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IoT-enabled Edge Impulse approach for heat stress prediction in outdoor settings

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ABSTRACT

Several international organizations of public health or countries have predicted the rise of heat-related illness cases due to climate change, which result high environment temperature. Previous studies of heat-related illness prediction using internet of things (IoT) and machine learning (ML) are mainly focusing on early detection or prediction of heat stroke incidence. To overcome the problem of heat stress prediction in outdoor settings, especially for an individual, the objective of this study is to identify a prediction method for heat stress using IoT technology and analyze the accuracy of the identified prediction model. Arduino nano 33 BLE sense with Bluetooth low energy (BLE) connectivity, HTS221 embedded environment temperature and humidity sensor, MLX90614 skin temperature sensor, and MAX30100 heart rate sensor were used to build IoT based wearable device. Besides, Python language is used for data pre-processing and data labelling after getting the sensor data from wearable device. Lastly, model training using neural network algorithms was directed in Edge Impulse. The result shows 94.6% of training accuracy with the loss of 0.27 and 90.22% of accuracy in testing set.

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1. INTRODUCTION

According to World Health Organization (WHO) research, there are 3.6 billion people currently reside in regions that are extremely vulnerable to climate change. Additionally, climate change is predicted to result in another 250,000 fatalities year between 2030 and 2050, just from heat stress, malaria, undernutrition, and diarrhoea alone [1]. Several countries like Malaysia, Singapore, and Philippine have reported high environment temperature starting in May 2023, which may result in the increase of hospital admission due to high risk of getting heat-related illnesses [2]–[4].

Heat stress is an initial stage of one of the life-threatening heat-related illnesses, which is heat stroke [5]. The person who is getting heat stress will have symptoms like physiologic strain in feeling muscle cramps, severe thirst, or showing decreased exercise performance, but heat stress may not affect core body temperature to turn high [6], [7]. Apart from that, whereas skin temperature and core body temperature differ by a ratio of 0.9 to 0.1, and increase in skin temperature may also indicate an increase in core body temperature [8]. In comparison to other low environment temperature and humidity condition tests, skin temperature significantly increases in high environment temperature and humidity conditions, according to Ojha *et al*. [9]. This suggests that measuring skin temperature can also be helpful in evaluating heat-related illnesses.

With the advance of internet of things (IoT) technology, wearable devices with various embedded sensors and functionality have been launched by many tycoon's manufacturers. IoT provides the ability of communicating between electronic devices and sensors through the internet [10], facilitating remote monitoring [11], control, and automation [12] of various processes, as well as real-time data collection and sharing [13]. With real-time data collection, machine learning (ML) algorithms can be used to analyze and discover patterns, correlations, and insights [14]. They can then utilize this knowledge to create precise predictions or decisions. Therefore, the combination of IoT and ML can greatly enhance early detection and prevention in the context of heat stress prediction. IoT device with sensors are able to keep track environment parameters and individual health parameters. In order to identify trends and relationships between the parameters and the incidence of heat stress, the gathered data can be processed and analyzed with ML methods by using Python modules and Edge Impulse platform.

Currently, many studies are focused on building a wearable device like wristband to detect heat stroke using IoT technology. For example, the research in [15], [16] developed a wristband to detect heat stroke but using different microcontrollers and sensors. Both wristbands consist of sensors like body temperature sensor, environmental temperature, and humidity sensor, but with different variety. Son *et al.* [16] used node MCU ESP8266 as microcontroller and sensors like pulse sensor amped, environmental temperature and humidity sensor (DHT22) and body temperature sensor (LM35). Whereas Javed *et al*. [15] included Arduino nano with SHT75 environmental temperature and humidity sensor, MLX90614 body temperature sensor, SpO2 blood oxygen sensor, and GSM/GRS module. GSM/GRS module is used to send alert messages to caregivers via phone numbers. This module is also been adopted to build an IoT based heat stroke alarm system to send reminder messages to user's family member if the user's body temperature evaluates to 40 °C and above detected by LM35 body temperature sensor [17]. As those studies are mainly on detecting heat-related illnesses using IoT technology but they do not extend towards heat-related illness prediction using ML.

Besides, ML approaches do involve in some researches but the focuses are specifically on forecasting mortality of heat-related illness incidence during heatwaves or predicting heat stress in certain populations like coal miners. In 2012 to 2014 summer periods, daily case numbers of heat stroke in Shanghai, Chongqing, Wuhan, Jinan, Ningbo, Hefei, and Shaoxing, China are collected, and random forest algorithm is used to predict heat stroke occurrence for heatwave in China [18]. Furthermore, random forest, logistic regression, XGBoost, and support vector machine are involved in heat-related illness mortality prediction by using "Heatstroke study" database in Japan for training the model [19]. Moreover, Roy *et al*. [20] achieved 99.73% accuracy in random forest and 99.93% accuracy in artificial neural network (ANN) while employing ventilation survey data to predict heat stress in an underground mining environment.

Based on the discussion above, there is limited research regarding heat stress prediction using IoT technology and ML focused on only an individual alone. So, this paper proposes a heat stress prediction approach using data collected from IoT wearable device and training the model using ML algorithm in Edge Impulse. This study aims to identify a prediction method for heat stress using IoT technology and to analyze the accuracy of the identified prediction model.

2. METHOD

Wearable device for heat stress prediction is built with one Arduino board, which act as an embedded device, different sensors like skin temperature sensor, heart rate sensor, environment temperature and humidity sensor. This wearable device is used for data collection purpose. There have 2 stages of data collection which is before and after the 10 minutes outdoor workout. Figure 1 shows the involvement process of the system. Wireless connectivity transmission like Bluetooth low energy (BLE), is used in transmitting the real-time sensors data from the wearable device to Android mobile application. Real-time data consists of skin temperature, heart rate status, environment temperature and humidity, they can be read from the Android mobile application, and meanwhile, all the readings are stored in Google Sheet. Then, the data stored will be preprocessed and labelled using Python programming language and upload to Edge Impulse for model training. Lastly, the risk of getting heat stress is evaluated. The workflow mentioned is shown in Figure 2.

To design a heat stress prediction wearable device, it requires all the hardware components in light weight and tiny for easy carry purpose. So, Arduino nano 33 BLE sense is used in this project since it is tiny compared to others Arduino board like Arduino UNO, and it is possible to run artificial intelligence (AI) program using TinyML and TensorFlow Lite. In addition, Arduino nano 33 BLE sense consists of some built-in sensors like HTS221 relative humidity sensor, while it also provides BLE connectivity [21].

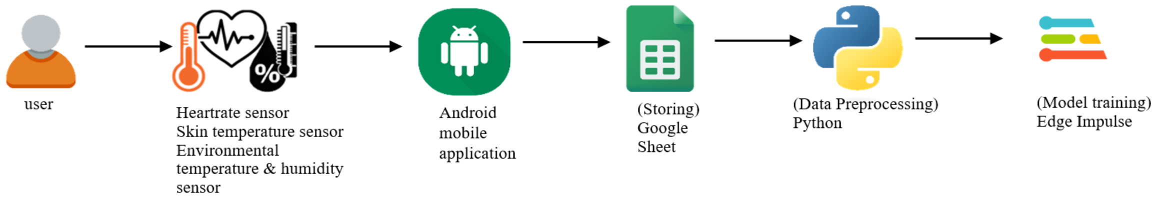

Figure 1. System process from sensor data acquisition to model training

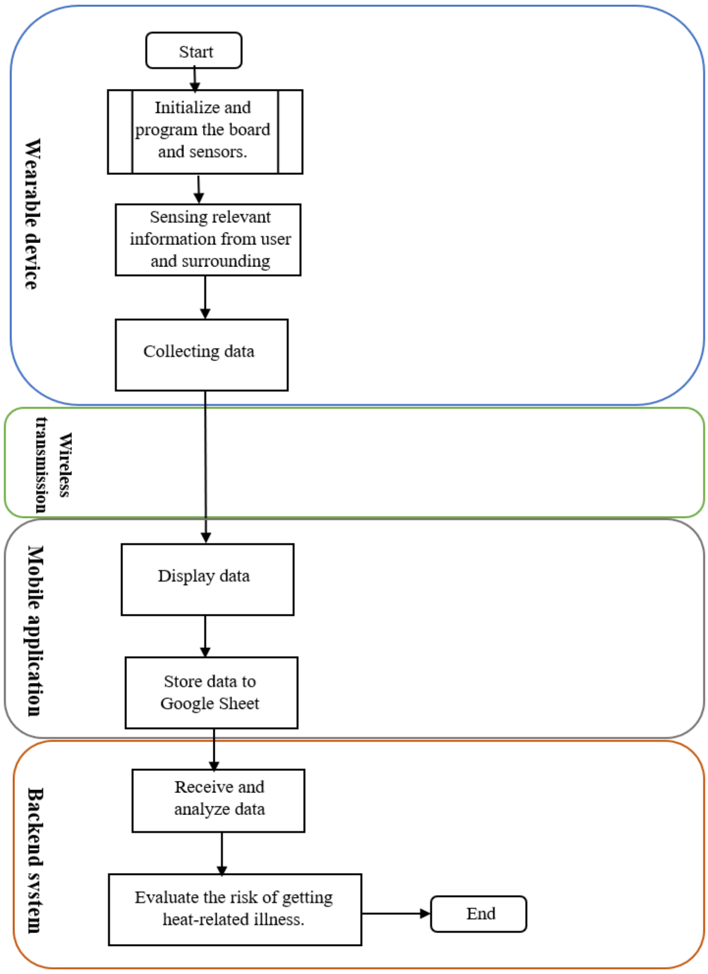

Figure 2. Workflow from wearable device to mobile app and backend system

As shown in Figure 3, Arduino nano 33 BLE sense with embedded environmental temperature and humidity sensor (HTS221) is attached on the breadboard and placed on the participants' arm side. Moreover, jumper wires are used to connect the board with other sensors like MLX90614 and MAX30100. For instance, MLX90614 body temperature sensor is a contactless infrared temperature sensor which used to measure participants' skin temperature is placed on inner side of the participants' wrist. Whereas, the heart rate sensor (MAX30100) is positioned on the participants' finger in order to measure participants' heart rate in beats per minute (BPM).

After the wearable device is built completely, the wearable device is ready to be programmed in Arduino integrated development environment (IDE). In this program, all the sensors are programs to read and print out respective readings by using specific libraries. For instance, ArduinoBLE version 1.3.4 by Arduino is used to build the BLE connection in order to connect and transfer sensors readings to others device. In addition, to program the embedded environment temperature and humidity sensor (HTS221) in Arduino nano 33 BLE sense, Arduino_HTS221 version 1.0.0 by Arduino is used to get the readings. Adafruit

MLX90614 Library version 2.1.3 by Adafruit is applied to the non-contact infrared thermometer, MLX90614, for the purpose of getting participant's skin temperature. Lastly, to get the BPM from the participants, MAX30100 heart rate sensor is program with some function provided from MAX30100lib version 1.2.0 by OXullo interscan.

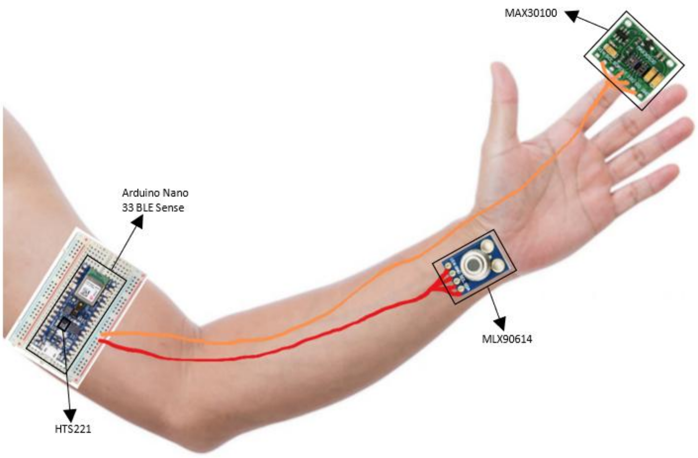

Figure 3. Wearable device

The Android mobile application is used to connect the wearable device (Arduino nano 33 BLE sense) via BLE connectivity. Once the wearable device is connected with the Android mobile application, participants are able to read all the sensor data in real time through the application, as shown in Figure 4. Additionally, BLE connection between the Android mobile application and wearable device will only active for 6 minutes. The purpose of having a 6-minutes' countdown timer is to ensure every round of data collection from participants are equivalent. Not only that, due to the buffer time for some sensor like the heart rate sensor (MAX30100), the additional 1-minute is recorded to ensure after the data filtering of the buffer time, every round of data collection will remain at least 5 minutes' data. Besides, when the connection is built between Android mobile application and wearable device, all real time data are able to be read on the application and at the same time, all the readings are stored in Google Sheet for further data analysis purposes.

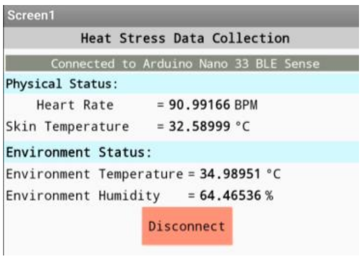

Figure 4. Mobile application interface with BLE connected

Data collection will be carried out twice, starting with 6 minutes before workout followed by 6 minutes' data collection after following a 10 minutes' video workout from YouTube. The participants are requested to do the workout in an outdoor setting. The workout video is created by AllblancTV from YouTube (https://youtu.be/N-15wUPnqpc) which include jumping jack, mountain climber, drop squat, butt kick, arm reach side lunge, squat twist knee up, stand cross toe touch, arm walking, high flank raise, lunge twist, Russian twist, standing side knee up, standing cross knee up, burpee, and high knee. Each action is 30 seconds, then followed by 10 second rest. According to one of the researchers, heart rate increases as a result of heat stress [22]. So, another data collection will be conducted after workout in order to analyze the possibility of getting heat stress. In this project, there are 32 participants consist of 22 male participants and 10 female participants, from the age range of 21 to 24 years old involved in the data collection. Major group of participants have reported no have health issues, only 2 participants have reported having health issues like asthma and skin allergic.

Once the data collection is completed, data collected in Google Sheet is being downloaded in comma-separated values (CSV) format. Then, pandas, one of the Python language libraries used for data analysis is used for doing some data preprocessing like removing duplicate data, checking missing data, replacing missing value with median and filtering the data. For example, skin temperature with the value below 33 °C and above 38 °C will be removed. The reason of removing skin temperature below 33 °C is because according to Surangsrirat, the average skin temperature will change from 33.2 °C [23]. According to Kadhim *et al.* [24], the comparison results between MLX90614 and the infrared thermometer for 24 years old patient can achieve 37.05 °C. Since the dataset collected for skin temperature are below 38 °C also, so the maximum of skin temperature value is assumed as below 38 °C. For the heart rate value, the readings below 60 BPM and above 200 BPM will be filtered out. This is because the minimum heart rate for adult is 60 BPM, whereas the maximum BPM can be calculated according to the age. In this dataset, the youngest participants are 21 years old, so the maximum BPM is 199, which is below 200 BPM [24], [25].

In addition, NumPy python library is used in the perturbing process. Apply perturbing using NumPy library is to generate synthetic data from the dataset. In order to avoid data imbalance issues during the data labelling, bias towards the majority class and poor performance in the minority class during the model training, heart rate values above 130 BPM are used for generate synthetic data. The reason of choosing data with heart rate values above 130 BPM is due to the research which stated heat stress will trigger a rise in heart rate by Coll *et al* [22]. After that, all the data is being resampled into 1-minute interval by calculating the average of each interval.

For the data labelling process ML algorithms like isolation forest and K-means are applied. Anomalies labels from isolation forest and K-means are indicated as -1 which means having the risk of getting heat stress, whereas the 1 label is representing as no have risk of getting heat stress. Around 15% of the data from the dataset are expected as anomalies are being set in isolation forest, so 70 data is being classified as -1. Besides, in K-means the threshold value is set as 85th percentile which means the assumption of the dataset consists of 85% of the distance between data and cluster are below threshold. So, for the top 15% above threshold will be labelled as -1. After getting the labels from isolation forest and K-means, both labels are combined to get 100 data labelled as -1 and 362 data labelled as 1.

Then, the Edge Impulse platform is used for training the ML model using neural networks technique. Firstly, the dataset uploaded will be automatically split into 80% of data to training set where 20% of data to testing set. In Edge Impulse, the ML pipeline is called impulse design. The impulse design consists of 3 blocks, which are input block, processing block, and learning block as shown in Figure 5. Start with the input data (input block), raw data (processing block), classification using neural network (learning block), and lastly the output will be in two categories, which are -1 and 1. Since this heat stress prediction is a classification problem, so classification option is chosen in the learning block. To train the model, neural network algorithm is used in Edge Impulse with 30 number of training cycles, 0.005 of the learning rates and 20% of the size of validation set as shown in Figure 6. The purpose of doing neural network in Edge Impulse but not started from stretch using Python language is that, Edge Impulse provided a simplicity platform to train or deploy the ML model, especially for the edge device without having advanced coding skills [26].

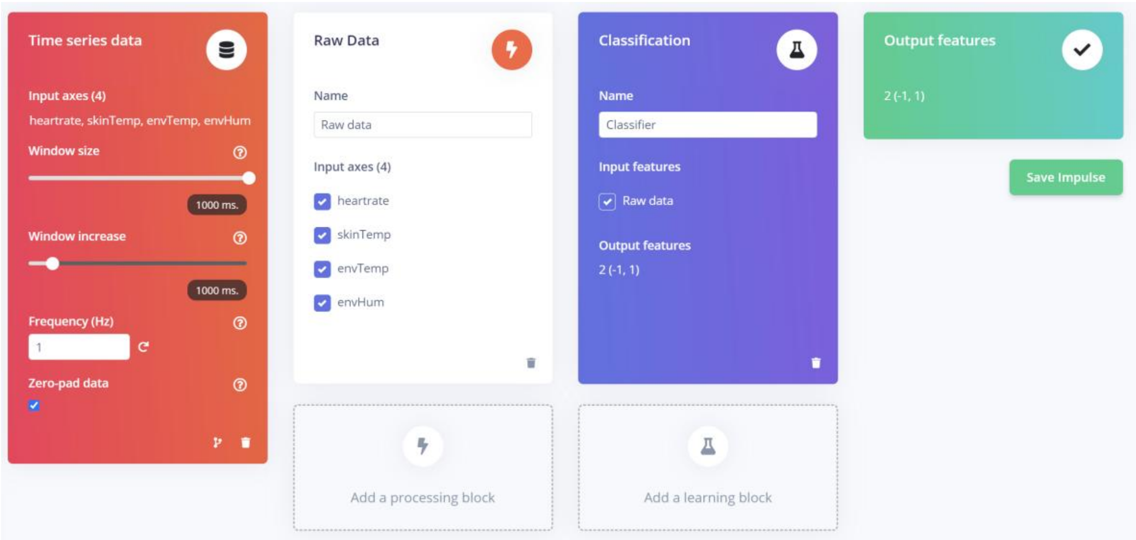

Figure 5. Edge Impulse design

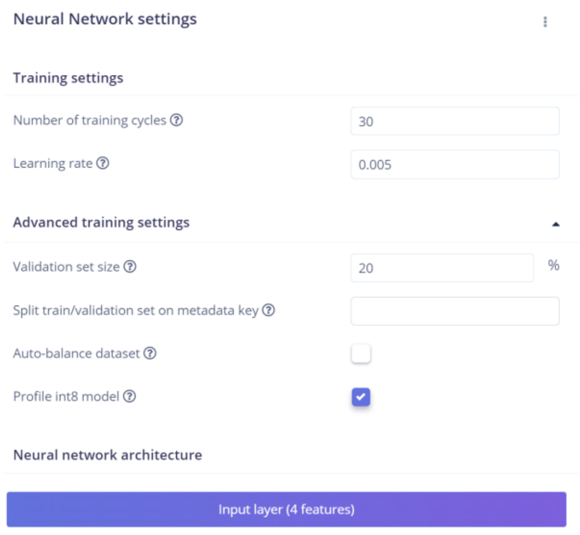

Figure 6. Neural network settings in Edge Impulse

Additionally, Edge Impulse also provided a 3-dimensional (3D) graph for all data after the neural network training to help user in determining which data is classified correctly and which is not. As shown in Figure 7, light green dots are data which have classified correctly with the -1 labels, whereas red dots are the data classified as 1 but the data actually belongs to -1. The dark green dots represent data which have correctly classified as label 1, whereas orange dots are the data which have misclassified.

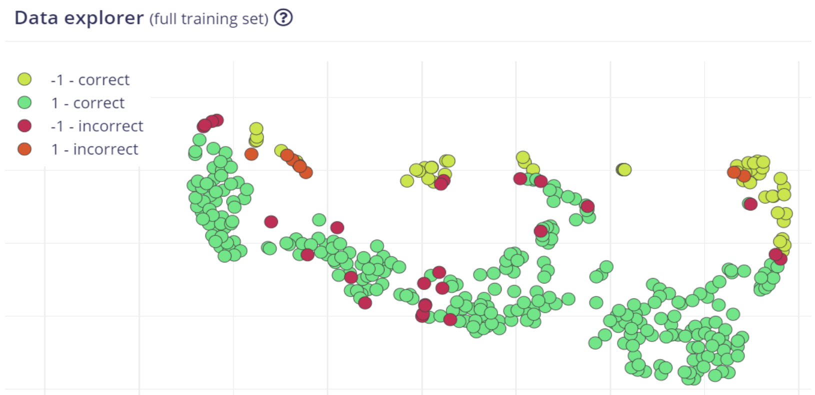

Figure 7. 3D graph after neural network training

3. RESULTS AND DISCUSSION

After the model training using neural network algorithm in Edge Impulse with 462 labelled data, the model performance is evaluated with the loss and accuracy percentage in training set and testing set. As a result, the training accuracy have received 94.6% with the loss of 0.27 by using neural network in Edge Impulse. Whereas the testing set achieved 90.22% of accuracy with 98.6% correct classified as label 1 and 61.9% correct classified as -1.

3.1. High risk of getting heat stress

Figure 8 shows one of the data being classify correctly as -1 with the heart rate value of 154.6546, skin temperature value is 34.1368, 35.2636 of environment temperature, and value of environment humidity which is 62.9845. According to some analyzation done with the data being classified as -1, one of the indicator of being classify as -1 is the heart rate value above 150. In other words, heart rate reading above 150 which being classified as -1 can be assummed as one of the indicator of high risk in getting heat stress in this analysis.

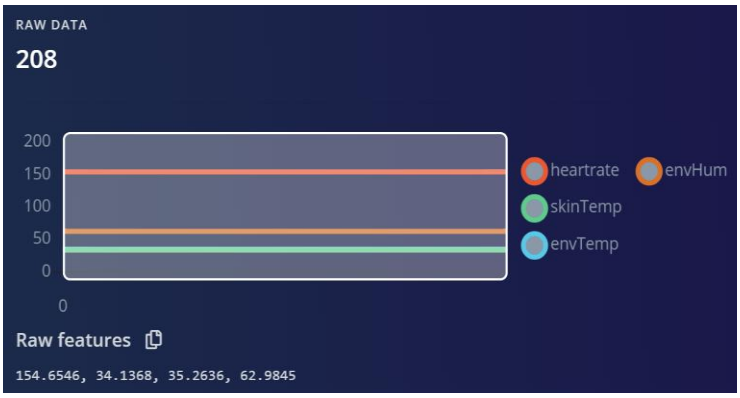

Figure 8. Actual label -1, correct classify as -1 (heart rate)

In addition, one of the condition of data being classified as -1 based on the overall data in class -1 is the environment humidity above 81. For example, Figure 9 shows that 83.7445 environment humidity for one of the data in dataset. The data is correctly classify into -1 class, and it also fulfilled the assumption of above 81 of environment humidity. Furthermore, environment temperature above 39 has a high possibility being classify as -1 is also one of the analysis result from the -1 class. Figure 10 shows that the environment temperature is 40.1158, environment humidity is 47.4887, heart rate is 84.6463, and skin temperature is 35.8303. Based on the result get from Edge Impulse, data shown in Figure 10 is correctly classify into class -1.

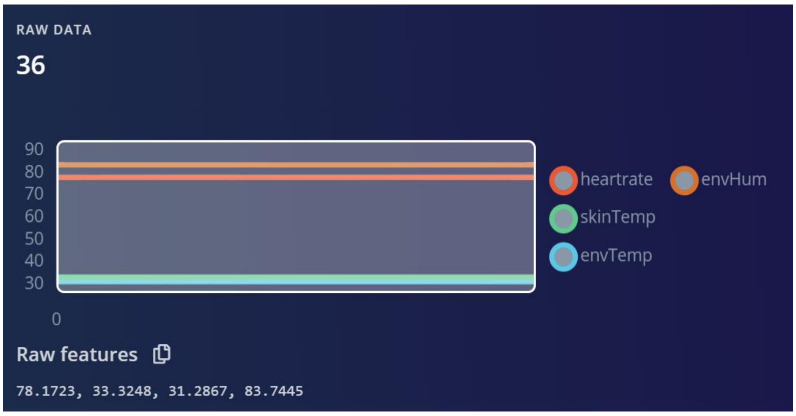

Figure 9. Actual label -1, correct classify as -1 (environment humidity)

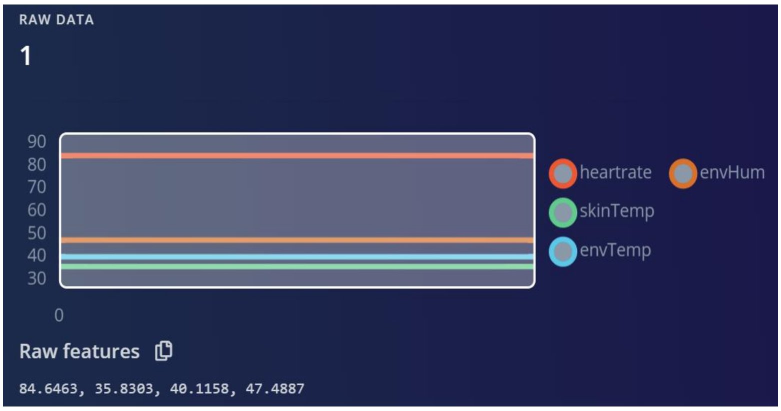

Figure 10. Actual label -1, correct classify as -1 (environment temperature)

Discussion on Figure 8 until 10 concluded some conditions of high probability to be classified as -1 class, which also means high risk of getting heat stress. For example, some conditions like heart rate value above 150, environment temperature above 39, and environment humidity above 81. From the analysis, either one of the conditions can trigger to be classified as anomalies.

3.2. High risk of getting heat stress but misclassified as low risk

On the other hand, data shown in Figure 11 is one of the data with an actual label of -1 but having heart rate reading of 111.8948, skin temperature reading of 34.0547, environment temperature reading of 35.8012, and environment humidity reading of 62.8161. These values do not fulfill any assumptions discussed before. During the testing, this data was misclassified into the label 1 class.

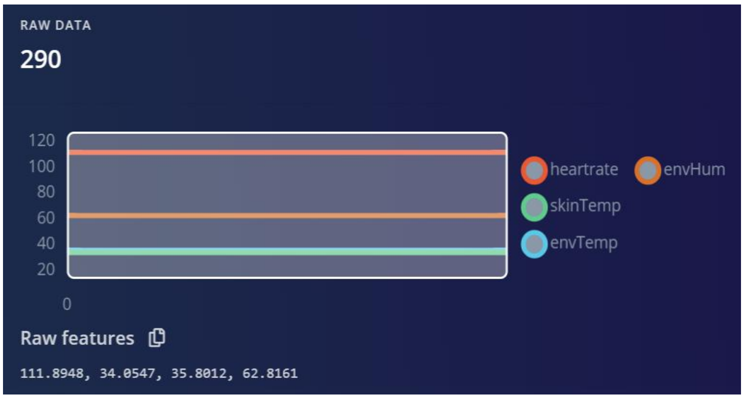

Figure 11. Actual label -1, misclassified as 1

3.2.1. Low risk of getting heat stress

Figure 12 shows data with actual label of 1 is correctly classified into class 1 during the testing. Classification class of 1 shows the low possibility of getting heat stress, and the reading should be below the assumption value that discussed above. The data in Figure 12 has all the attributes values below the analysis value, like heart rate equal to 83.3290, which is below the analysis value above 150.

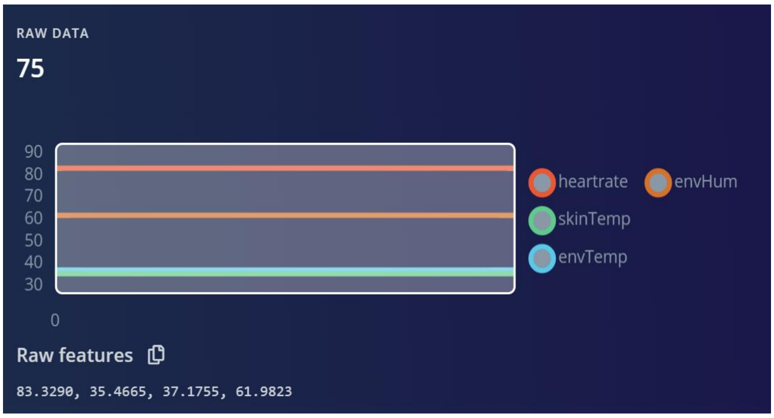

Figure 12. Actual label 1, correct classify as 1

3.2.2. Low risk of getting heat stress but misclassified as high risk

Lastly, Figure 13 represents one of the data with actual label 1 but being misclassified as -1. All the reading achieved in this data like heart rate 82.0336 is below 150, 31.8197 of environment temperature is below 39 and 79.4198 of environment humidity is below 81. The reason of the data being misclassified may be because of the training model yet to learn this pattern of data well.

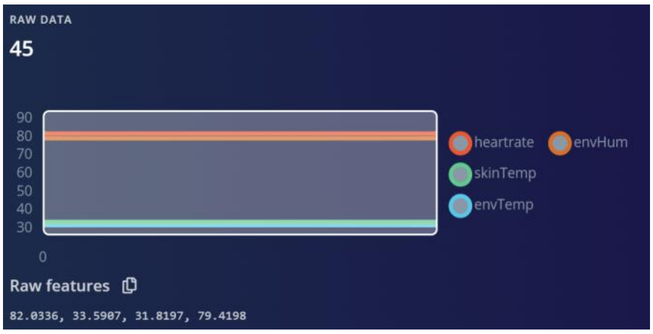

Figure 13. Actual label 1, misclassified as -1

4. CONCLUSION

This paper develops a wearable device using IoT technology which able to interact with Android mobile application and storing the sensor data in Google Sheet. Not only that, neural network algorithm used in Edge Impulse to train the heat stress prediction model has achieved 90.22% accuracy. The relationship between each attribute used in heat stress prediction, like heart rate, skin temperature, environment temperature, and environment humidity, has been studied and discovered. Besides, this paper have lack of various patterns of data used for heat stress prediction. For instance, one of the discussion above discussing, the heart rate readings, skin temperature readings, environment temperature, and humidity readings do not belong to any of the conditions being analyzed before, but its actual label is -1. This might be one of the unseen or hidden patterns discovered by the training model. In order to justify this pattern of data, more data may need to be added in the future for further analysis and also to train a better training model to predict heat stress. Furthermore, Arduino nano 33 BLE sense is one of the fully supported development boards in Edge Impulse, which means this Arduino board can simply plug and play on Edge Impulse platform to perform live classification with the model trained in the platform. In future, we hope to not only perform live classification but also compile the model trained in Edge Impulse into Arduino nano 33 BLE sense since Edge Impulse also allowed this. With the model compiled into Arduino board, the model can be deployed on the Arduino boards without any Internet connection.

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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.

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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

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

Ethical review and approval were waived for this study due to the data is sourced from previous research.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [SY]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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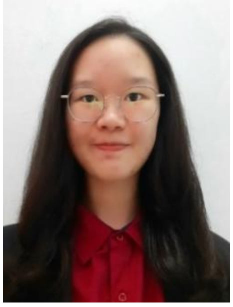

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