Development of a TinyML based four-chamber refrigerator (TBFCR) for efficiently storing pharmaceutical products: Case Study: Pharmacies in Rwanda

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ABSTRACT

Medical products are very sensitive to temperature; the improper temperature may lead to their inefficacity. Apart from products that are stored at room temperature, remaining medical products are stored in electronically controlled refrigerators. A lot of researchers have proposed different refrigeration systems controlled with the help of the internet of things (IoT). Due to some issues such as storage capacity, computing energy, and computing speed, data processing in IoT-based applications is generally done at the cloud through cloud computing technology. Those applications are suffering issues like latency, data control, internet connectivity, network traffic, and operation cost. In this paper, we are experimentally developing a four rooms fridge controlled with an Arduino board that embeds a machine learning (ML) algorithm to control the temperature for efficient storage of medical products. We tried to develop an ML model that will monitor the closing and opening of the fridge door (while taking some medicines), predict and display the remaining time for the internal temperature to go beyond the acceptable temperature range. The result from our experiments shows that the model runs onto the controller and can predict well the internal fridge temperature at an accuracy of 96%.

KEYWORDS

TinyML, Smart fridge, Internet of Things, Edge Impulse

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1 INTRODUCTION

In the Rwandan healthcare system, medicines recommended by a medical doctor are generally found in private and public pharmacies and hospitals. Pharmaceutical products have some indication related to their storage conditions (temperature, light, and humidity). To respond to the indicated storage conditions, medicines are kept either at room temperature or in medical fridges. When it comes to temperature, the world health organization (WHO) indicates that pharmaceutical products are mainly stored in four different temperature conditions: room temperature (20 to 25 Degree), cool storage condition (8 to 15 Degree), Cold storage condition (2 to 8 degree), and fridge storage condition (-4 to 2 Degree) [1]. Researchers have demonstrated that with the help of new technologies such as IoT and machine learning, fridges that keep pharmaceutical products can be remotely be controlled and monitored for efficiently managing their internal temperature.

Traditionally, for IoT applications, data are sent to cloud databases from where they are analyzed through different algorithms. This process consumes a lot of resources such as bandwidth and power (during data transmission). Apart from these resources, there is also an issue with data privacy, latency, and connectivity. Recently, it has been found that machine learning algorithms that were running in the cloud or computer with enough resources, can be compressed so that they can be embedded in cheap, small, and low-power microcontrollers. These lite machine learning models that can be embedded in a small controller are known as TinyML. It has been demonstrated that the TinyML technology is overcoming the challenges faced while using the internet of things.

Since 2019, Zach Shelby and Jan Jongboom [2] came out with the idea of building a platform called Edge impulse to help developers to build intelligent devices that can host machine learning models for facilitating edge computing. While creating this platform, they were believing that this idea will make positive changes in society. Through this platform, data are directly collected (or uploaded from a drive) and used to develop and train a model that will be finally loaded into a microcontroller.

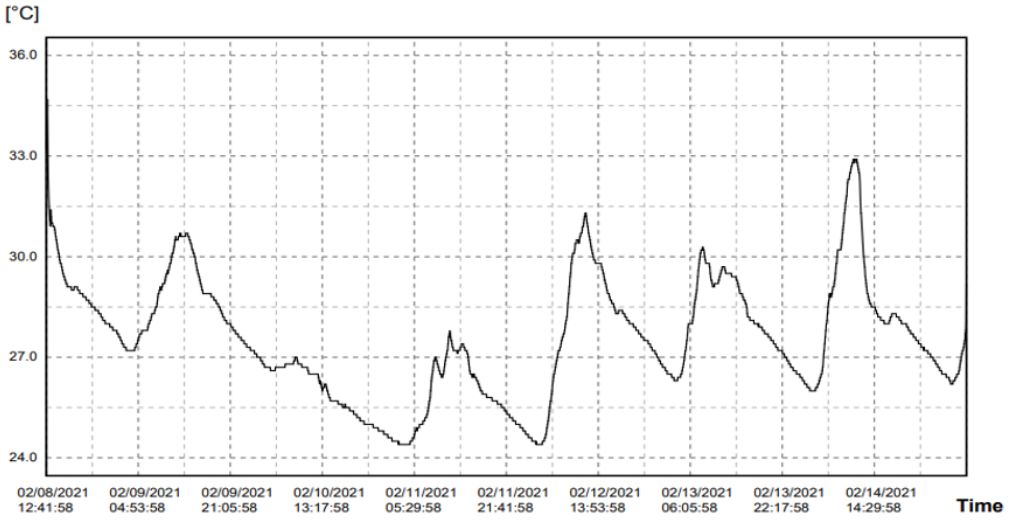

Figure 1: Temperature in Bugarama

Table 1: Bugarama & Musanze Temperature information

Labeling	Recommended range [° C]
Room Temperature	20 to 25
Freezer	20 to -10
Cold /Refrigerator	2 to 8
Cool	8 to 15

This work proposed an intelligent four chambers intelligent fridge that hosts a machine model for responding to the storage conditions of medicines as recommended by the World Health Organization (WHO.) The development of this model was achieved by using the Edge impulse platform.

1.1 Related works

A good number of researchers have demonstrated the different challenges of IoT including power and security. In the work of [8], researchers demonstrated that IoT devices face some challenges such as power and connectivity. Lin and the team [9–12] stated that security and privacy are the two challenges of IoT when it comes to smart homes. Researchers in the works of [13, 14] found that the security issue of IoT technology can be solved by using some technologies such as Brock chain and fog/edge computing. Motivated by the information got from pharmaceutical products labels and the climate parameters (such as temperature) in some places in Rwanda, we developed an intelligent fridge that shall be used to efficiently store medicines and which will not be affected by the above-cited IoT challenges.

The rest of this work is organized as follows: Section 2 gives details of what motivated this research work, Section 3 deals which the method and techniques that have been used in this research, Section 4 discusses different results resulting from this work and Section 5 concludes.

2 MOTIVATION

This research study was generally motivated by the climate of Rwanda in respect to the storage condition of the medical pharmaceutical product as indicated by their manufacturer.

2.1 Temperature as medicine storage condition

As per WHO recommendation, there are four different storage conditions for medicines: room temperature, freezer, and cool. Considering Table 1, to efficiently store medical products it is better to use a controlled temperature store. Our research is concentrated on medicines that are stored at room temperature. In Rwanda, we have some places where the temperature goes out of the allowed range of room temperature (below or above).

This is the case of Bugarama and Musanze, Figure 1 and Figure 2.

In a place like Musanze and Gicumbi the temperature goes sometimes below 20 degrees while in a sample place like Bugarama, the temperature goes beyond 25 Degree.

Table 2 consolidates the temperature values recorded from Bugarama and Musanze at different times, these values show that the temperature in these two different places is out of the room temperature range.

2.2 Medicines labeling

Storage temperature ranges are indicated by the manufacturer on the medicine's cover. Without going in deep into the effect of temperature on medicines, in this research we are considering that storing medicines without respecting what was indicated on the medicine will affect it and will have an effect on its efficacy.

Figure 3 shows that Diltiazem Hydrochloride has been manufactured to be stored at a temperature between 20 and 25 degrees,

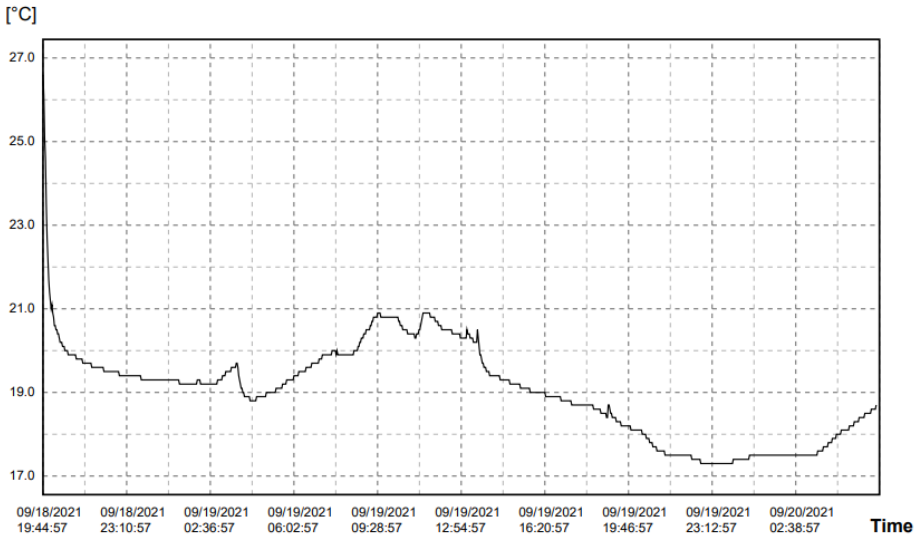

Figure 2: Temperature in Musanze

Table 2: Bugarama & Musanze Temperature information

Region	Lowest temperature [^{o} C]	Highest temperature [^{o} C]	Average [^{o} C]
Bugarama	24.4	34.7	27.7
Musanze	17.3	26.6	19

Figure 3: Diltiazem is indicated to be stored at a temperature between 20 and 25 Degree

in absence of light and medium without an excess of humidity. The above-indicated temperature range is for room temperature, however, many places, especially in Rwanda, will have room temperature that is out of the 20-25-degree range. Incorrect temperature and relative humidity (RH) are the most important factors involved in drug degradation.

3 MATERIALS AND METHODS

To respond to all of the above challenges, we came out with the idea of designing and developing a multi-chamber fridge so that the user can store any medical product based on the storage condition as indicated by the manufacturer.

For making the fridge more intelligent, we tried to control it with machine learning technology so that it can help in controlling the opening and closing of the fridge door. The fridge could even

Figure 4: The proposed fridge

be monitored and controlled from the cloud with the help of the internet of things(IoT) [15–22], to overcome the issue of security, cost, efficiency, and latency that are usually available in cloud computing [23, 24], we tried to develop a four-chamber fridge in which we embedded a machine leaning into a microcontroller (TinyMl) [25,26,27,28,29]. The proposed fridge can is shown in Figure 4

We designed and developed the proposed solution through 4 phases:

- Fridge enclosure design and development,
- Circuit design development,
- Machine-learning model development, and
- Machine-learning model deployment.

The fridge enclosure has been developed using some timbers. After its development, we followed the steps Figure 5

The proposed model can be explained into three colors

Blue: In the edge impulse platform, data used for model development and training can directly be generated from hardware or be uploaded from a computer local drive. This phase has been completed through our published paper [30].

During this phase, we initially have in mind that when the fridge door is opened, the time required for the internal temperature to reach the upper value depends on the internal temperature at the time of opening, the outside temperature, and the daytime. However, after building the model, we find that the daytime doesn't have much impact. As it can be seen in Figure 6, at the time of opening

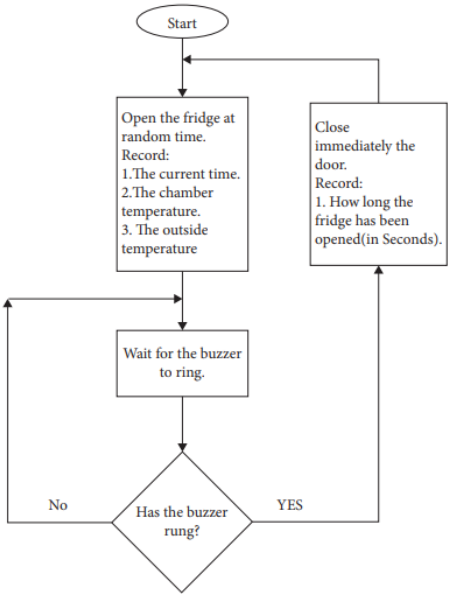

Figure 6: Data Collection flowchart

the fridge, the value of inside and outside temperature, and the day time have been recorded, the fridge was kept open until the buzzer rung (at this time the internal temperature reached the upper accepted level) then the time taken was recorded, 182 samples have been recorded.

Red: During this phase, with the help of collected data, we have used the edge impulse platform [31] to build, train and optimize the model that will be uploaded to the fridge controller.

Yellow: in this phase, the developed model is on a microcontroller and is working based on its intended use. The whole development happened in the following steps:

3.1 Frame design and development

With the help of Solidworks [32], the fridge to be used for efficiently storing medicine has been designed. Generally, the fridge has five chambers where four chambers are used for medical storage and the main chamber is used for generating cooling. The design and the development are shown in Figure 7 and Figure 8

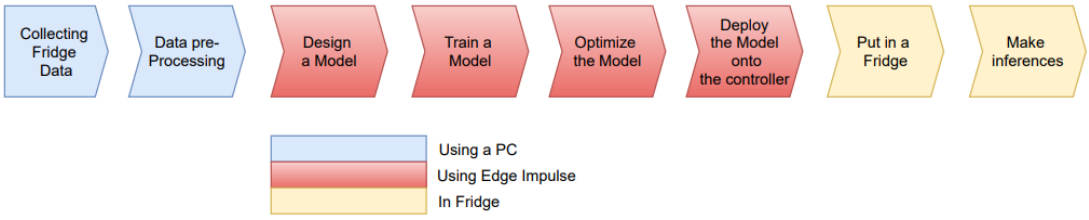

Figure 5: followed steps

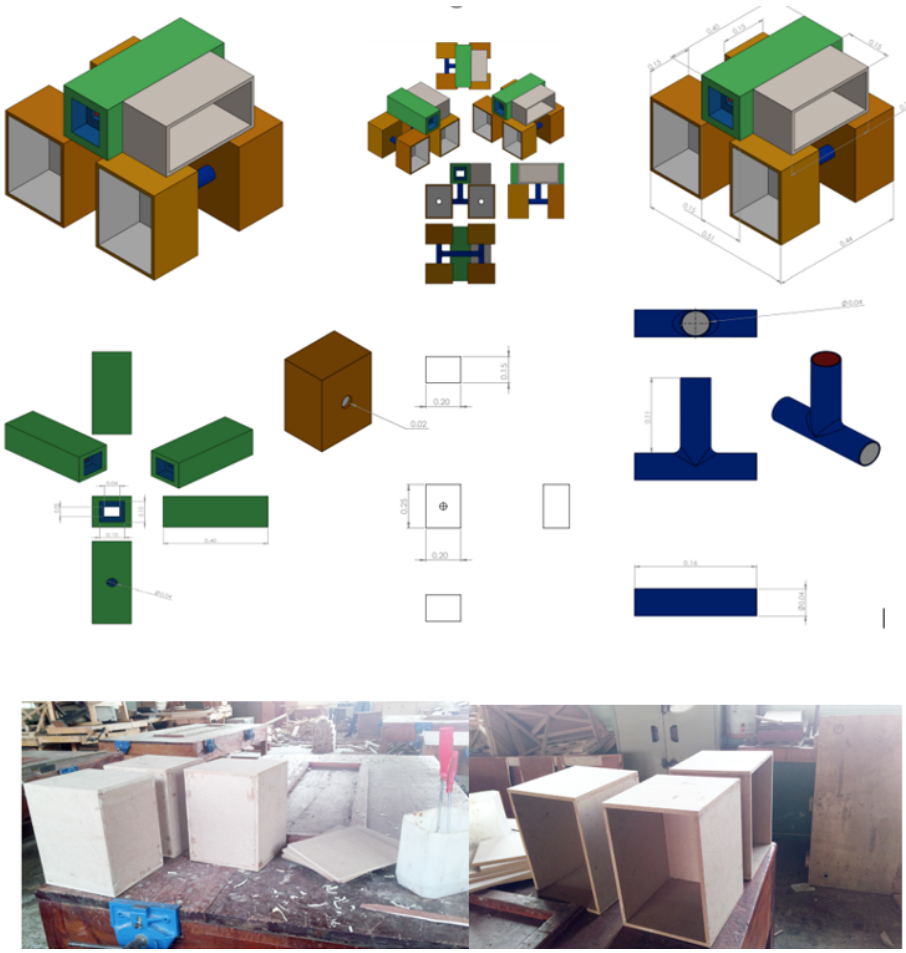

Figure 7: Four chambers fridge design and development

3.2 Circuit design and development

Basically, the dataset can be generated in two ways: human-generated dataset (voice, photos, social media,..) and scientific measurement (using sensors). We have generated data using sensors. The part that controls the fridge is made by Arduino 33 BLE sense board from Arduino company.

A door magnetic switch for getting information about the opening and the closing of the fridge, one temperature sensor for capturing the internal temperature for a particular room, and another temperature sensor for capturing the temperature for the surrounding environment, and an LCD screen to display the results from the model as indicated in Figure 9

3.3 Model development and deployment

After designing the fridge and its control circuit, a tinyML model has been developed with the help of edge impulse studio [31]. Basically, this phase is accomplished through 3 steps:

- data acquisition (data collection): for this phase, we didn't collect data, rather we have uploaded the dataset that we got from our previous work.
- Model creating and training: the edge impulse studio has a way of creating and training the model with the help of the acquired/uploaded data.
- Model deployment: The target device for our mode is an Arduino nano 33 BLE sense. After developing and testing the model, edge impulse has a way of generating a C++ library that will be combined with some other Arduino sketches at the time of connecting temperature sensors and door magnetic switch. Figure 10 shows that the regression model has been used in our work.

3.3.1 Working principle. After loading the model into the fridge, we tested the working principle as follow:

As per Figure 11, if the fridge is opened, the information about the inside and outside temperature will be recorded and taken to the model that has been loaded in the fridge. Remembering that our model has two independent variables (InTemp and Outtemp) and one dependent variable (time required for the room temperature to go beyond the accepted temperature range). Then the results are displayed on the LCD screen. During the testing of our model, we have recorded 17 samples.

Figure 8: Finished four-chamber fridge

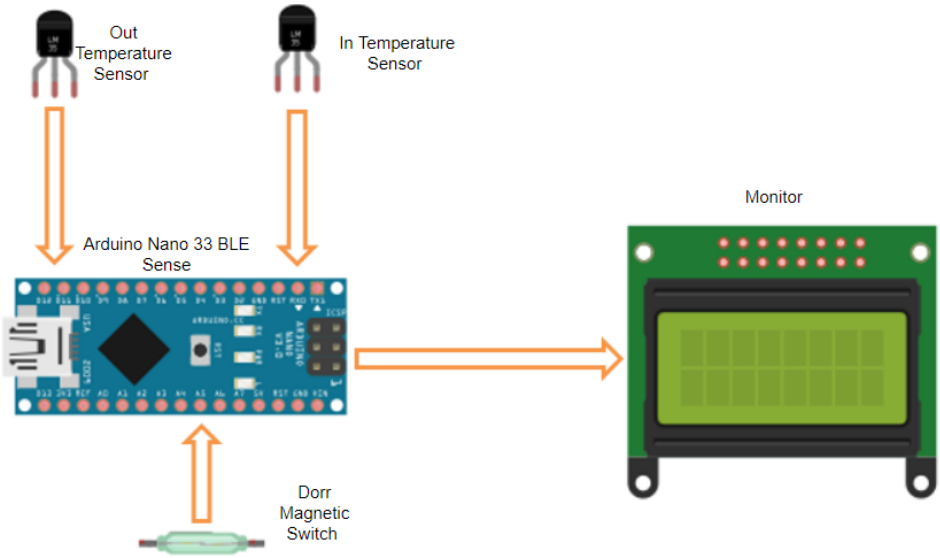

Figure 9: Proposed circuit diagram

4 RESULTS AND DISCUSSIONS

After testing the developed prototype, we tried to record data for three months. But simulating the opening and closing of the fridge have been done in only 12 days. It has been observed that the opening of the fridge increases the internal temperature and after a few minutes, the temperature will reach the maximum accepted value. The time taken to reach this value depends on the initial internal temperature and the external temperature. During the testing phase, the result in Table 3 has been observed. From Figure 13, we can see that the hardware part is made from an Arduino 33 BLE sense as a controller, a GSM module (SIM800L) as sometimes we may need to send data to the cloud, three sensors (In and out temperature sensors, door magnetic switch), a DC to DC converter to match power supplies, an LCD to display the results and a power supply to provide the required power.

It has been observed that when the outside temperature is high, it will take short time for the temperature to increase and reach the maximum allowed value. The same condition will also happen when the internal temperature (at the time of opening) Is higher or near the upper-temperature value.

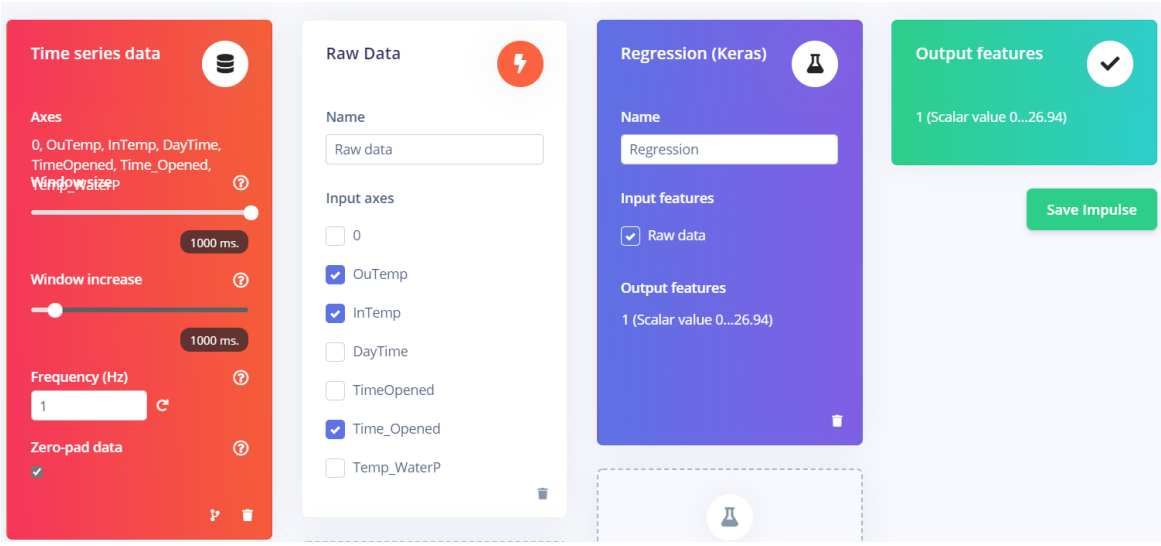

Figure 10: Model training in Edge impulse studio

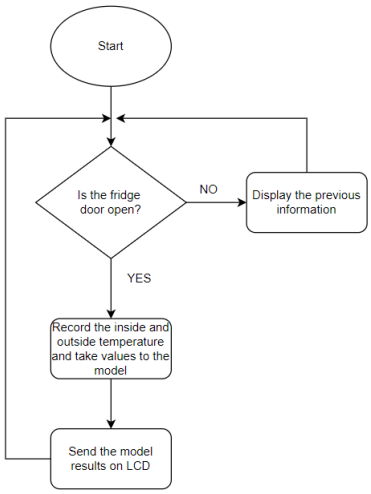

Figure 11: Working principle flowchart

During the 3 months of testing, we recorded 182 samples for the outside temperature, the inside temperature (at the opening time), and the time taken for the internal temperature to reach the maximum allowed temperature. Figure 12 shows the relationship between recorded data.

We have tested the model that has been embedded into the fridge and the results from the table below have been observed. The true values are values taken during the data collection phase and observed values are the ones observed on the LCD screen.

From Figure 14 and Table 3 Experimental results, it can be seen that the model that has been embedded in a microcontroller works well and it can be used to monitor and predict the internal temperature of a fridge. When we calculate the correlation coefficient between the value found while collecting data (true value) and the values observed after loading the model into the controller (model value), it was found to be 0.957940. This means that the accuracy for this model is about 96%.

Table 3: Experimental results

True value [Min]	Observed value [Min]
2.3	2.4
2.8	3.3
1.6	2.0
2.4	2.3
1.2	1.1
0.4	0.7
1.6	1.7
0.9	1.2
0.6	1.0
1.6	1.6
1.1	0.9
3	2.6
1.3	1.1
4.2	3.3
3.5	3.1
4.3	3.5
3.2	3.0

5 CONCLUSION AND FUTURE RESEARCH

The design of both hardware and software for the proposed solution has been successfully completed. The test results have demonstrated that the idea of embedding a machine learning model in a small microcontroller can work. The comparison between data observed while doing data collection and data displayed after loading the

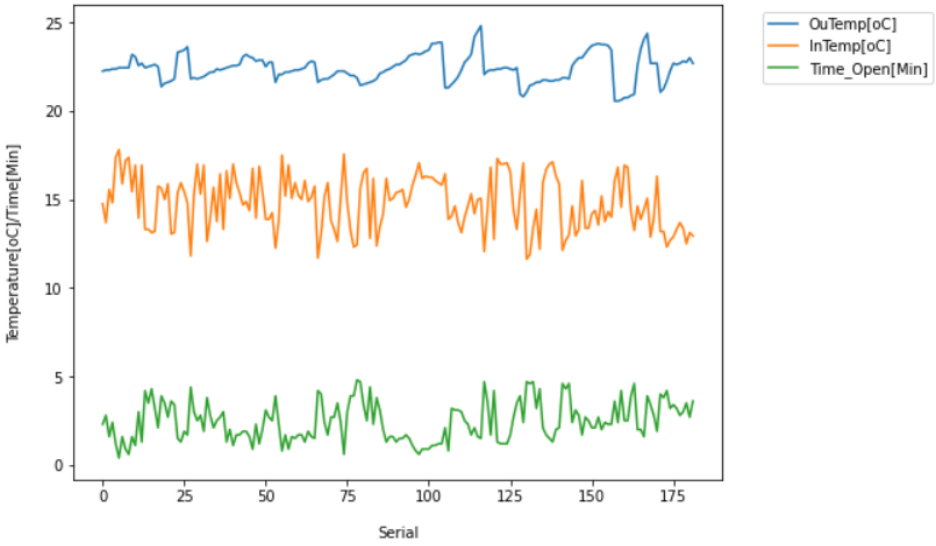

Figure 12: Collected fridge data

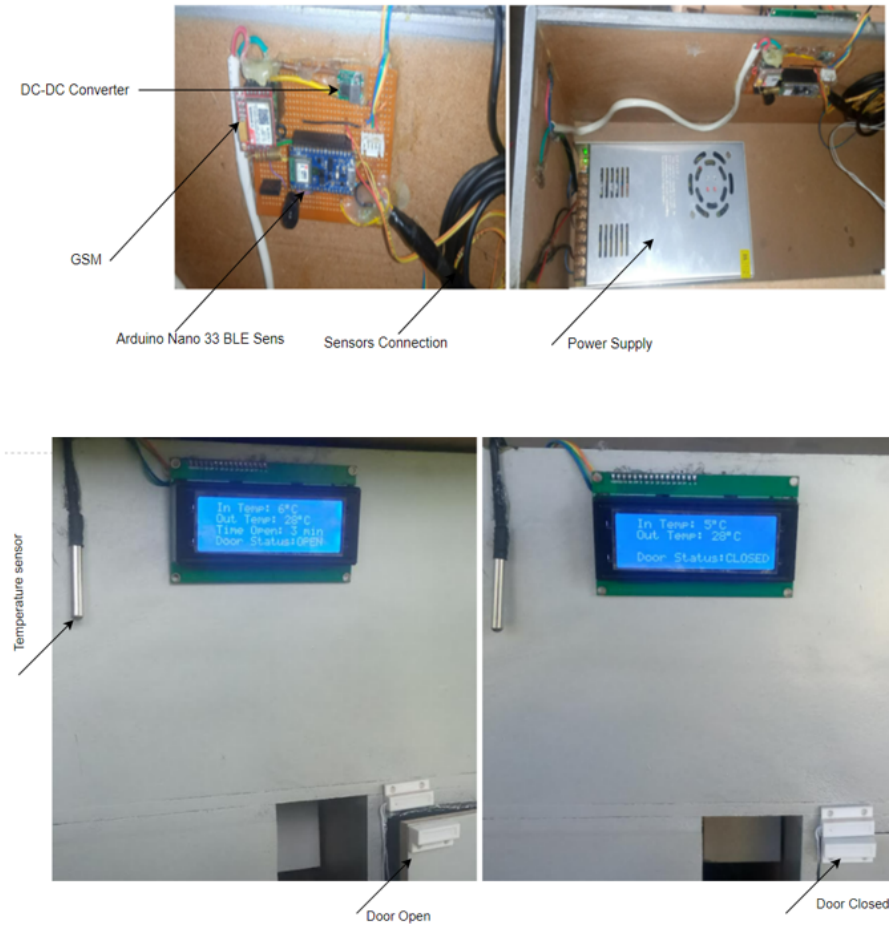

Figure 13: Developed prototype

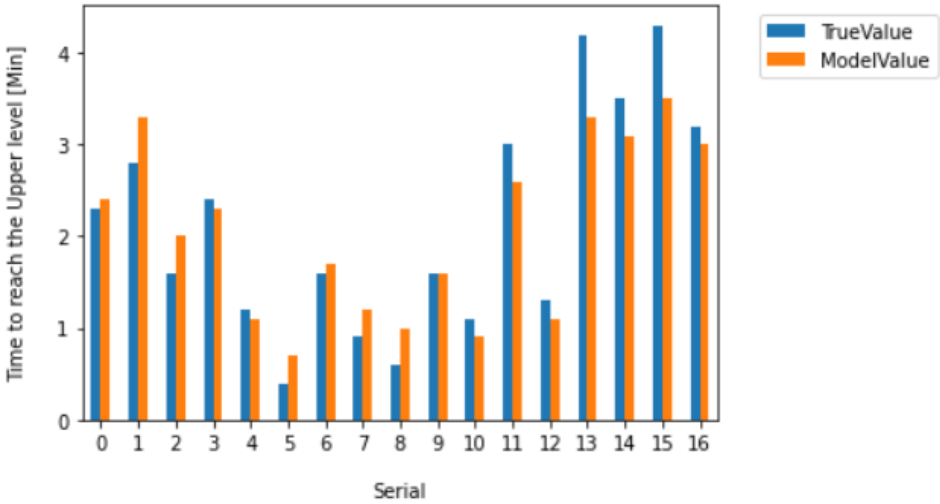

Figure 14: TinyML model accuracy

model into the fridge controller shows that the model is accurate at 96%.

Therefore, an intelligent fridge (with a machine learning model) can efficiently work without sending data to the cloud. For this proposed solution, the challenges of latency data control security and internet connectivity that have been observed in the internet of things applications, will not be observed as the full control of the fridge will be locally done. For healthcare technology, especially in medicine storage in fridges, the proposed model shall be used to efficiently store temperature-sensitive products while locally monitoring the opening and the closing of the fridge.

In our future research, we planning to update our model so that it can accommodate the issues related to fridge power consumption.

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