algorithmic selection, despite obstacles like class imbalance and data scarcity. This highlights the revolutionary potential of machine learning in tailored healthcare interventions. Data visualization of heatstroke probability vs age and temperature is as shown in Figure 6 and 7. The graph from Figure 6 shows that the chances of heat stroke increase with increase in age. The chances are more for people of age above 65. Graph in Figure 7 shows variation of temperature from 20 to 45 degrees. The data shows that the increase in temperature increases chances of heatstroke significantly.

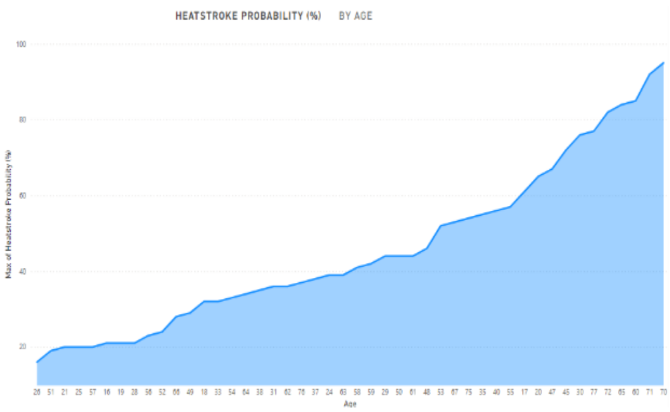

Figure 6. Data visualization of heatstroke probability vs age graph

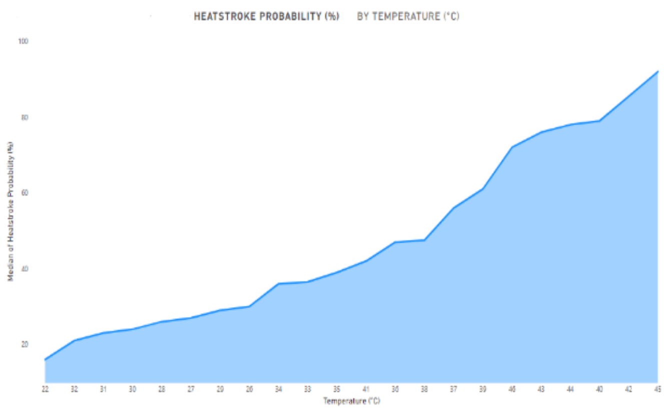

Figure 7. Data visualization of heatstroke probability vs temperature graph

2.4. Deployment of the machine learning model with frontend integration

To provide real-time prediction capabilities and user involvement in the last phase of our project, we had to install the ML model, namely the random forest classifier (RFC), and integrate it smoothly with our frontend. By utilizing technologies like Flask and Pickle, we managed a seamless deployment process that allowed our IoT-based heat stroke prevention device to give consumers proactive alerts and customized risk assessments.

First, we used Pickle, a Python tool for serializing and deserializing Python object structures, to serialize our trained RFC model. Our trained model was transformed into a byte stream through this method, making it simple to store and transfer across many platforms and contexts. Through serialization, we were able to incorporate our model into our deployment process effectively without sacrificing performance or functionality. Next, we developed a RESTful application programming interface (API) that offered endpoints for model inference using Flask, a lightweight Python web framework. A server-side application was made possible using Flask, which oversaw taking input data from the frontend, processing it through an ML model for prediction, and instantly sending the results back to the frontend.

Our frontend application could easily interface with the ML model running in the backend thanks to our Flask-powered API, allowing for the dynamic prediction of heat stroke risk depending on user inputs and sensor data. Through the provision of tailored insights and useful recommendations inside the web application interface, this integration improved the user experience. Our deployment architecture was made strong and scalable by combining Flask for backend API development with Pickle for model serialization. This allowed our ML model to be seamlessly integrated with the front-end user experience. This deployment technique increased the heat stroke prevention device's efficacy in proactive health monitoring and the prevention of heat-related disorders by enabling it to give timely and precise forecasts.

3. RESULTS AND DISCUSSION

The use of the internet of things-based heat stroke prevention device has provided important new information on its effectiveness and its influence on proactive health monitoring. This section provides a thorough examination of the device's feature significance, predictive performance, user profile insights, and effectiveness of real-time monitoring. We also present a comparative comparison of machine learning classifiers, and we wrap up with some practical advice and suggestions for further study and advancement. Table 1 shows the comparative analysis of machine learning classifiers.

Accuracy: The percentage of correctly categorized cases relative to the total number of examples is known as accuracy. It is computed by dividing the total number of forecasts made by the number of correct guesses. Accuracy in classification tasks is a general indicator of the model's performance over all classes.

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \quad (1)$$

Precision: is defined as the ratio of actual positive predictions to all of the model's positive predictions. It is calculated by dividing the total number of true positives by the sum of true positives and false positives, and it shows the accuracy of positive forecasts. Exactness is especially important when the expense of false positives is substantial.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Recall: The model's capacity to accurately distinguish positive cases from all real positive instances is measured by recall, which is sometimes referred to as sensitivity or true positive rate. By dividing the total number of true positives and false negatives by the number of true positives, it is computed. When misidentifying negative occurrences is less harmful than missing good ones, recall becomes important.

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

F1-Score: The F1-Score is a single measure that balances memory and accuracy. It is calculated as the harmonic mean of recall and precision. The F1-Score is derived as the weighted average of accuracy and memory, with excellent precision and recall valued at 1 and poor precision and recall valued at 0. Because it takes into account both false positives and false negatives, the F1-Score is especially helpful when there is an imbalance between the number of positive and negative cases.

$$F1 - Score = \frac{2\times Precision \times Recall}{Precision + Recall} \quad (4)$$

Table 1. Comparative analysis of machine learning classifiers

Classifier	Accuracy	Precision	Recall	F1-Score
Random forest	0.87	0.84	0.80	0.86
Support vector	0.81	0.81	0.81	0.79
Decision tree	0.81	0.74	0.76	0.84

Predictive performance: the internet of things-based heat stroke prevention device has demonstrated remarkable predictive performance, particularly through the utilization of RFC. With an impressive accuracy rate of 87%, the RFC exhibited exceptional prowess in forecasting the likelihood of heat stroke occurrences. Moreover, precision, recall, and F1-score metrics, standing at 0.84, 0.8, and 0.86 respectively, underscored the classifier's robustness in accurately identifying cases of heat stroke risk. These metrics collectively highlight the device's capability to minimize both false positive and false negatives, ensuring reliable and precise predictions.

Significance of features: a comprehensive analysis of feature significance revealed invaluable insights into the factors influencing heat stroke susceptibility. Physiological metrics such as blood pressure, pulse rate, and body temperature emerged as significant predictors, reaffirming their pivotal role in assessing vulnerabilities associated with heat-related disorders. By prioritizing these physiological measures and their intricate interplay with environmental factors, the classifier enhances prediction accuracy and reliability, offering a nuanced understanding of heat-related risks. Efficiency of real-time monitoring: the device's real-time monitoring capabilities have facilitated early identification of heat-related hazards, enabling prompt intervention and preventive measures. Seamless integration of Firebase with the React web application has empowered users with actionable insights through effective data synchronization and visualization. By granting users access to real-time health measurements and predictive analytics, the device enhances situational awareness and fosters proactive health management, ultimately leading to improved health outcomes and overall well-being.

4. CONCLUSION

The development of IoT sensors to detect heat stroke is a revolutionary step towards the protection of public health and safety. With the help of these state-of-the-art tools, a new age of proactive approaches has begun, one that allows for early diagnosis, ongoing monitoring, and prompt alarms to reduce the risks and avoid heat-related illnesses. IoT sensors provide unmatched precision, efficiency, and dependability compared to traditional approaches, which frequently fail to deliver timely insights and thorough risk assessments. This is demonstrated by thorough analysis and real-world implementation scenarios. Furthermore, the gadgets' easy-to-use warning mechanisms improve their accessibility and usefulness, guaranteeing that those who are susceptible to heat stroke receive critical medical attention promptly. The efficient distribution of vital information made possible by these systems increases the overall efficacy of programs aimed at preventing heat stroke.

In the coming years, the field of heat stroke detection is expected to see significant progress due to continuous breakthroughs in machine learning algorithms, cloud-based systems, and sensor technology. These developments could provide internet of things devices previously unheard-of levels of capability. With machine learning algorithms' capacity to improve prediction models, more accurate and customized risk assessments may become possible. While advances in sensor technology can provide prompt intervention and prevent heat-related diseases, they can also boost sensitivity and reliability. Cloud-based solutions provide centralized data storage and processing, speeding up monitoring and response times. In the end, the thoughtful use of internet of things solutions for heat stroke detection have the potential to completely transform public health protocols by enabling preventative actions that, by carefully utilizing cutting-edge technologies, might save countless lives in hot settings.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration. The contribution of authors is shown in following table.

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Karishma Prashant Salunkhe			✓	✓			✓	✓	✓					
Vidit Pravin Agrawal				✓	✓			✓	✓					

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Author states no conflict of interest.

DATA AVAILABILITY

The authors do not take any support for the findings.

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