UNIVERSITY OF RWANDA
COLLEGE OF SCIENCE AND TECHNOLOGY
AFRICAN CENTRE OF EXCELLENCE IN INTERNET OF THINGS

DEVELOPMENT OF AN INTERNET OF THINGS (IoT) BASED FOUR CHAMBER SMART FRIDGE FOR PROPER STORAGE OF DIFFERENT PHARMACEUTICAL PRODUCTS BASED ON THEIR LABELED STORAGE CONDITIONS

PhD. Thesis submitted in the fulfilment of requirements of award of PhD Degree in Internet of Things – Embedded Computing Systems

Joseph HABIYAREMYE

October 2022

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October 2022

Approval

Joseph HABIYAREMYE, a Ph.D. student of UR-ACEIoT student ID 218014367, successfully defended the thesis entitled "**DEVELOPMENT OF AN INTERNET OF THINGS (IoT) BASED FOUR CHAMBER SMART FRIDGE FOR PROPER STORAGE OF DIFFERENT PHARMACEUTICAL PRODUCTS BASED ON THEIR LABELED STORAGE**", which he prepared after fulfilling the requirements specified in the associated legislations, before the thesis examination members whose signatures are below.

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Date of Defense: 29/08/2022

Declaration

I hereby declare that the dissertation entitled "**Development of an IoT based four chambers smart fridge for proper storage of different pharmaceutical products based on their labeled storage conditions**" to be submitted for the Degree of Doctor of Philosophy is my original work and the dissertation has not formed the basis for the award of any degree, diploma, associateship or fellowship of similar other titles. It has not been submitted to any other University or Institution for the award of any degree or diploma.

Joseph HABIYAREMYE

To my spouse and children,

Summary

The general goal of this thesis is to present the findings of research done on an efficient way of managing temperature-sensitive medical products with the help of the internet of things (IoT) and machine learning (ML). This study was conducted considering the case of medical pharmacies in Rwanda. This is a thesis by articles that contains three articles. Each article presents a specific contribution to the whole research work. Generally, after identifying that there is poor management of temperature, a four-chamber fridge that is based on IoT was proposed. The development of this fridge passed through three main phases: The first phase was dealing with the design and the development of the whole enclosure. The second was about electronic circuit design and development. During the same phase, we have identified the best way for data transmission specifically for the case of Rwanda. During the last phase, data have been analyzed and some mathematical models were developed.

In the first article, details about the development of the fridge that has four chambers have been presented. In this paper, the fridge enclosure and the electronic control circuit have been designed and implemented. In most IoT applications, data are sent to remotes database for being processed and analyzed this has been found to be associated with different challenges such as connectivity issues, data security, and data latency. The main purpose of this work was to prove that a compressed machine learning model can be developed and embedded in low resources microcontrollers. With this, we had an idea of controlling the fridge temperature by monitoring the frequency of opening and closing the door while picking some items and finally predicting what will be happing in the near future. This will make the fridge intelligent without sending data to the database. We have finally achieved our objectives and an Arduino library was developed. 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%.

During the second article, we had an idea of taking our fridge as a sensor node that can communicate by sending some data to the cloud. Then our task was to find the best communication protocol that is used by considering the Rwandan situation. For any communication protocol, there is a need for a well-structured communication infrastructure for building a network of sensor nodes. This infrastructure is mainly composed of gateways, repeaters, and base transceiver stations (BTS). Considering that Rwanda is a country with a lot of hills that will not allow a line of sight communication and considering that the Global System for Mobile Communications (GSM) network covers 96% of the country, we decided to choose General Packet Radio Services (GPRS) as communication protocol. Therefore, we experimentally developed a model that can predict a life span of a GPRS-based sensor node with reference to the received signal strength indicator (RSSI) at a particular location. We acquired current consumption for the sensor node in different locations with their corresponding received signal quality and we tried to experimentally find a mathematical data-driven model for estimating the GSM/GPRS sensor node battery lifetime using the received signal strength indicator

(RSSI). The results from the experiment showed that this model can be used to predict GPRS sensor node life span, replacement intervals, and dynamic handover which will, in turn, provide uninterrupted data service. Through the analysis, it has been even found that when there is a reduction of −30 dBm in RSSI, the current consumption of the radio unit of the node will double.

In the third article, one method of analyzing data that has been sent to the cloud during the second article's work was presented. This was a multivariate regression model which can be used to monitor the internal temperature of a pharmaceutical fridge specifically when a pharmacist is selling medical products by predicting what will be the temperature in a given period after the fridge got opened. It is clear that when a given room of a fridge is opened, the internal temperature increase. In this research, a multi-room fridge was proposed. The developed fridge had a screen that keep displaying the current internal temperature of every room and the time required for the temperature of a particular room to go beyond the acceptable range in case it is opened. We proposed that, before a pharmacist opens a fridge he/she will first check the room for a longer time. The developed model was evaluated using the coefficient of determination R2 and was found to be 77%. It has to be noted that, this study was not interested in the impact of temperature fluctuation on pharmaceutical products. The presented articles have different methodologies and this has been indicated in every article.

Keywords: Internet of things, Machine learning, LabVIEW, GPRS, TinyML, Edge Impulse, Multivariate regression, Smart Fridge, Thermo-electric cooler, Arduino 33 BLE Sense, WSN; GPRS sensor node; RSSI; GEKKO APM

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Acronyms

3G : Third Generation
4G : Fourth Generation
AI : Artificial Intelligence
ANN: Artificial Neuro Network
APM : Application Monitor
AT : Attention
BC : Battery Capacity
BL : Battery Life span
BLE: Bluetooth Low Energy
BTS: Base Transceiver Stations
C : Celsius
CNN: Convolution Neuro Network
CoAP : Constrained Application Protocol
CRT : Controlled Room Temperature
CSV: Comma Separated Value
CTC : controlled temperature chain
DB : Database
DC : Direct Current
DC-DC; Direct Current to Direct Current Converter
GPRS : General Packet Radio Service
GPS : Global Positioning System
GSM : Global System for Mobile Communication
HTTP: Hypertext Transfer Protocol
IBM : International Business Machine
IC : Integrated Circuit
IETF: Internet Engineering Task Force
IoMT : Internet of Medical Things
IoT : Internet of Things
KNN: K-Nearest Neighbour
LabVIEW: Laboratory Virtual Instrumentation Engineering Workbench
LAN: Local Area Network
LC : Load Current
LCD : Liquid Crystal Display
LEACH : Low Energy Adaptive Clustering Hierarchy
LoraWAN : Long range Wide Area Network
M2M : Machine to Machine
ML : Machine Learning
MQTT: Message Queuing Telemetry Transport
MySQL: Structured Query Language
NFC : Near Field Communication
NTC : Negative Temperature Coefficient
RFID : Radio Frequency Identification

RH: Relative Humidity
ROC : Receiver Operator Characteristic
RSSI: Received Signal Strength Indication
SCADA: Supervisory Control and Data Acquisition
SNR : Signal to Noise Ratio
SVM : Support Vector Machine
TBFCR : TinyML Based Four-Chamber Refrigerator
TCP : Transmission Control Protocol
TEC : Thermo-Electric Cooler
TinyML: Tiny Machine Learning
UDP : User Datagram Protocol
WAN : Wide Area Network
WHO : World Health Organization
WIFI: Wireless Fidelity

Acknowledgment

This thesis and research work in general, could not have been completed without support from different corners.

I would like firstly to thank the full support of the University of Rwanda, College of Science and Technology (CST) through the African Center of Excellence in Internet of Things (ACEIoT) where the funding support was generated.

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My thanks go to the center management that encouraged me while pursuing my Ph.D. research program.

In addition, I would like to thank my colleagues and classmates. I finally thank my family members for their wise counsel and sympathetic ear.

Chapter 1: Introduction

In Rwanda just like in other developing countries, medical products in pharmacies and medical stores are not always stored in proper conditions as indicated by their manufacturers. In such countries where temperature and humidity can be far outside the indicated range, there is little evidence that a suitable and controlled temperature chain (CTC) is being established for CRT medicines. In some places, vaccines are- not stored under controlled room temperature (CRT) conditions at present. Pharmaceutical drug storage is the pharmacist's most important responsibility. The pharmaceuticals are to be stored under conditions that prevent contamination and, as far as possible, deterioration. During the manufacturing process, precautions that should be taken about the effects of the atmosphere, moisture, heat, and light are indicated on the container of the pharmaceuticals. The cost of generating and maintaining the storing conditions is also an issue. This cost includes buying the storing equipment, the power consumption of the equipment, and the maintenance charges. The purpose of this research was to develop an intelligent system to optimize the efficiency of storing pharmaceutical products that are sensitive to temperature. This system will be managed by a powerful machine learning model that will be able to monitor any change in temperature in the storage.

In reference to the guidelines developed by the World Health Organization (WHO) which should be followed during the maintenance of the cold chain of any pharmaceutical product which state that pharmaceutical products are mainly stored in four storage conditions: room temperature, cool, cold, and freezer, we developed a smart fridge with four chambers and each chamber represents one of the storing condition as recommended by WHO. The developed fridge can be used to store four different medicine categories or for storing medical products of the same type considering that the user can set any temperature range for any room. Based on the guidelines, room temperature varies between 20 and 25 degrees Celcius, however, in some places in Rwanda, room temperature goes beyond the above range. Therefore, people are getting confused considering that any ambient environment will be at room temperature and this confusion will finally affect pharmaceutical products. During this research, the above challenge has been verified by keeping temperature data loggers in some places like Bugarama and Musanze, this resulted in the temperature in Bugarama being found to be beyond the normal room temperature while the temperature in Musanze was below the room temperature range.

The development of the fridge was done in three main phases: Phase one was about the development of the enclosure, which was developed with the help of timbers and was finally thermo-isolated by some thermos-isolator materials. The second phase was about designing and developing some electronic circuits for generating and controlling the temperature. The developed fridge has a main chamber where low temperature is generated, and thermo-electric technology was used to generate cooling. In the same phase, circuits for data gathering and transmission were designed and developed. Every chamber has two sensors: a door magnetic sensor for monitoring the opening and the closing of the room door, and an internal temperature sensor for capturing the internal room temperature. Apart from this, the whole fridge has an external temperature sensor to monitor the external temperature. The last phase was to work on some machine learning models which are helping to process and analyze data from the fridge. In the same phase, information about fridge temperature, and the status of the different doors of the fridge is sent to a remote server so that fridge can be remotely monitored through a web application.

Through this research, we have also made the fridge a standalone unit and intelligent by embedding some machine learning model so that the frequency of opening and closing the fridge while taking some medicines can be monitored for keeping the internal temperature within the acceptable range. In this process, the edge impulse was used. Through this platform, a machine learning model was developed, trained, and converted to an Arduino library to be combined with some sketches so that that model could be embedded in an Arduino board (Arduino 33 blue sense). This is detailed in Chapter III. In chapter IV, we studied the communication protocol that may be used for transmitting the fridge data. We finally found that, for the case of Rwanda, General Packet Radio Services (GPRS) is most convenient as the Global System for Mobile communication (GSM) is covering 96% of the geographical area of the country. In the same chapter, some challenges with the GPRS protocol such as the power consumption has been analyzed and it has been demonstrated that the data transmission will require a huge amount of power in an area where the GSM signal is weak. In chapter V, we demonstrated that the fridge can be remotely monitored with the help of some artificial intelligence (AI) models.

1.1. Related concepts

This reach work had a target of finding a proper way for efficiently storing temperature-sensitive medical products, this section provides all of technologies and concepts that supported the development of this work.

1.1.1. Introduction to internet of things

The internet of things (IoT) is the internetworking of physical devices, vehicles (also referred to as "connected devices" and "smart devices"), buildings, and other items—embedded with electronics, software, sensors, actuators, and network connectivity that enable these objects to collect and exchange data. In 2013 the Global Standards Initiative on the Internet of Things (IoT-GSI) defined the IoT as "the infrastructure of the information society."[1] The IoT allows objects to be sensed and controlled remotely across existing network infrastructure, creating opportunities for more direct integration of the physical world into computer-based systems and resulting in improved efficiency, accuracy, and economic benefit. The following Figure 1 illustrates the general structure of the IoT system.

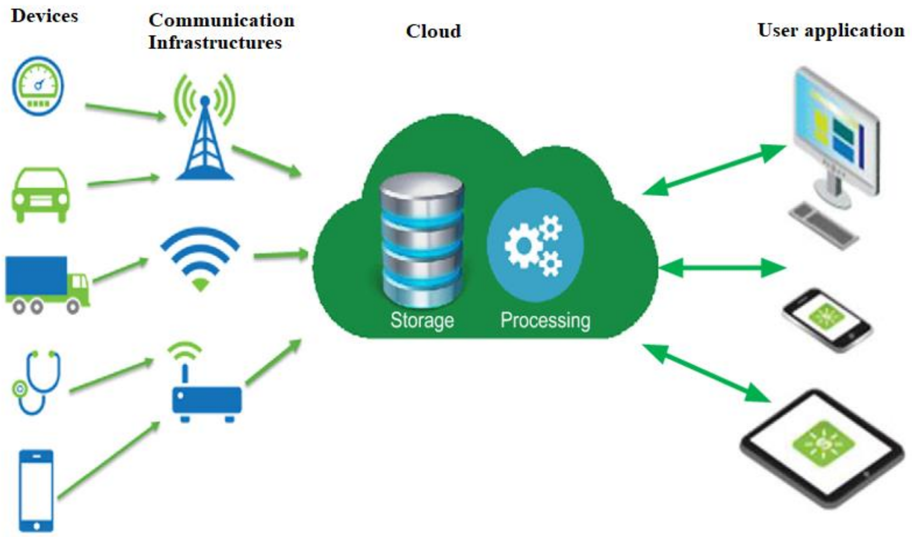

Figure 1: The general architecture of IoT[2]

When IoT is augmented with sensors and actuators, the technology becomes an instance of the more general class of cyber-physical systems, which also encompasses technologies such as smart grids, virtual power plants, smart homes, intelligent transportation, and smart cities. Generally, an IoT system has four parts: device (sensor node), communication infrastructure (communication protocol and communication devices), cloud, and application

1.1.2. Sensor node

A sensor node is a part of an IoT system that is in contact with the real world. It generally has the role of collecting data from physical conditions through sensors or acting back on physical conditions with the help of actuators [3]. A sensor node has four parts: Sensor unit, actuator unit, microcontroller, power supply, and radio unit.

1.1.2.1. Sensor unit

This part is made by sensors, a sensor can be defined as a device that will convert a physical quantity such as temperature, pressure, humidity, or motion to an electrical quantity. Sensors will be chosen based on the IoT application under consideration.

1.1.2.2. Actuator unit

As the name indicates, this is the part of a sensor that makes some actions. By definition, an actuator will convert an electrical quantity to a physical quantity like motion, or heat, …A sensor node can exist without having actuators, this is the case of IoT applications where only monitoring actions are required. The structure of a sensor node is shown in Figure 2.

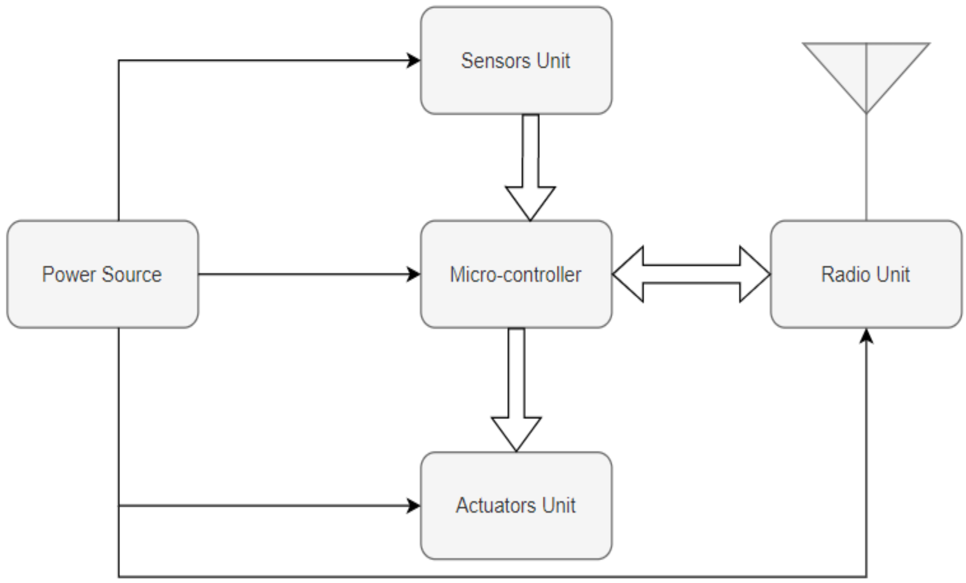

Figure 2: Simplified diagram of a sensor node

1.1.2.3. Microcontroller

A microcontroller is considered the brain of a sensor node. Is defined as a computer on a single integrated circuit (IC). As a computer, it has a processor, input/ outputs, and some memories. Within this part, some data pre-processing are done. A microcontroller is chosen based on the application.

1.1.2.4. Radio unit

In IoT applications, data are transmitted to remote servers for analysis, the radio unit commonly known as the transceiver unit is used to transmit or receive data. The radio module is chosen based on the communication protocol which is being used.

1.1.2.5. Power supply

Each sensor node must have an energy source that mainly has a direct current (DC) voltage below 12V. This part will supply the node with the required power so that it can be able to transmit or receive data. Devices are supplied by small batteries or from regulated power from the utility power supply system.

1.1.3. Communication infrastructure and protocols

In IoT applications, data are transmitted to a remote database for the purpose of storage, processing, and analysis. Apart from the radio unit available in a sensor node, before reaching the database, sometimes data pass through a gateway.

1.1.3.1. Gateway

Basically, a gateway can be defined as a hub that is used to link IoT [4]devices or sensor nodes. Gateway is selected based on the communication protocol that has been used for the sensor node radio unit.

1.1.3.2. Communication protocols for IoT applications

1.1.3.2.1. Bluetooth

An important short-range IoT communications Protocol / Technology. Bluetooth has become very important in computing and many consumer product markets [5]. It is expected to be key for wearable products, again connecting to the IoT albeit probably via a smartphone in many cases. The new Bluetooth Low-Energy (BLE) or Bluetooth Smart, as it is now branded as a significant protocol for IoT applications. Importantly, while it offers a similar range to Bluetooth it has been designed to offer significantly reduced power consumption.

Pros:

- Every smartphone has Bluetooth where the technology is continuously being upgraded and improved through new hardware
- Established and widely used technology

Cons:

- Hardware capabilities change very fast and will need to be replaced
- Running on battery the lifetime of an iBeacon is between 1 month to 2 years
- If people switch off Bluetooth, there are issues in usage.

1.1.3.2.2. Zigbee

ZigBee is similar to Bluetooth and is majorly used in industrial settings[6]. It has significant advantages in complex systems such as offering low-power operation, high security, and robustness and it is well-positioned to take advantage of wireless control and sensor networks in IoT applications. The latest version of ZigBee is the recently launched 3.0 which is essentially the unification of the various ZigBee wireless standards into a single standard.

1.1.3.2.3. Wifi

WiFi connectivity is one of the most popular IoT communication protocols, often an obvious choice for many developers, especially given the availability of WiFi within the home environment within LANs[7]. There is a wide existing infrastructure that offers fast data transfer with the ability to handle high quantities of data. Currently, the most common WiFi standard used in homes and many businesses is 802.11n, which offers a range of hundreds of megabits per second, which is fine for file transfers but may be too power consuming for many IoT applications.

1.1.3.2.4. Z-wave

Z-Wave is a low-power RF communication IoT technology that is primarily designed for home automation for products such as lamp controllers and sensors among many other devices[8]. A Z-Wave uses a simpler protocol than some others, which can enable faster and simpler development, but the only maker of chips is Sigma Designs compared to multiple sources for other wireless technologies such as ZigBee and others.

1.1.3.2.5. Cellular

Any IoT application that requires operation over long distances can take advantage of GSM/3G/4G cellular communication capabilities[9]. While cellular is clearly capable of sending high quantities of data, especially for 4G, the cost and power consumption are too high for many applications[10]. But it is ideal for sensor-based low-bandwidth-data projects that will send very low amounts of data over the Internet.

1.1.3.2.6. NFC

NFC (Near Field Communication) is an IoT technology. It enables simple and safe communications between electronic devices, specifically smartphones, allowing consumers to perform transactions in which one does not have to be physically present[11]. It helps the user to access digital content and connect electronic devices. Essentially it extends the capability of contactless card technology and enables devices to share information at a distance that is less than 4cm.

Pros:
- Does not require power
- Established and widely used technology

Cons:
- Highly insecure
- Ongoing cost per card
- Tags need to be present as identifiers and be handed over before
- Not compatible with smartphones

1.1.3.2.7. LoRAWAN

LoRaWAN is one of the popular IoT technologies, that targets wide-area network (WAN) applications[12]. The LoRaWAN is designed to provide low-power WANs with features specifically needed to support low-cost mobile secure communication in IoT, smart city, and industrial applications. Specifically meets requirements for low-power consumption and supports large networks with millions and millions of devices, data rates range from 0.3 kbps to 50 kbps.

1.1.3.2.8. Sigfox

Sigfox is a long-range network for machine-to-machine (M2M) applications, with less power consumption than others[13]. That makes it a good choice for connecting remote devices that have to run on batteries for long periods without charging batteries.

1.1.4. Important communication coverage parameters

In wireless communication, data are transmitted from the transmitting end to the receiving end. A transmitter will send the signal with a given amount of power. There are two important parameters named: RSSI and signal-to-noise ratio (SNR) that help to define the quality of the communication between the transmitter and receiver [14], [15]. For data to be transmitted, the communication has to be well established this means that the receiver has to be receiving a strong signal, and this is related to the receiver's sensitivity, in other words, it defines how much the receiver can hear. RSSI indicates the quality of communication between a transmitter and receiver. This strength is expressed in dBm and it is a negative value, the closer to zero the better the signal is. Typically, RSSI varies between 0 to -120 dBm. On the other hand, SNR is defined as the ratio between the received power signal (meaningful information) and the power of the background noise power level considering that noise is an unwanted signal. SNR is defined in decibels (dB) and varies from 0 to -120 dB. The closer the value is to -120 dB, the better which means that there is little signal interference.

1.1.5. Applications of IoT systems

In the internet of things, devices are made to communicate by sharing information. With this, a lot of applications have been born including healthcare[16], smart city[17], agriculture[18], industrial automation[19], disaster management[20]. Different IoT applications are shown in Figure 3. Generally, IoT helps to make life easier and more comfortable.

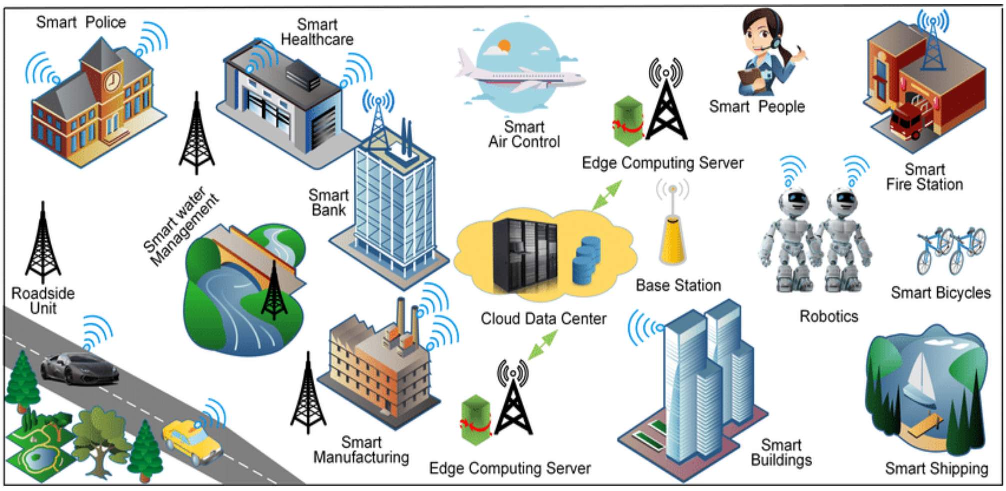

Figure 3: Different IoT applications [21]

1.1.5.1. IoT in the healthcare system

One of the most important things in the healthcare system is data. When the Internet of things meets the healthcare system, we can talk about the internet of medical things (IoMT). Applications like remote patient monitoring, clinical trials, telehealth, predictive maintenance, things like wearable devices, smart medicine despises, and telemedicine are commonly found. In supply chain management, companies are facing a lot of challenges at the various node of the chain due to shipment visibility, increasing customer churn rate, and compliance requirements. Every day millions of tons of temperature-sensitive goods are produced, transported, stored, or distributed worldwide[22]. When it comes to cold chain control and monitoring, companies need to take some critical measures to avoid temperature fluctuations that result in recalls and illnesses and ultimately affect brand reputation, this can be achieved through a controlled cold chain or smart cold chain[23]. The cold chain for temperature-sensitive products such as vaccines and other pharmaceutical products needs to be controlled from the manufacturing site, in transit, in the warehouse, and different stores. Improper temperature control is the key reason why some vaccines are spoiled or wasted by pharmaceutical companies[24]. To maintain the quality of pharmaceutical goods, every product requires a different temperature, cold chain monitoring solution is required to maintain the proper temperature of the pharmaceutical warehouse/store and during its logistics. For the product in the warehouse, temperature maintenance is compulsory. It has been predicted that the global biomedical refrigerators and freezers market will be nearly 5 billion USD by 2026[25]. It is within this background that our research idea was born for controlling the temperature in pharmacies, especially retail pharmacies.

1.1.6. Challenges of IoT systems

IoT digitalizes physical assets such as sensors, devices, machines, gateways, and networks. It connects people to things and things to things in real-time. A typical IoT network can grow rapidly resulting in an exponential increase in variety, velocity, and the overall volume of data. This opens opportunities for significant data creation and revenue generation, but the real challenge for IoT environments is how to analyze the large volume of information from all sources and act in real-time. However, have been identified to have about five different challenges[26]:

1.1.6.1. Security

Security is on everyone’s mind today, as cyber hackers continue to invent different techniques to help them to access hidden data. Security is one of the major challenges for any application.

1.1.6.2. Awareness

The lack of awareness from the community arises, people are not understanding what is the importance of connecting devices such as lights, and home appliances to the internet we all should understand why we need to connect them to the internet.

1.1.6.3. Privacy

Suppose that you are having a wearable device, you could be tracked on monitored by a hacker without being identified then if there is a threat, there is no way to deal with it.

1.1.6.4. Connectivity

The requirement for wired and wireless connectivity is also a challenge in IoT applications. In communication systems, connectivity is linked with power consumption. When a sensor node connects to a network and sends or receives data a considerable amount of power is consumed.

1.1.6.5. Data Storage

When working with IoT applications, the question of where to store collected data arises. For these applications, the cloud is mandatory for storage, and this will automatically bring in the issue of security[27]. Then from there, other sub-questions will be raised such as: which cloud? how to identify? it, how much does it cost?, Do we need a cloud?

1.1.7. Data processing and analysis

In internet of things applications, data are generated from sensor nodes and they are either stored in an open cloud, or a private cloud. Data can be classified into two types, structured data meaning data are in the table, and unstructured data such as audio, image, and video. In other to make data useful, we need to do some processing on them. Primary, data can be analyzed by either using descriptive or predictive methods[28]. There are two primary categories of analytics: descriptive which basically deals with historical information about data means when talking about what worked, what didn't work and trying to adapt the way to do it in the future. On the other side, predictive when it comes to seeking future information based on what happened in the past. Predictive data analytics is very close to artificial intelligence.

1.1.7.1. Artificial intelligence

In computer science, artificial intelligence is related to some theory and development that a computer system uses when it tries to perform some tasks that are normally done by a human being. This means it is a technique that enables machines to mimic human behavior machine. This is depicted in Figure 4. Those tasks are generally: speech recognition, visual perception, predicting what will happen in the future, making some decisions, doing languages transaction, and object classification.

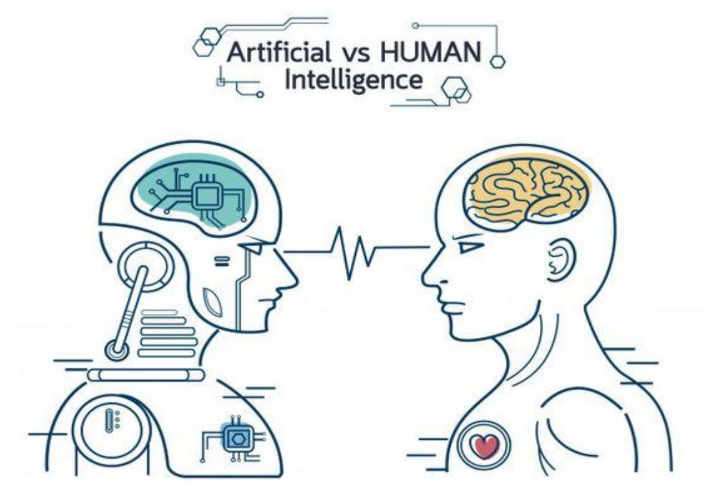

Figure 4: Artificial intelligence explained : [Photo from freepik[29]]

The term artificial intelligence (AI) was initially generated by John McCarthy in 1956 [30] at a conference. He defined AI as the science and engineering of making machines intelligent so that they can work like human beings [31]. AI is being applied in different fields such as healthcare, robotics, marketing, business analytics, and others. Figure 5 below depicts the relationship between AI and its subfields.

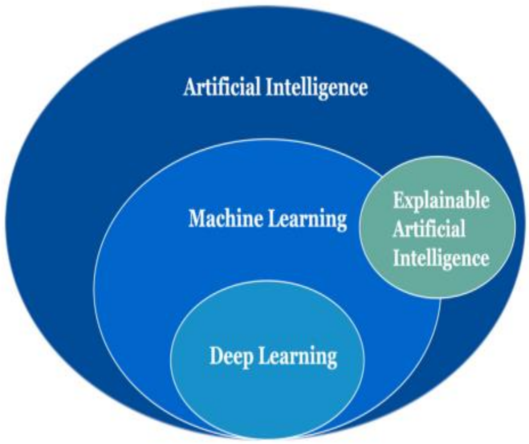

Figure 5: The relationship between AI and its subfields [31]

Artificial intelligence has two subsets named: machine learning and deep learning.

1.1.7.1.1. Machine learning

We can talk about machine learning when a computer learns from data using some algorithms targeting the performance of a task without being programmed. Basically, algorithms like linear regression, logistic regression, K-Nearest Neighbour (KNN), decision tree, support vector machine (SVM), Naïve Bayes, K-Means, Random Forest, Dimensionality Reduction related Algorithms, and Gradient Boosting algorithms are found in machine learning. Generally, machine learning is a subset of AI where the machine can work like a human being while taking a decision but after feeding them with some data.

1.1.7.1.1.1. Steps of machine learning

Machine learning has granted computer systems entirely new abilities. In machine learning, algorithms are fed with relevant data (generally, historical data) for performing the assigned task. The following are steps to go through while dealing with machine learning[32]. Machine learning phases are shown in Figure 6.

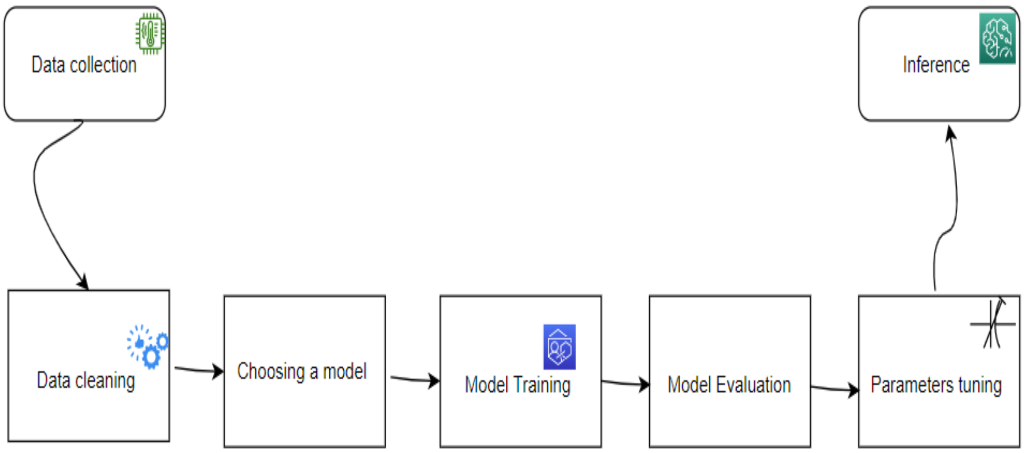

Figure 6: Steps involved in Machine learning application

1.1.7.1.1.1.1. Gathering data

This is the most important step because the quality and the quantity of the data will determine how good is your model.

1.1.7.1.1.1.2. Data preparation

In this step, received or recorded data (raw data) are loaded in a suitable place for being prepared for use. This is even the time where we can talk about data pre-processing and data cleaning. Image data are received with some errors. Most found state in data is unwanted respondents, incomplete responses, missing values, useless variables, and wrongly entered/ recorded values. If the data are not cleaned properly, it leads us to the wrong decision.

1.1.7.1.1.1.3. Choosing a model

Many models have been created by scientists and engineers and data science, some are suitable for images, some are for numeric others are for texts.

1.1.7.1.1.1.4. Training

The goal of training is to get a model, which helps for answering the question correctly and a good model is created during a process called training. After cleaning the data, data are split into parts: training data and testing/evaluation data. The training phase is the core phase of machine learning.

1.1.7.1.1.1.5. Evaluation

There are several metrics to evaluate machine learning modes depending on whether you are working with regression or a classification model. There are some tools like confusion matrix and receiver operating characteristic curve (ROC)/ Area under the ROC Curve (AUC).

1.1.7.1.1.1.6. Hyper parameter turning

hyper-parameters are parameters that can be adjusted and fine-tuned in other to improve the accuracy of a machine learning model. In case it is needed to optimize or improve the training model, a data scientist does this by going back and tuning some model parameters.

1.1.7.1.1.1.7. Inference

The last step of machine learning is to use the model for its intended use. This may be either classification, prediction, or both.

1.1.7.1.1.1.8. Deep learning

This is a subset of machine learning. This type of machine learning is inspired by the structure of the human brain. In this category, we find powerful algorithms for handling sophisticated tasks.

1.1.8. Cloud, fog, and edge computing

In internet of things applications, data from sensors can be stored and analyzed locally or in the cloud [33]. Basically, cloud computing can be understood as computing that is done over the internet. These computing services are linked with some infrastructure such as servers, software, algorithms, storage, databases, networking, and analytics. Fog, edge, and cloud are graphically represented in Figure 8.

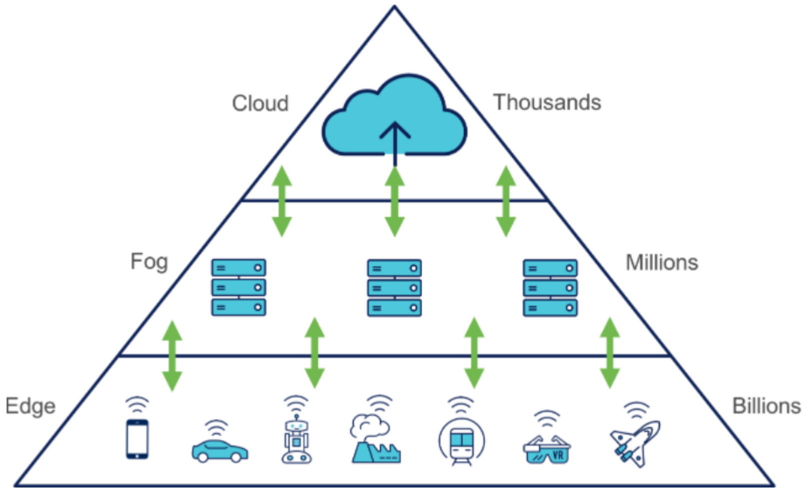

Figure 7: Edge, Fog, and Cloud Computing [34]

Cloud computing provides services with flexibility and high availability with optimized ownership. However, it has been observed some issues like congestion in network infrastructures which is producing some latency that can impact the production means by affecting the system capacity, efficiency, and security. Edge and fog computing are IoT technologies where the computation of data is done closer to where data are generated (sensor node)[34]. These two technologies came as solutions to address the above problem. The fog can be considered as a layer that is between the edge and the cloud layers. The fog computing device is receiving data from the edge and processes them before they reach the cloud. There is some confusion between the terms fog and edge computing, maybe it's because both make the processing or data handling near their source.

When the data manipulation is done at the sensor node, this will reduce the processing time by omitting the transfer of data to a centralized point and back to the edge point which is resulting in efficiency in data processing and reduction in internet bandwidth requirement. With this, the operating cost is reduced too. Apart from this, the interaction with the public network is reduced which will make the security more controlled. It can be concluded that both edge and fog computing will improve the bandwidth, reduce the data latency & congestion, enable autonomous operations, and boost security and privacy[35], [36]. When it comes to artificial intelligence if models or algorithms are embedded into edge devices with few computing resources, (which means they are made to be light) we talk about Tiny Machine Learning (TinyML).

1.1.8.1. TinyML

The term TinyML stands for Tiny Machine Learning[37]. It is an emerging technology in the public domain. This lies at the intersection of embedded systems and machine learning. It involves processing complex models on ultra-low-powered microcontrollers. Generally, for TinyML applications, internet connectivity is not required[38]. The most important feature of deploying ML algorithms on the edge TinyML devices is that they can work for months or even years due to their low power consumption. Some applications that are commonly handled by edge devices are speech recognition, image recognition, and gesture detection using motion sensors. The formulation of TinyML is depicted in Figure 8.

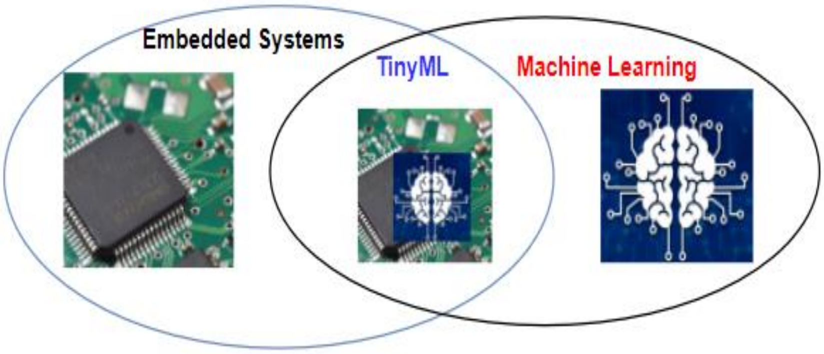

Figure 8: TinyML Formulation

As even indicated above for edge computing technologies, there are many benefits of using TinyML systems rather than IoT-based solutions such as low power consumption, low latency, low bandwidth, less expensive, data privacy, and more security as there is no connectivity [39]. Unfortunately, not many development boards are made to implement the machine learning model now. But the most popular ones are the SparkFun Edge boards and the Arduino 33 BLE sense board. To facilitate the development of TinyML, the Arduino company has collaborated with Edge impulse, a development platform that enables us to train, test, and finally deploy machine learning models to compatible Arduino boards.

1.1.8.2. Edge Impulse

The combination of machine learning and embedded computer technology opens an entirely new space called "embedded machine learning", this has enabled us to take advantage of new computing technologies that make microcontrollers more and more efficient at the same time, and new techniques in machine learning have enabled us to apply machine learning that can run on little low-power devices. This enables us also to combine real-time sensor data, audio, and video together and process them on small microcontrollers in real-time, and detect what is happening without going to the cloud. Within the above background, a platform called "Edge Impulse" was created by Zach Shelby and Jan Jongboom with the purpose of availing this embedded machine learning technology to everyone. This platform is being used by developers and enterprises [40]. The development of an embedded machine learning model through edge impulse seems to be too easy for an embedded systems developer. Phases through which a library to be embedded in the controller is generated are shown in Figure 9.

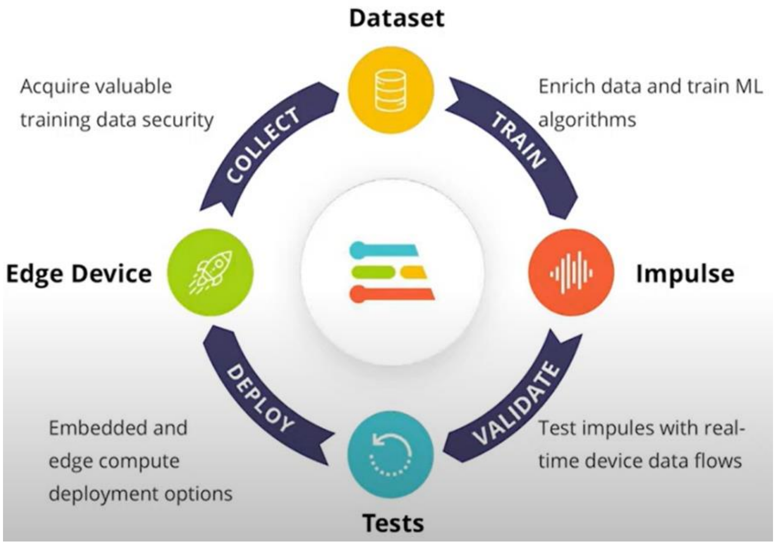

Figure 9: Process in edge impulse [40]

The Edge Impulse is a cloud-based platform that covers the whole machine learning workflow from creating datasets and training machine learning models up to the generation of an open-source library to be deployed onto the targeted device. Data can be directly recorded from the field or uploaded from a local drive on the computer[41]. After getting the data, the next step is to design what is called the impulse which is a mix of processing blocks and learning blocks. Block is chosen based on the application or project type. The next step is to generate features that will be fed into the neuro network, then there is a place named a featured explorer that is being used for viewing features that have been generated for classes.

When the training is ended, it is also required to verify if the developed model can perform well on the test set. Finally, the platform will have a place where a developer can choose the target device which will be compatible with the library to be developed. After choosing the target device, the model will be built if the building is completed, and a zip file will be automatically downloaded. This is the library that will combine with other code for completing the project which is under development.

1.2. Personal Motivation

This research study was generally motivated by the climate of Rwanda vis-à-vis the storage condition of the medical pharmaceutical product as indicated by their manufacturer.

1.2.1. Temperature as medicine storage condition

As per the world health organization (WHO) recommendation, there are four different storage conditions for medicines[42]:

Table 1: Pharmaceutical storage requirement as per WHO

Nº	Labeling	Recommended temperature range [^{0}C]
1	Room Temperature	20 to 25
2	Freezer	20 to -10
3	Cold /Refrigerator	2 to 8
4	Cool	8 to 15

Considering the above Table 1, to efficiently store medical products it is better to use a controlled temperature store. Our research is concentrated on medicines that are said to be stored at room temperature. In Rwanda, there are some places where the temperature goes out of the allowed range of room temperature as specified in Table 1. This has been identified with the help of a data logger manufactured by ThermElc [43], a world-leading company for producing products that are used for monitoring cold. The detailed specifications of the data logger are indicated in Table 2. This recorder has been kept for some weeks in BUGARAMA (2°41′50″S 29°00′30″E) [44] in the southwest of the country and MUSANZE (1°30′S 29°38′E) [45] in the north of the country. The used temperature data logger is shown in Figure 10. And its technical specifications are shown in Table 2.

Figure 10: RC-5+ Data Logger

Table 2: Data Logger Specification

Nº	Item	Details
1	Temperature range	-30 to 70
2	Accuracy	-20°C~40°C, accuracy ± 0.5°C; Remaining ± 1 ° c
3	Recording capacity	32000 sets
4	Built-in sensor	NTC Thermistor
5	Connection Interface	USB
6	Battery Type	CR2032 Button Cell
7	Shelf Life	1 year
8	Recording interval	2 Min (Standard)
9	Model	RC-5
10	Product Size	80x33x14(mm)

Referring to the Rwanda Meteorology Agency[46], the temperature is not equally distributed in Rwanda.

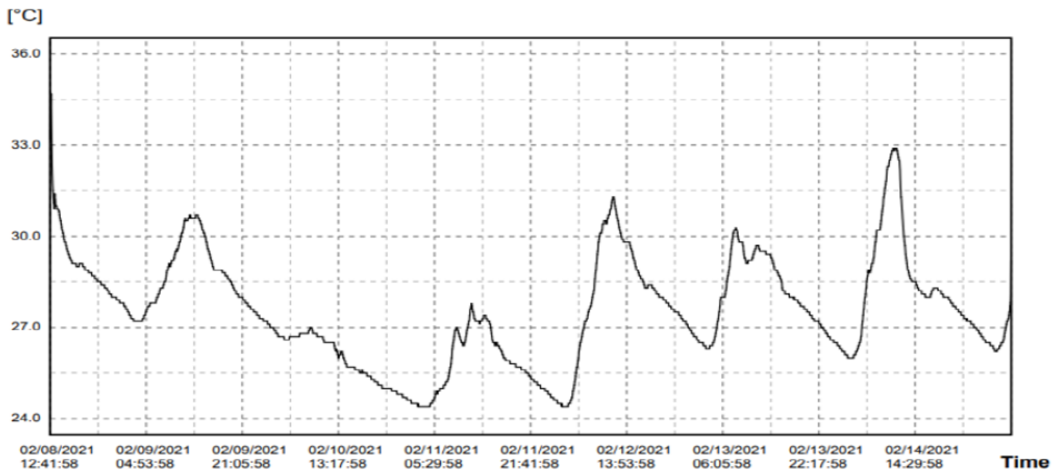

Figure 11: Temperature Variation Bugarama City

Figure 11 and Figure 12 indicate temperatures recorded from BUGARAMA and MUSANZE respectively. Generally, in Musanze the temperature goes sometimes below 20°C while in a place like Bugarama, the temperature goes beyond 25°C.

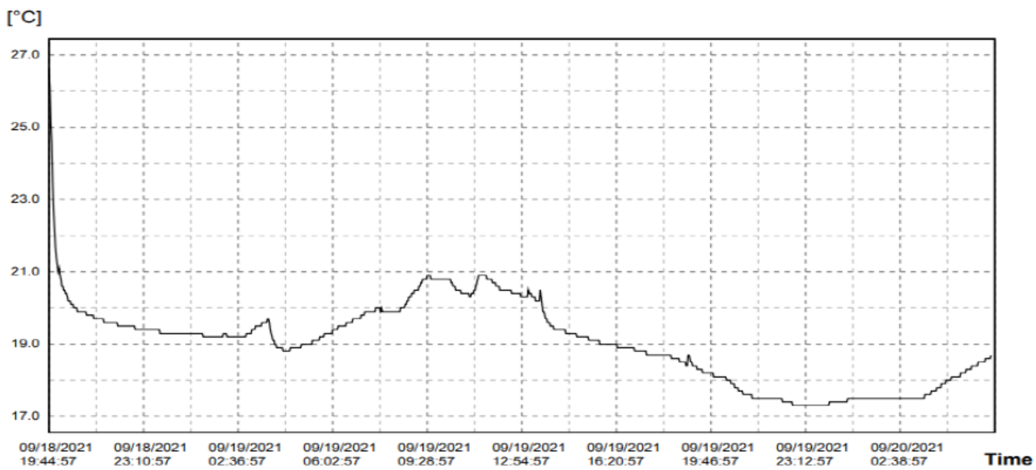

Figure 12: Temperature variation in Musanze city

1.2.2. Medicines labeling

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

Figure 13: Diltiazem is indicated to be stored at a temperature between 20-25 Degree

For example, the above Figure 13shows that Diltiazem Hydrochloride must be stored at a temperature of 20-25 degrees, in absence of light and in a 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 out of the 20-25-degree range. Incorrect temperature and relative humidity (RH) are the most important factors involved in drug degradation in medicines stores.

1.3. Problem statement

Pharmaceutical products such as medicines, vaccines, and reagents are sensitive to temperature. Referring to their chemical structures, they can either be stored at room temperature, freezer or just at a cool temperature. Any of the above storage conditions has its specific temperature range as per WHO. Manufacturers for pharmaceutical products respect the storing requirement by even indicating the temperature storage requirement for each product. For the room temperature range, the accepted range is between 20 and 25 Degree Celsius. In some places in Rwanda such as Bugarama, Gicumbi, and Musanze, the temperature goes beyond the above range, the temperature may go above or below range. When there is a temperature fluctuation on these products, their efficacy will be affected which will result in issues in the intended use of the product.

1.4. Research objectives

The general objective is to design and develop (implement) an IoT-based standalone smart fridge with four chambers in different temperature conditions to be used for medical shops or anywhere controlled medical storage is needed.

Specific objectives

1. To design and develop a hybrid (which can work from main supply (220V) and 12V DC from solar energy) four-chamber fridge with some algorithms to efficiently control temperature and collect data from different chambers.
2. To wirelessly transmit different data from the fridge to an online server and local machine and develop an application for the local machine.
3. To analyze data from different chambers using some intelligent algorithms which will help users to have information about the storage condition of medicine, give some alerts about medicine storage conditions to the pharmacy manager, and this will help in monitoring the fridge based on how often the fridge has been opened.

1.5. Overview of major contributions

In this section, an overview of the major contributions of this research is discussed. This research started by identifying two regions in the country where one region has an average temperature of 27.5^{0}C (highest 34^{0}C, lowest 24.5^{0}C) and the other region has 23.1^{0}C(highest 39.4^{0}C, lowest 18.7^{0}C) considering WHO guidelines of pharmaceutical product storage, the efficacy of medicines stored at room temperature, will be affected in the above regions. Generally, our major contribution goes around by designing and implanting an efficient smart storage environment in response to the following problems:

1. Improper storage of medicines that are supposed to be stored at room temperature. This problem is observed in the area where the ambient temperature goes beyond the WHO room temperature range.
2. Deviation or fluctuation of internal fridge temperature due to how frequently the fridge is being opened and closed while taking medicine.

We came out with the following solutions:

1. Design and development of an intelligent fridge with an AI model to monitor the impact of opening and closing the fridge door targeting an efficient way of storing medicines. This can work without internet connectivity.
2. Specification and requirement for data transmission in any location in Rwanda.
3. Development of a mathematical AI model to help in remotely monitoring the fridge targeting an efficient way of medicines storage.

These three solutions will constitute the main theme of the three chapters of the thesis and have been addressed in three journal publications. Details are shown in Figure 14.

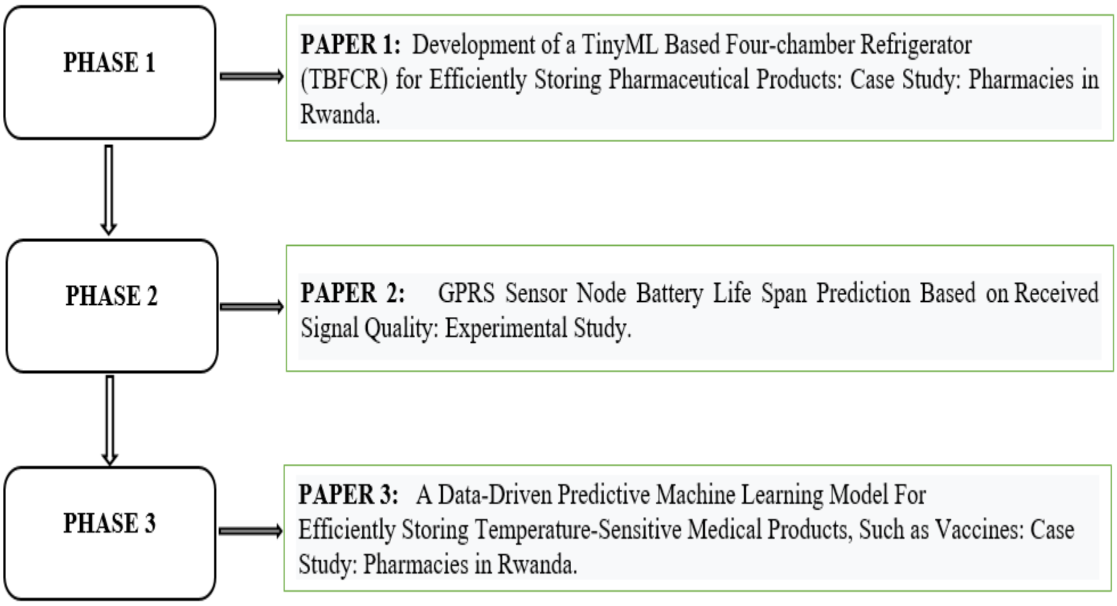

Figure 14: Research Development phases

1.5.1. Thesis outline

This thesis is built on published papers. Those papers will be referred to throughout this thesis. The thesis has 8 chapters where 3 of which are prologues of the three published articles where personal and team contribution, the context of the article, and recent development are detailed. Chapter 2 provides some prologue to the first article while chapter 3 gives the basic details on the design, development of the fridge enclosure, and its control circuit. In the same chapter, we have demonstrated that the fridge can be independently intelligent by being embedded with some machine learning models.

For an IoT fridge, data that are being generated must be sent to the cloud for being manipulated (processed & analyzed), data transmission protocol has been chosen by considering the case study of pharmacies in Rwanda where there are a lot of hills and lack of IoT infrastructures in place. Chapter 4 provides some prologue to the second article while chapter 5 describes an experiment conducted. In this experiment, the GPRS protocol together with a mathematical model of a GPRS-based sensor node was adopted. Chapter 6 provides some prologue to the third article while through chapter 7 we indicate a multivariate machine learning regression model that was hosted in the cloud for manipulating data from a remote fridge. Finally, chapter 8 concludes the thesis and provides some recommendations for future research directions. The graphical representation in Figure 15 depicts the outline of this thesis.

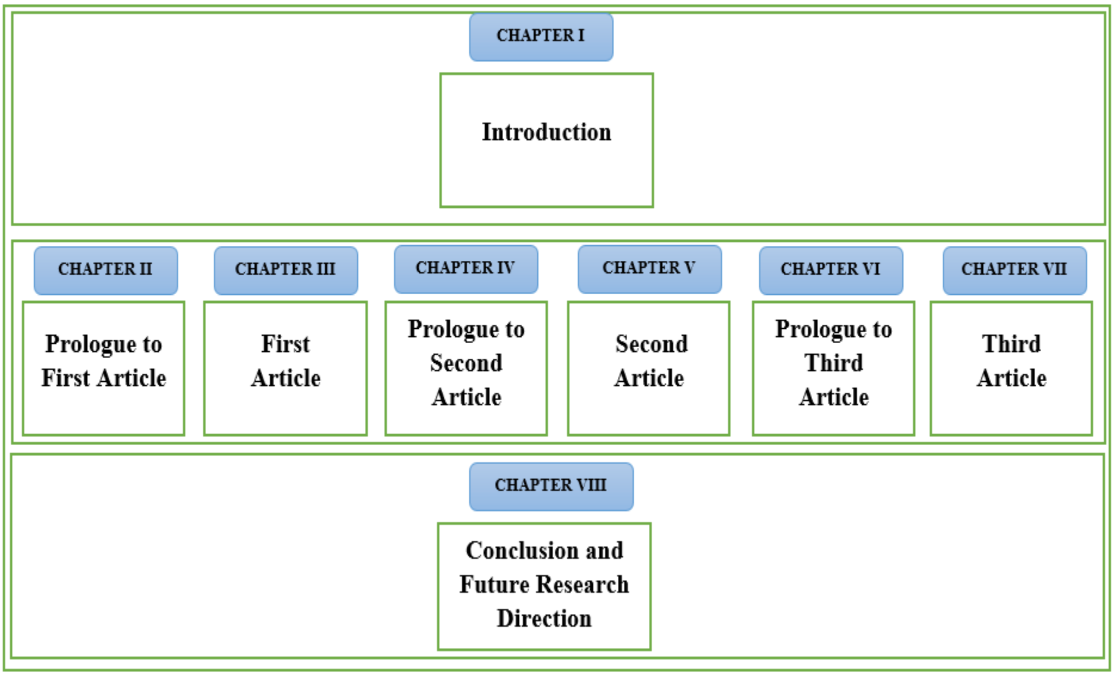

Figure 15: Thesis organization

Chapter 2: Prologue to First Article

2.1.Article details

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

Habiyaremye.J, Zennaro. M, Mikeka. C, Masabo.E. ICMLC 2022: 2022 14th International Conference on Machine Learning and Computing (ICMLC), February 2022 Pages 337–346, https://doi.org/10.1145/3529836.3529932.

Personal contribution: The basic idea of developing a stand-alone four-chamber intelligent fridge was generated from my side. The option of using Edge impulse for generating a compressed machine learning model was guided by Zennaro.M. I implemented the hardware and software of the aforementioned fridge. I did most of the writing with the guidance of Zennnaro. M, Mikeka.C, and Masabo.E.

2.2.Context

Machine learning models have shown great importance in processing data. Initially, machine learning models were processed with the help of machines with powerful resources. For IoT applications, data are generally processed and analyzed in the cloud. This was found to be associated with different challenges such as data latency, data security, data privacy, and power consumption specifically during data transmission. To overcome all those challenges, the machine learning model can be compressed so that it can be embedded in low resources microcontrollers. It is within the above background that we developed a fridge that can predict the upcoming internal temperature regarding how frequent is being opened.

2.3.Contributions

The primary contribution of this paper is to bring a new machine learning model Arduino-based library. For Arduino users who need to control a temperature of a temperature-controlled environment and predict what will happen in the near future to the internal temperature, they may use an Arduino Nano 33 BLE Sense and combine our developed library with their codes. This will simplify their tasks.

2.4.Recent development

This paper is very recent; it has been only in the last month. There are therefore no more recent developments to report.

Chapter 3: Development of A Tinyml-Based Four-Chamber Refrigerator (Tbfcr) For Efficiently Storing Pharmaceutical Products: Case Study: Pharmacies in Rwanda

3.1.Introduction

In the Rwandan healthcare system, medicines are recommended by a medical doctor and they are generally found in private, public pharmacies, and hospitals. Pharmaceutical products have some indications 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 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 degrees), and fridge storage condition (-4 to 2 Degree). Researchers have demonstrated that with the help of new technologies such as IoT and machine learning, fridges that keep pharmaceutical products can be remotely controlled and monitored for efficiently managing their internal temperature.

Traditionally, for IoT applications, data are sent to cloud databases from which 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. This article proposed an intelligent four chambers intelligent fridge that hosts a machine model for responding to the storage conditions of medicines as recommended by the WHO. The development of this model was achieved by using the Edge impulse platform.

3.2.Related works

The idea of embedding some machine learning models into microcontrollers is somehow new. However, they are some researchers who got interested in the area. Zin Thein Kyaw [47] tried to apply TinyMl to cold chain monitoring systems with the help of edge impulse. Signoretti [48] and the team came out with a solution for compressing data on TinyML devices so that models can work perfectly. Raza[49] proposed a practical solution of embedding machine learning models in the drone so that they can be able to make the decision themselves by consuming low power. The work in [50] reviews different applications and current progress in TinyML-based applications. The work in [51] detailed the application of TinyML in autonomous vehicles by embedding a CNN into their controllers. A good number of researchers have demonstrated the different challenges of IoT including power and security. In the work of [52], researchers demonstrated that IoT devices face some challenges such as power and connectivity. The work in [53] and [54] stated that security and privacy are the two challenges of IoT when it comes to smart homes. Researchers in the works of [55], [56] 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 product 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.

3.3.Materials and methods

To respond to all 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. However, the fridge could even be monitored and controlled from the cloud with the help of the internet of things(IoT) this was explained in the work of Fujiwara[57], the work of Juan Luis[58], the work of Davood[59], the research work for Avinash[60]. To overcome the issue of security, cost, efficiency, and latency that are usually available in cloud computing, we developed a four-chamber fridge in which we embedded a machine leaning into a microcontroller (TinyML). The use of TinyML has also been adopted by Sudharasan[61], Sanchez-Iborra[62], Loghin[63], and the same were also detailed in the work of [64] The proposed fridge is illustrated in Figure 16.

Figure 16:The proposed intelligent fridge which will be controlled by AI

We designed and developed the proposed solution through 4 phases:

1. Fridge enclosure design and development,
2. Circuit design development,
3. Machine-learning model development, and
4. Machine-learning model deployment.

The fridge enclosure has been developed using some timbers. After its development, we followed the steps in Figure 17,

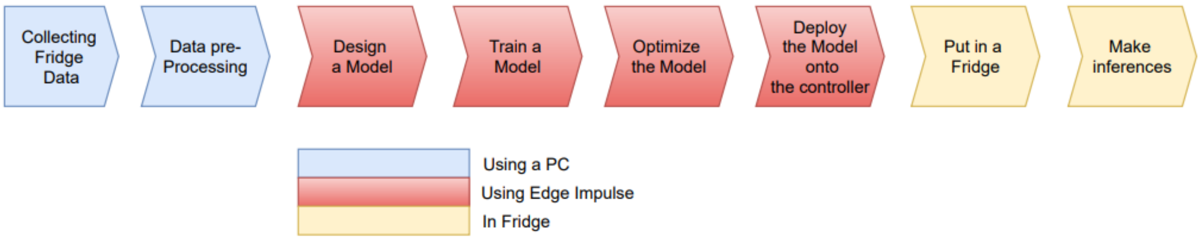

Figure 17: Steps through which a machine learning model was developed.

The proposed model can be explained in three colors as shown in Figure 17:

- **Blue**: In the edge impulse platform, data used for model development and training can directly be generated from hardware or uploaded from a computer local drive. This phase has been completed through our published work[65].

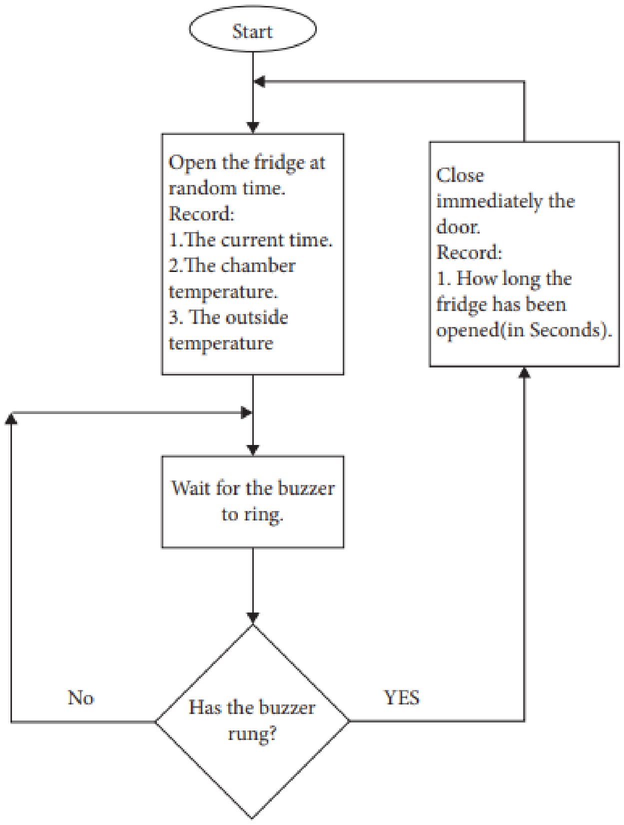

Figure 18: Data Collection flowchart

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 18, at the time of opening the fridge, the value of inside and outside temperature, and the daytime 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 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:

3.3.1. Frame design and development

With the help of Solidworks[66], 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 19.

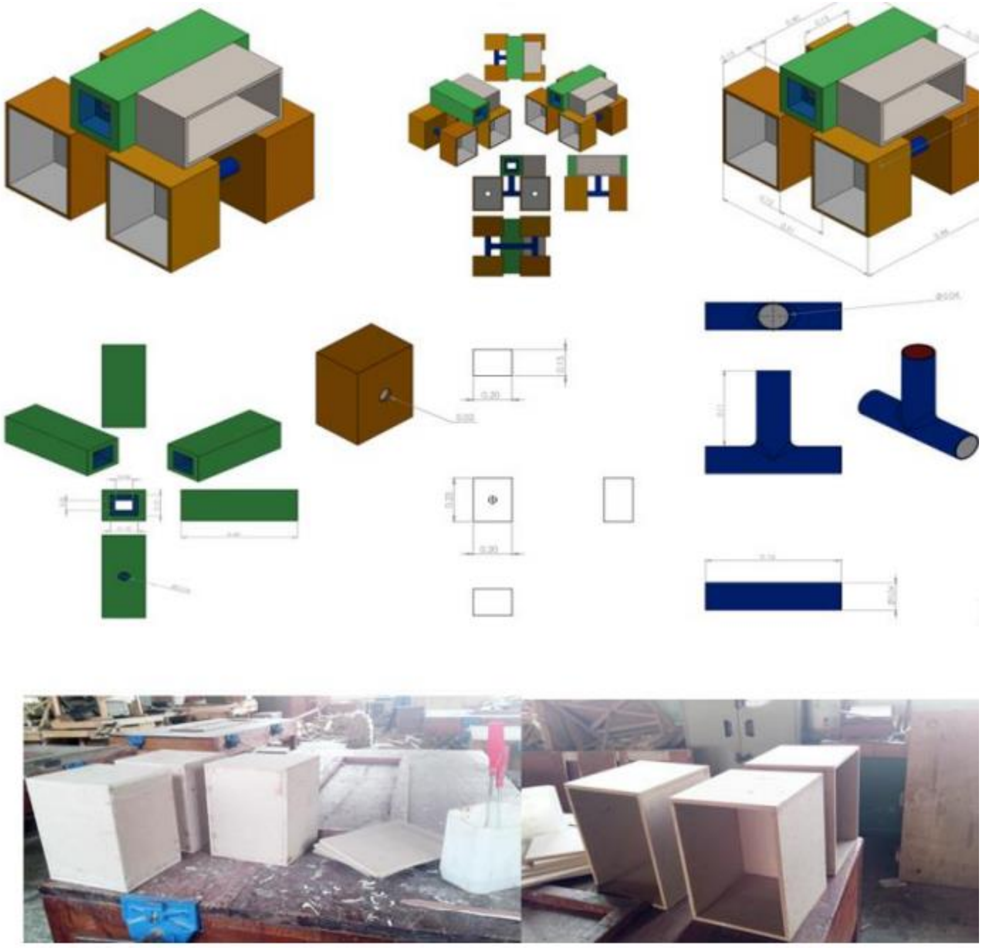

Figure 19: Four chambers fridge design and development

3.3.2. 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[67]. Figure 20 illustrates the schematics circuit diagram that has been used.

Three sensors have been used:

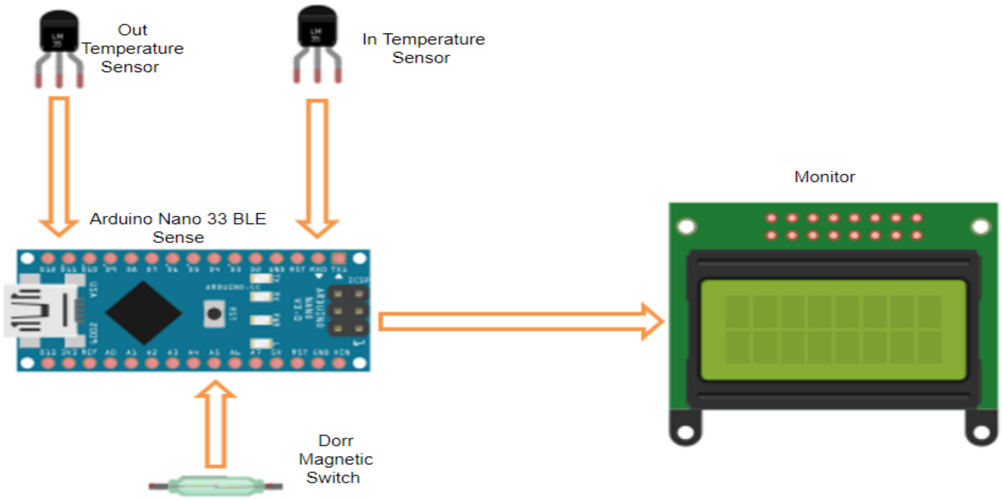

Figure 20: Proposed circuit diagram

A door magnetic switch for getting information about the opening and the closing of the fridge, one temperature sensor for capturing the internal temperature of a particular room, another temperature sensor for capturing the temperature of the surrounding environment, and an LCD screen to display the results from the model as indicated in Figure 21.

3.3.3. 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. Basically, this phase is accomplished through 3 steps:

1. data acquisition (data collection): for this phase, we didn't collect data, rather we uploaded the dataset that we got from our previous work.
2. 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.
3. 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 the door magnetic switch. Figure 21 shows that the regression model has been used in our work.

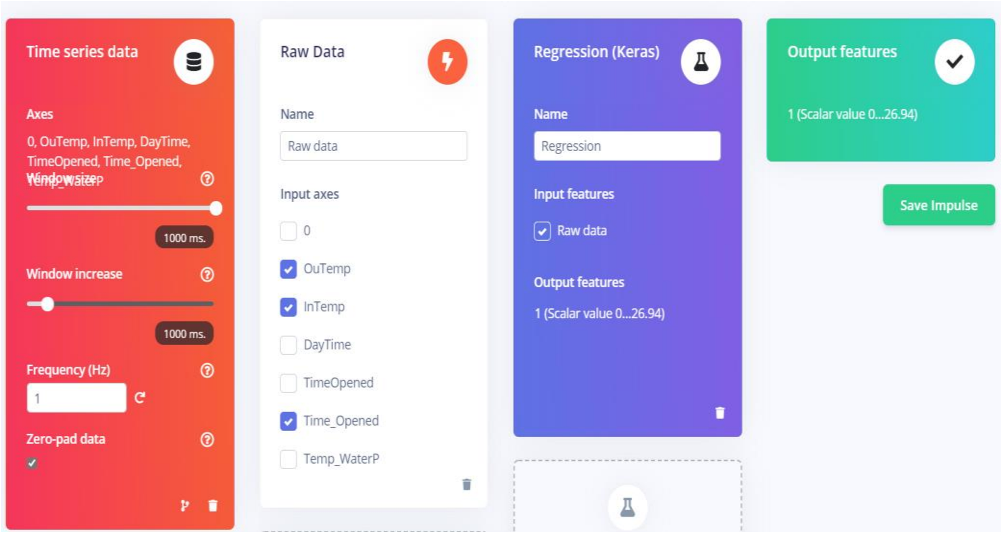

Figure 21: Model training in Edge impulse studio

3.3.3.1 Working principle

After loading the model into the fridge, we tested the working principle as follows: As per Figure 22, 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 into the fridge.

Remember 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 Liquid Cristal Display (LCD) screen. During the testing of our model, we recorded 17 samples.

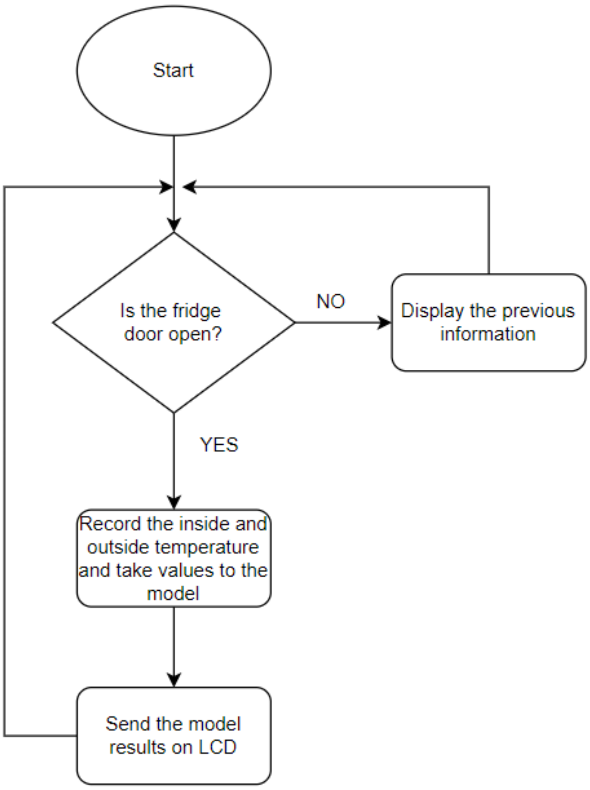

Figure 22: Working principle flowchart

3.4. 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 23, 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.

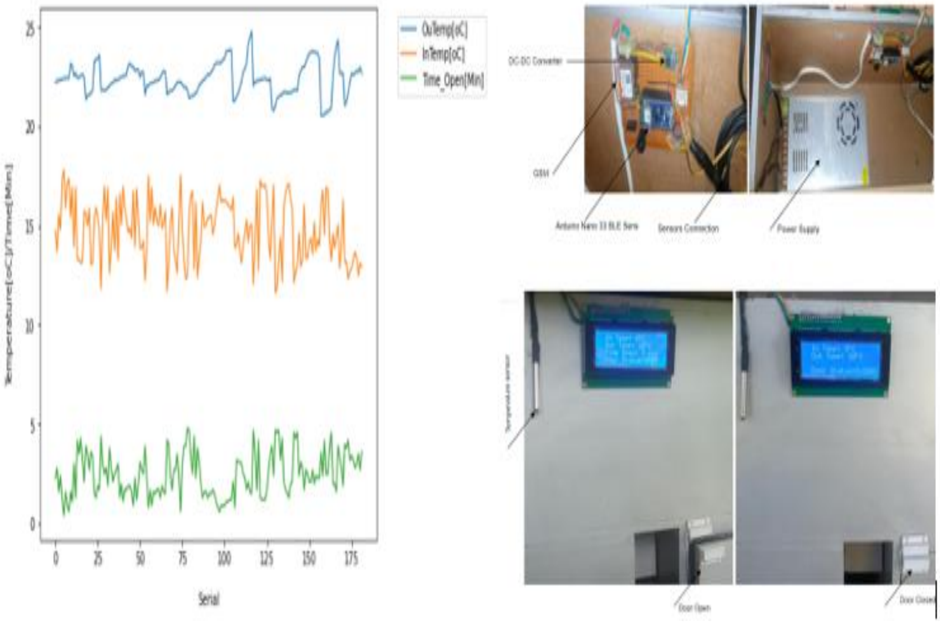

Figure 23: Collected fridge data and the developed fridge

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. 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 24 shows the relationship between recorded data and the true values.

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

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.

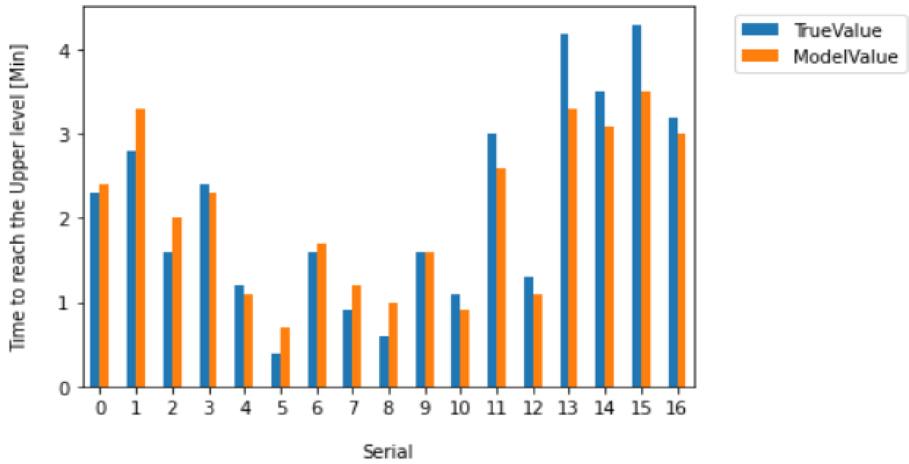

Figure 24: TinyML model accuracy

From Figure 24 and Table 3, it is 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 of this model is about 96%.

3.5. Summary and Limitation

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 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 on 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

During this research work, the developed prototype was made from timbers. This made some difficulties when it comes to heat isolation. We think there was some uncontrolled heat leakage and we think that if the prototype could be made of aluminum metal with good heat isolators, this would improve the accuracy of the developed Arduino library.

Chapter 4: Prologue to Second Article

4.1.Article Details

GPRS Sensor Node Battery Life Span Prediction Based on Received Signal Quality

Habiyaremye, J.; Zennaro, M.; Mikeka, C.; Masabo, E.; Kumaran, S.; Jayavel, K.: Experimental Study. Information 2020, 11, 524. https://doi.org/10.3390/info11110524

Personal contribution: The basic idea of experimental development of a mathematical model that can be used while predicting the life span of a GPRS-based sensor node was generated from my side. I implemented the hardware and software of the sensor node. I did most of the writing with the guidance of Zennnaro. M, Mikeka.C, Kumaran,S , and Jayavel, K

4.2.Context

For almost IoT applications, data from sensor nodes are transmitted to remote databases. The success of this depends on a good plan and installed network infrastructure. Based on the situation, communication protocols such as Lora, Sigfox, ZigBee, and GPRS can be used. As the main purpose of the whole research was to link fridges of pharmacies which are distributed in the whole country. Therefore, the GPRS protocol was chosen as the best communication protocol to be used referring that the GSM network coverage in Rwanda is at 96%. Literature shows that the battery consumption depends on the signal quality (RSSI) in a particular area. Therefore, a mathematical model that can be used for predicting the lifespan of a sensor node that works on GPRS protocol vis-a-vis of the signal quality was proposed.

4.3.Contribution

Sometimes, in IoT applications, sensor nodes are stand-alone units that are running on batteries and those nodes are placed in remote locations where frequent accessibility is limited.
The contribution of this article is the developed mathematical model. This model demonstrates the relationship between power consumption and signal quality in a particular area. The more power is consumed by the node, the more the life span is limited. Therefore, with this model, the battery life span will be monitored which will easier the node maintenance and battery replacement plan.

4.4.Recent Development

Since the development of the aforementioned model, different researchers have improved their research. This is the cause of Debeshi Dutta[68] who proposed a way of monitoring cattle activities by using the GPRS protocol. The same work has been recognized by Ruibiao Chen[69] through his work of developing an efficient user clustering strategy and power allocation design for downlink NOMA systems. The developed model was taken under consideration by Cunwei Yang[70] while developing a model that helps track people during the pandemic through an indoor-outdoor tracking system.

Chapter 5: GPRS Sensor Node Battery Life Span Prediction Based on Received Signal Quality: Experimental Study

5.1.Introduction

The internet of things (IoT) is expected to transform almost countless industries including retail, manufacturing, energy, healthcare, education, and transportation. Before building your first IoT network, you must consider some parameters like the availability of unlicensed frequency and degree of occupancy, availability of service provider, the number of devices to be deployed, number and frequency of message, minimum latency, maximum payload, battery duration, etc. These parameters are the ones to determine the cost of your network [71]. However, the chosen technology will have a big impact on the whole network cost. In Rwanda, especially in Kigali, building a sensor network for IoT applications that can work on technologies like Lora and Sigfox may imply a higher initial cost because of the geographical situation of the country; this will require a lot of base stations or gateways. The GSM cellular network covers 96.4% of the country [72]. This means that any application based on cellular communication will not cost a lot as the network infrastructure is already in place. In this paper, we are trying to work on a GSM/GPRS sensor node that can be used to build a WSN or IoT application in Rwanda, without spending a lot of money and we will try to mathematically demonstrate the impact of received signal strength indicator (RSSI) on the power consumption of GPRS Sensor node which will finally help in estimating battery life span. There is a challenge for sensor nodes supplied by batteries, due to power consumption which will even determine the lifetime of the node and the network in general.

The battery energy is influenced by the operating temperature and the total current consumption of the node[73]; apart from this, sampling rate, signal strengths, and network topology affect the battery life of the sensor node[74], while other researchers found that factors like energy harvesting, energy transfer, energy conservation, and efficient routing techniques can help in prolongation of the lifetime of a sensor node[75], [76]. The big percentage of power consumed by the sensor node is taken by the transceiver or radio section: receiving part 26.67% and the transmitting part 33.3 %. In cellular communication, a mobile phone is communicating with the nearest base transceiver station (BTS); the output power from a mobile phone will depend on received signal strength information (RSSI) at that particular location. If the distance between the mobile phone and the nearest BTS is high, the mobile phone will use a lot of power trying to amplify for getting better reception for that weak signal [77]. On the other hand, if the distance is short the phone will output low power as the signal is strong enough which makes communication easy. The scenario which is happening is almost the same as in human being communication; when someone with whom you are communicating is far away, you will have to use a lot of energy for the communication to be effective and if you are near each other, low energy is used for communication.

The amplification of the received signal does not require any extra battery power but, in the situation when the received signal is weak, the mobile phone will try to boost its transmitter power expecting that it will increase the quality of the signal from the base station. Then the increase in transmitter power will drain the battery more than in a location with good signal quality. A GPRS sensor node is like a mobile phone, it will transmit data through its nearest BTS as it is shown in Figure 24. In this paper, we are trying to show that when our sensor node has poor signal quality it will try to increase its transmitter power for better reception; this will consume a lot of energy from the battery. In the end, we will demonstrate the relationship between the power consumption and the signal quality (RSSI) at a particular location and this relationship will bring us to mathematically estimate the battery life of a GPRS sensor in that region. In this paper, we have tried to record the current consumption of our GPRS sensor node for six different locations with different received signal strength information (RSSI) levels. For each location, we have recorded:

a. Reference current which is the consumed current when the GSM/GPRS module is switched off.
b. GSM current is current when the module is switched ON and connected to the network. And,
c. GPRS current is current when the module is transmitting data to a remote server and the RSSI value. Each of the above parameters has been recorded for 24.

The received strength signal indicator (RSSI) is an important parameter that shows the quality of the signal which is being received by a receiver; this parameter depends mainly on the power which has been transmitted, the distance between the transmitter and receiver, and the medium between the transmitter and receiver[78]. A lot of research has been conducted about the localization of the receiving sensor node using RSSI and some research demonstrated that there is an impact of RSSI on the drainage of the battery. In this paper, we found the mathematical model which shows the effect of the RSSI on the power consumption of a receiving GPRS-based sensor node, and from here we estimated the sensor node lifetime.

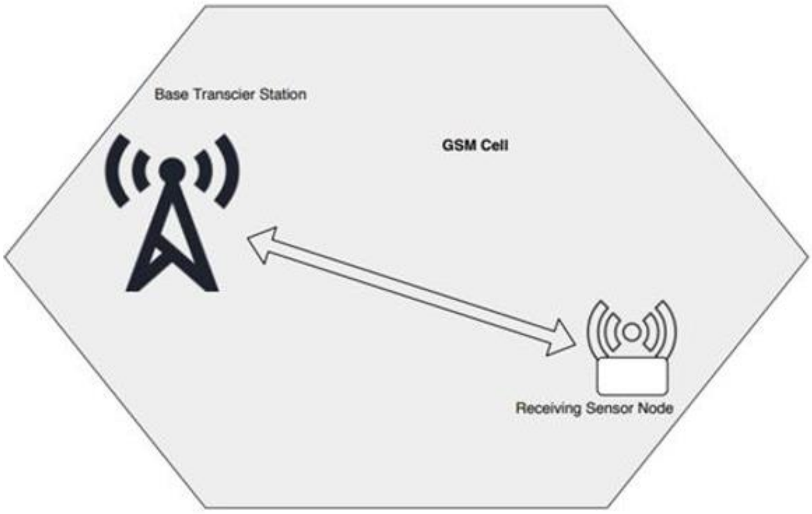

Figure 25: GPRS Sensor node in GSM Cell

In this work, we did our experiment with an IoT application that we can call “Remote temperature monitor (RTM)” which is sending temperature from five different locations to a remote server at a rate of 20 s; we then try to see how this application will consume current in different locations remembering that each location will be defined by its RSSI. Then we used results from our measurement to derive a mathematical model that links the received strength signal information and the sensor node lifetime. With this, it will be possible to quantitatively understand how poor signal quality will reduce the lifetime of a sensor node, especially a GSM-based node.

Basically, we considered our sensor node as a mobile phone with only one application for sending data to the cloud. This can be applied both indoors as well as outdoor. During our modeling, we were supposing that:

1. Our sensor node is not moving,
2. The rate with which the sensor node is transmitting data is fixed, all sensors in the network are not moving, and
3. The sensor node is dead if and only if the battery voltage drops to 70% of its full charged voltage [79]

Our contribution was to develop a data-driven mathematical model that shows the impact of RSSI on the battery life of GPRS/GSM-based sensor nodes in a particular location.

5.2.Related works

The issue of battery and network life span is not new. Researchers have tried to develop some models for data flow, power management schemes, and power harvesting means targeting to prolong the network lifetime. Leonardo, M.[80] and his teams proposed a software-based approach to estimate both the state of charge and the voltage of batteries in WSN nodes based on the use of a temperature-dependent analytical battery model. In the work of [81], they presented a routing technique that enhances the lifetime of a wireless sensor network. Felicia Engmann [82] proposed that power may be harvested by using different technologies such as solar to keep the network alive. Aleksejs Jurenoks [83] have described the conditions of distribution of network nodes that determine coefficients that affect the network lifetime. Karimi[84] have proposed an approach for reducing energy consumption in a WSN based on an enhanced cluster head selection method. For optimizing the energy consumption in WSN, routing protocols can also be adjusted. It is within this regard that Trupti tried to modify LEACH [85] protocol to optimally route data in the network while providing a low power consumption. Apart from the issue of battery life span, researchers also tackled the relationship between battery drainage and RSSI. Lo’ai A. Tawaleh [86], worked on GPS as a location application for a mobile phone and tried to demonstrate that a GPS signal with a higher signal-to-noise ratio SNR means high RSSI consumes less energy while less SNR signals consume a lot of energy. The works in [87] and [88]demonstrated that smartphones express quick battery drains when they are in locations with low signal quality (RSSI) for GSM or WIFI. However, the team was not able to quantitatively bring a relationship between the battery drainage and the signal quality. To the best of our knowledge, this is the only work that brings a mathematical relationship between RSSI and the current consumption of a GPRS sensor node which will help during network planning.

5.3.Material and Methods

In this work, we did three types of experiments: RSSI recording experiment, current consumption recording experiment, and data transmission experiment. We used SIM800L GSM/GPRS module which was supplied from a 12 V DC power source through an MP1584 adjustable step-down DC to DC converter which helped us to get 4.2 V from 12 V and enough current for the module as it can consume up to 2000 mA[89]. Basically, the experimental set-up has two parts as shown in Figure 26.

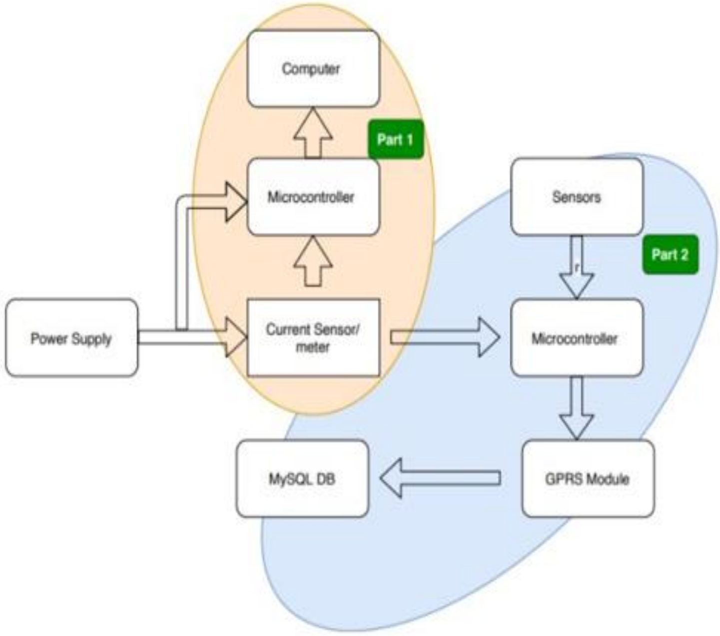

Figure 26: System Block Diagram

5.3.1. Current Measuring: Part 1

This is the part that helped us for acquiring data for being analyzed in Python. It is composed of a second Arduino Uno board and a current sensor, details are shown in Figure 27. With this setup, by using national instrument software Laboratory Virtual Instrumentation Engineering Workbench (LabVIEW) we made a simple program to help us to send data that are coming from the current sensor to an Excel file. From there, data were manually fetched for being analyzed in Python.

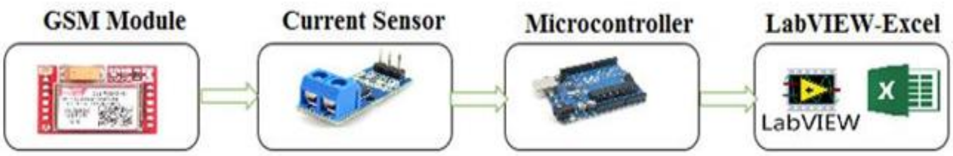

Figure 27: Current Acquisition process

5.3.2. Sensor Node: Part 2

This is the main part of our experiment, which is the one to sense, locally analyze, and send data to a remote database (MySQL DB). It is composed of an Arduino Uno board (Arduino, Turin, Italy) as a microcontroller, sensors (20 K NTC Temperature sensors (JINAN BESTAR INC., Jinan, China)) circuitry, and communication mean (GSM/GPRS Module). The GSM 800L module consumes a maximum of 2 A current so that it can connect to the GSM network with this feature, to supply the module we used an MP1584 (Shenzhen Hengsaisi Technology Co., Ltd., Shenzhen, China) DC-DC converter. Ni LabVIEW[90], is a National Instrument graphical programming language that is mainly used for data acquisition. In the same way, we have used LabVIEW to help us to acquire, display, and send data to Excel. Figure 28 shows that while data are being sent to Excel, they are displayed on the LabVIEW front panel.

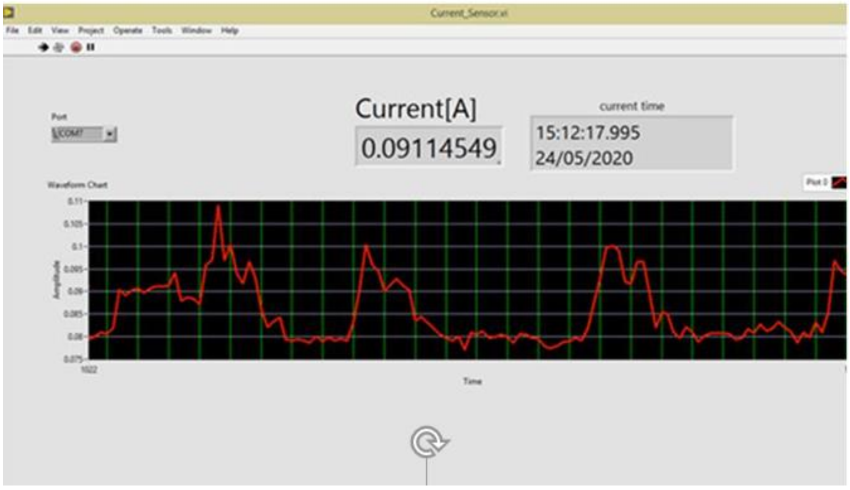

Figure 28: Current Acquisition process, LabVIEW Graph

5.3.3. Important Specification about SIM800L

In this work, the SIM800L (SimCom, Shangai, China) GSM module was used as a radio unit. The following Table 4 indicates some important specifications used in this work.

Table 4: Important GSM 800L Specification

Feature	Implementation
Power supply	3.4 V–4.4 V
Power saving	typical power consumption in sleep mode is 0.7 mA
Transmitting power	Class 4 (2 W) at GSM 850 and EGSM 900, Class 1 (1 W) at DCS 1800 and PCS 1900
GPRS connectivity	GPRS multislot class 12(default), GPRS multislot class 1 12 (option)
Data GPRS	GPRS data uplink transfer: max. 85.6 kbps
SIM interface	Support SIM card: 1.8 V, 3 V
External antenna	Full modem interface with status and control lines, unbalanced,

	asynchronous, 1200 bps to 115,200 bps

5.3.4. Useful AT Command for this Research Work

A microcontroller communicates with the GSM module through some commands known as AT commands. The following Table 4 shows AT commands which have been used in this work.

Table 5: Some AT Commands used in this work

AT Command	Explanations
AT+CREG?	Network registration
AT+SAPBR=3,1,	Connecting to GPRS
AT+SAPBR=1,1	Activation for bear profile
AT+HTTPINIT	Initialization for HTTP Services
AT+HTTPPARA	Set HTTP Parameter values
AT+HTTPACTION	HTTP Method action
AT+HTTPREAD	HTTP Read server response
AT+HTTPTERM	Terminate HTTP Service
AT+CSQ=?	Signal quality report

5.3.5. Battery/Network Life Span

The information about the signal quality in a given area can provide an idea about the energy which is being consumed when the device is trying to connect and send/receive data.

5.3.5.1.Experiment Setup

In this work, we had a target of getting information about the impact of the signal quality represented by received signal quality information (RSSI) on the current consumption of GPRS-based sensor nodes. Our experiment had two main parts: the data acquisition part and the data transmission part. Each part has its own microcontroller. This can be seen in Figure 29 below.

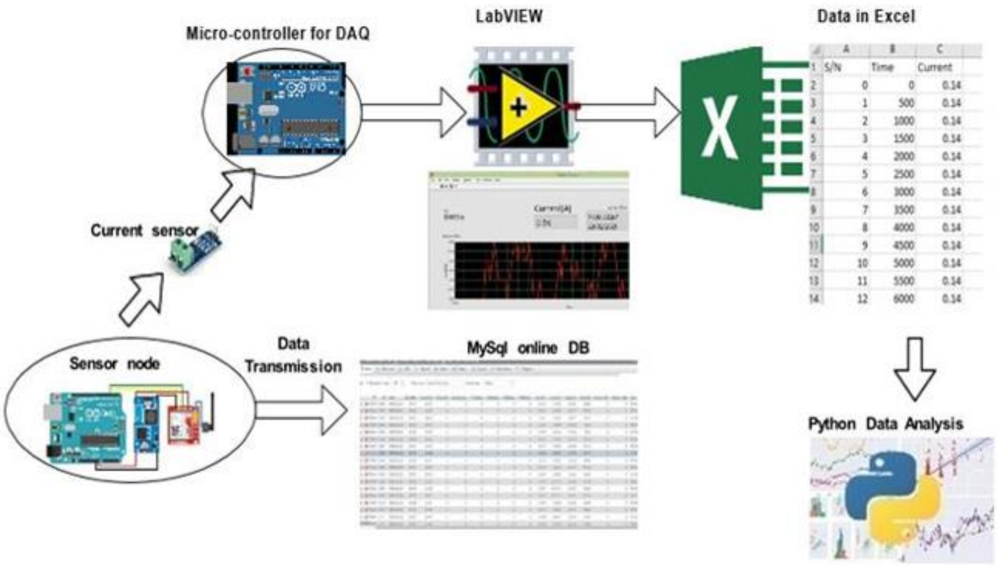

Figure *29*: System Configuration

5.3.5.2.Data Acquisition Part

This is the part in which we collected data about the current consumption for a given location targeting to know the impact of RSSI on the current consumption in that particular area. For the record, we spent 24 h. To achieve this, we used an Arduino Uno-based microcontroller, an ACS712 (Shenzhen Hongxuan Electronic Co., Ltd., Shenzhen, China) current sensor, and Ni LabVIEW[91]. The picture for our experiment is shown in Figure 30.

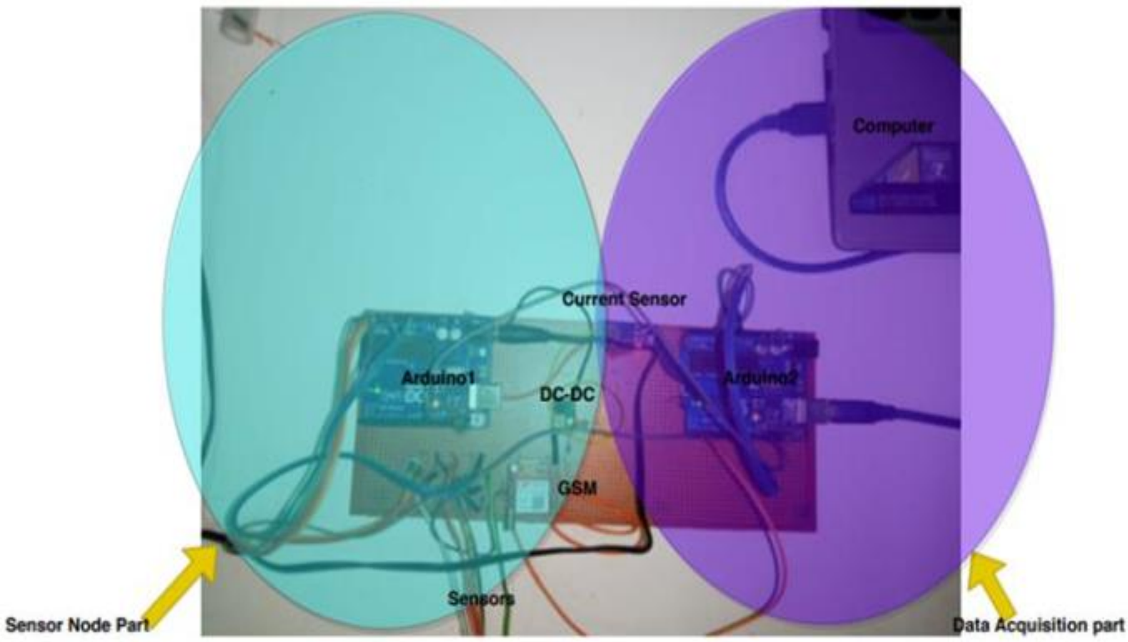

Figure 30: The picture for the experiment's components

Current data from six locations (with their RSSI values) have been recorded considering four different scenarios.

5.3.5.2.1. Scenario1: Reference Current Acquisition

The condition which is taken as reference was a condition when part 2 (sensor node) was powered off. This time, the current sensor recorded some values and these values were considered reference current values. We did this for each location because there could be a few changes in electronic circuitry while moving from one location to another. It is a kind of calibration.

5.3.5.2.2. Scenario2: GSM Current Acquisition

In this scenario, the GSM module was switched ON and it was connected to the GSM network then the corresponding current consumption was recorded too. The current consumed in this situation is the same as the sensing current and the current required for connecting to the network.

5.3.5.2.3. Scenario3: GPRS Current Acquisition

During this step, with the help of AT commands, the microcontroller for the sensor node was programmed for sending temperature data to a remote database every 20 s, then the current consumption for the whole sensor node was recorded. The total current consumed in this situation is the same as the sensing current, the current required for connecting to the network, and the current for sending data to a remote server.

5.3.5.2.4. Scenario4: RRSI Acquisition

Received Signal Strength Indicator (RSSI) indicates the strength of the signal power received by a receiving sensor node. RSSI has many applications in wireless networks including localization[92], [93],[94], as the distance between the transmitting and receiving devices depends on RSSI. In general, when the distance between those two devices increases, the value of RSSI will reduce. The RSSI value depends on a lot of parameters, including the distance between transmitter and receiver, the geometric orientation of sensors, and the environment characteristics such as rain, temperature, and humidity[95]; it can also vary with interference from the neighbor network or your own network[96]. Apart from this, the RSSI varies with the presence of a human being[97]. The quality of a network depends both on the transmitter and the receiver[98]. On the receiving node, RSSI will depend on the power from the transmitter, the sensibility, and the orientation of the antenna toward the transmitter. The information about the received signal power can be calculated by the formulae below[99], [100]:

$$P_r = P_t . G_t . G_r \left(\frac{\partial}{4\pi d}\right)^2 \tag{1}$$

When a signal travel from the transmitting antenna to the receiving antenna, it gets weak due to the distance and obstacles between both antenna. Referring to the reseach in [98] RSSI in dB is generally given by:

$$\mathrm{RSSI[dBm]} = -10\,\mathrm{n}\log(\mathrm{d}) + \mathrm{A} \tag{2}$$

Where:

P_t ,G_t are taken as the power from the transmitter and the antenna gain respectively in dBm,

P_r, G_r: The power for the receiver and its antenna gains respectively,

∂ and d: The signal wavelength and the distance between transmitter and receiver's antennas respectively.

n: the path − loss constant: This value will vary based on obstacles between the transmitter and receiver.

A: the value for RSSI when the distance between the transmitter and receiver is 1m.

If an AT command requesting the signal quality is sent to a GSM SIM 800 Module, the module will respond will TA (Terminal Adaptor) value. The following Table 6 indicates the relationship between the TA value and the RSSI value[101]

Table 6: Mapping between TA value and RSS in dBm

SN	TA Value	RSSI [dBm]	Condition
1	2	109	Marginal
2	3	107	Marginal
3	4	105	Marginal
4	5	103	Marginal
5	6	101	Marginal
6	7	99	Marginal
7	8	97	Marginal
8	9	95	Marginal
9	10	93	OK
10	11	91	OK
11	12	89	OK
12	13	87	OK
13	14	85	OK
14	15	83	Good
15	16	81	Good
16	17	79	Good
17	18	77	Good
18	19	75	Good
19	20	73	Good
20	21	71	Excellent
21	22	69	Excellent
22	23	67	Excellent
23	24	65	Excellent
24	25	63	Excellent
25	26	61	Excellent
26	27	59	Excellent
27	28	57	Excellent
28	29	55	Excellent
29	30	53	Excellent

In our experiment, the GSM module will get a signal from the nearby base station (BTS) of the GSM network. For getting information about the RSSI value at a particular location from BTS, through the microcontroller we sent some AT commands. When AT+CSQ AT command is sent to the GSM module, it will respond with the location's signal quality in the form of TA value. Data information responded by the module is received by the controller and then sent to Microsoft Excel through National Instrument LabVIEW. The acquisition process is shown in Figure 31 and its corresponding LabVIEW dashboard in Figure 32.

Figure 31: RSSI acquisition process

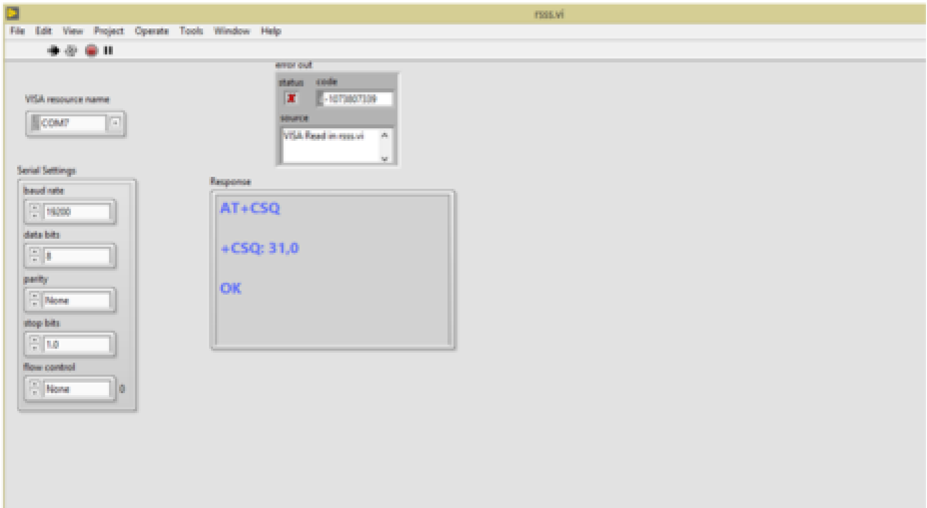

Figure 32: RSSI Acquisition LabVIEW graph

5.3.5.3.Data Transmission Part

This is the part that can even be called a sensor node. It is made with four subparts: microcontroller, GSM/GPRS Module, sensors, and the remote server; the circuit diagram is shown in Figure 33. During this work, we had the idea of sensing the temperature from five different locations and sending them to a remote database using the GPRS protocol. We were sending values every 20 s.

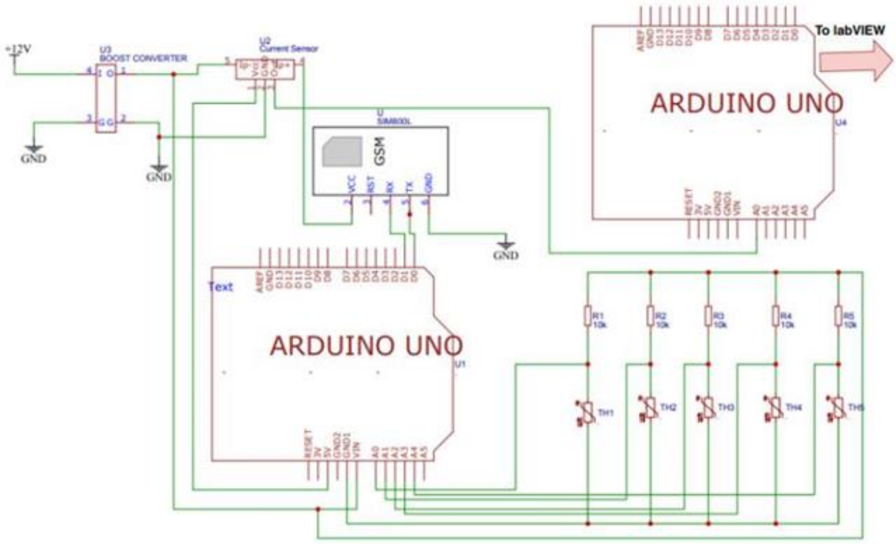

Figure 33: Schematic Diagram

5.4.Data Analysis and Discussion

The power consumption of the radio unit can be in different operating modes: idle mode which is the mode where the device will be consuming very little current and this time the device does not send or receive any data, with one or two active modes depending on the work. The functional block diagram of the sensor node is shown in Figure 35; from this, the total power consumed can be given by the formula below: A node can be given by the formulae below:

$$P_t = P_s + P_{mcr} + P_r \tag{3}$$

Where:
P_t: Is to total power consumed by the sensor node, P_s the total power consumed by the sensor(s),
P_{mcr}: The power consumed by the microcontroller unit and P_r the total power consumed by the radio unit.

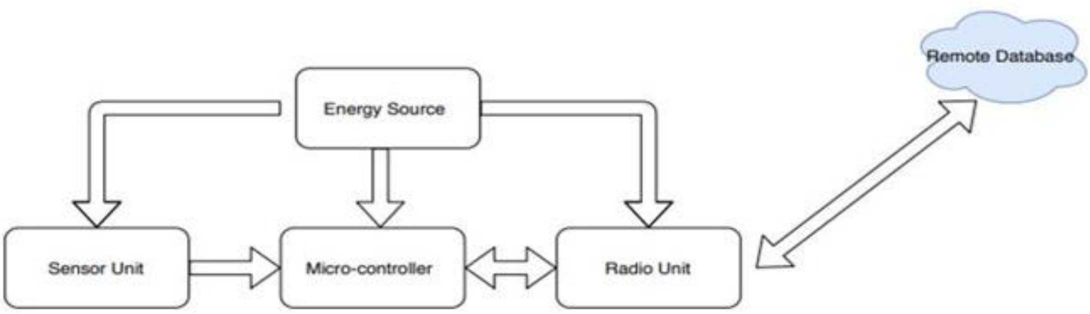

Figure 35: Sensor Node Block Diagram

The radio unit power can also be detailed as follow:

$$P_r = P_i + P_a + P_t \tag{4}$$

Where: P_i is the power when the device is in idle condition, P_a active power, when is ready to transmit/ receive data and P_t the tail power when the module is transmitting/receiving data.

5.4.1. Sensor Node Current States and Transition

A sensor node has three units that consume power: sensing unit, controller unit, and radio unit. The radio unit is the unit which is consuming a lot of power which is equal to 60% (33% for receiving and 27% for transmitting) and the remaining power is used for sensing/acting and processing units. The graph of Figure 36 shows the current transition of our node from the time it is switched on up to the time when it is transmitting data to a remote database. When the node is switched ON, it took around 60 s consuming low power to get ready to connect to the GSM network and this took an average current of 1.1 mA. We found that the module takes 20 s while the jump from the idle state to active mode (the time when the module connects to the GSM network), this transition state consumes an average current of 19.7 mA.

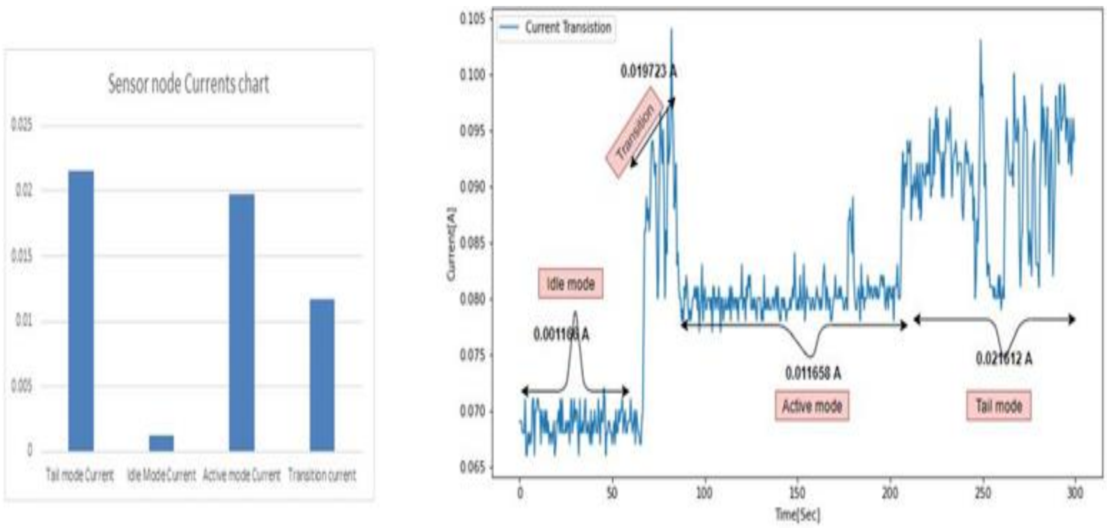

Figure 36: Current transition process and consumption in different modes

It was seen that when the module connects to the network and transmits data at a constant preprogrammed frequency, it will consume an almost constant current and this will change when there is a change in RSSI value. In our experiment, the active mode has the current for GSM and the current for GPRS and the GPRS current will overshoot each 20 s. The graph of Figure 36 has been produced in location 3 where the signal quality RSSI was 83 dBm. The active mode is the mode where the module has received the AT command for data transmission and it is preparing to send data and the tail mode is the mode during which the module is sending data to the remote server.

5.4.2. RSSI vs. Current Consumption

Researchers found that when a GSM module in a GSM network has low signal quality, the module will put a lot of effort into trying to get better signal reception; this will make the module consume more power. The following Table 7 to Table 12 show the impact of the received signal quality on the current consumption of the GSM module. Data have been recorded in six different locations. For each location, we tried to make an average for the consumed current.

Table 7: Current consumption in location 1, where RSSI is 75dBm

No	Time [s]	GSM-Current [A]	GPRS-Current [A]	RSSI [TA]	RSSI [dBm]
1	0	0.011	0.023	19	75
2	0.5	0.013	0.028	20	73
3	1	0.012	0.025	19	75
4	1.5	0.013	0.022	19	75
5	2	0.012	0.016	20	73
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
172,800	86,400	0.01	0.01	19	75
Average		**0.129**	**0.016**	**19.21**	**75**

Table 8: Current consumption in location 2, where RSSI is 83dBm

No	Time [s]	GSM-Current [A]	GPRS-Current [A]	RSSI [TA]	RSSI [dBm]
1	0	0.011	0.021	13	87
2	0.5	0.011	0.019	17	80
3	1	0.011	0.02	18	81
4	1.5	0.014	0.02	18	81
5	2	0.014	0.023	16	79
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
172,800	86,400	0.011	0.016	14	85
Average		**0.011**	**0.017**	**15.20**	**83**

Table 9: Current consumption in location 3, where RSSI is 53dBm

No	**Time [s]**	**GSM-Current [A]**	**GPRS-Current [A]**	**RSSI [TA]**	**RSSI [dBm]**
1	0	0.014	0.009	31	53
2	0.5	0.016	0.008	31	53
3	1	0.011	0.008	31	53
4	1.5	0.015	0.008	31	53
5	2	0.021	0.005	31	53
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
172,800	86,400	0.006	0.009	31	53
Average		**0.006**	**0.008**	**31**	**53**

Table 10: Current consumption in location 4, where RSSI is 73dBm

No	**Time [s]**	**GSM-Current [A]**	**GPRS-Current [A]**	**RSSI [TA]**	**RSSI [dBm]**
1	0	0.011	0.008	19	75
2	0.5	0.007	0.008	18	77
3	1	0.011	0.006	20	73
4	1.5	0.012	0.007	19	75
5	2	0.01	0.007	21	73
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
172,800	86,400	0.008	0.006	21	71
Average		**0.0102**	**0.012**	**20**	**73**

Table 11: Current consumption in location 5, where RSSI is 65dBm

No	**Time [s]**	**GSM-Current [A]**	**GPRS-Current [A]**	**RSSI [TA]**	**RSSI [dBm]**
1	0	0.01	0.011	24	65
2	0.5	0.022	0.009	24	65
3	1	0.028	0.011	24	65
4	1.5	0.031	0.01	24	65
5	2	0.028	0.009	24	65
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
172,800	86,400	0.007	0.009	25	63
Average		**0.010**	**0.013**	**24**	**65**

Table 12: Current consumption in location 6, where RSSI is 63dBm

No	**Time [s]**	**GSM-Current [A]**	**GPRS-Current [A]**	**RSSI [TA]**	**RSSI [dBm]**
1	0	0.015	0.035	26	61
2	0.5	0.022	0.034	26	61
3	1	0.028	0.036	26	61
4	1.5	0.026	0.039	26	61
5	2	0.031	0.034	26	61
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
172,800	86,400	0.087	0.129	25	63
Average		0.058	0.011	25	63

The GSM currents were recorded when the module was connected to the network and by disconnecting the cable which links the module to the microcontroller. This time, the module was not able to receive AT command from the microcontroller. The graphs for all six locations show that the GSM current is almost constant and that the GPRS current changes according to how often data are transmitted. The results from measurements taken from six different locations show that if a GPRS sensor node is located in a place with poor signal quality, the node will consume more current.

Among these six locations, location 2 was the one with poor signal quality (83 dBm) the node was consuming 17 mA, while location 3 was the one with excellent signal reception, where the sensor node was consuming around 9 mA. Considering location 3 and location 6 with 53 dBm and 63 dBm respectively, from those two locations, the results from our experiments show that when the RSSI value reduces by 10 units, the current consumption will increase by 2.91 mA. It can also be seen that between our location with low signal quality (location 2) and location with excellent signal quality (location 3) there is a difference of 30 dBm of RSSI value; this reduction in signal quality made the current double. We observed that on each graph in Figure 37, there is an overshoot each 20 s, at this time the module was receiving a GPRS AT command to send data to a remote database. On the same graphs, we can observe that the GPRS protocol consumes more power than the GSM protocol.

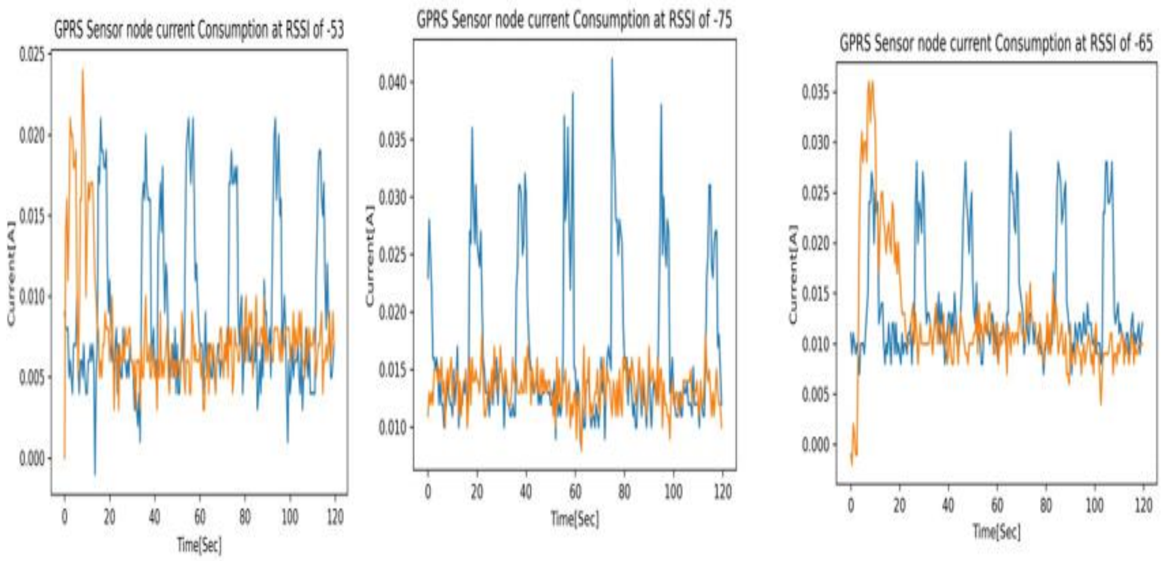

Figure 37: Current consumption vs RS

One of the useful services of the GSM protocol is the transmission of voice which can go to a maximum of 14.4 kbit/s. The GPRS protocol was one of the major developments of the GSM network which can support packet switching techniques to accommodate high-speed data rate and fast data communication which can go up to 170 kbit/s. In our application, there is no voice transmission as there is no microphone or/and speaker connected to the module.

However, the module is transmitting some data to a remote database using GPRS protocol; therefore, the module consumes more power when it is used in GPRS protocol. It has even been proven by Wataru Toorisaka[102]. that the power consumption increases with data rate. The results from Table 13 consolidate all results from six locations and they are plotted in Figure 38.

Table 13: Consolidated data for current consumption for all six locations

Location	Average RSSI [TA]	Average RSSI [dBm]	Average Current [A]
Location 1	19.2	75	0.016
Location 2	15.2	83	0.017
Location 3	30.8	53	0.008
Location 4	24.3	65	0.012
Location 5	19.7	73	0.013
Location 6	25.48	63	0.011

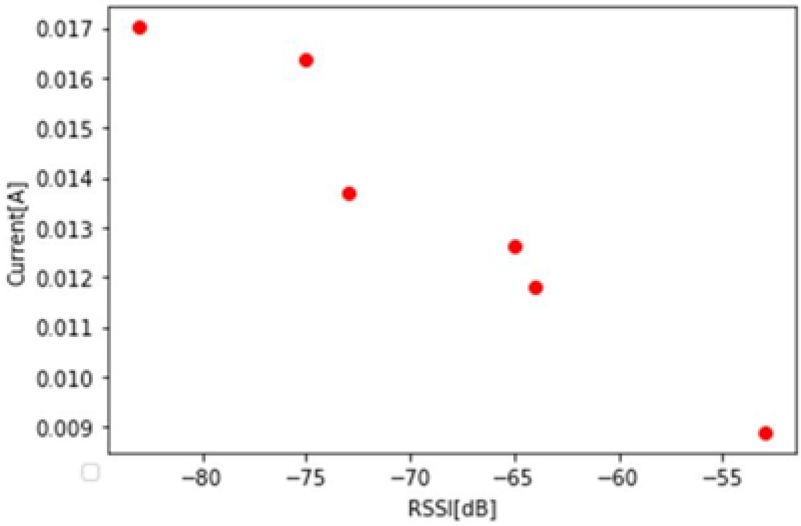

Figure 38: RSSI vs. current consumption

5.4.3. SIM 800L Based Sensor None Life Time Estimation

5.4.3.1.Battery Life Calculation

Even if the RSSI value depends on a lot of factors, when it is measured, we assume that the measured value has been found by taking under consideration its affecting factors. Our data analysis result shows that the average consumption for our sensor node in a particular location depends on the received signal quality at that location; this can be shown in the average currents in Table 7. Considering that our sensor node will be supplied by a small battery of Y Volts with XmAh capacity, let us estimate the lifetime for a sensor node that is working on the GPRS protocol. Considering that Lc is the average load current in Amperes, Bc is the capacity of the battery in mAh, and the battery lifetime in Hours B_l, then the battery life can be given by the battery capacity over the load current.

$$B_l = \frac{Bc}{LC} \tag{5}$$

Based on equation (5), Lc is the total current of the sensor node and is the summation of the current consumed by the sensor unit, microcontroller, and radio unit. Then the equation (5) can be written as:

$$Bl = \frac{Bc}{Cs + Cmr + Cr} \tag{6}$$

Where:
Cs is the sensory unit current, Cmr is the microcontroller current, and Cr is the radio unit current.
In our experiment, we recorded the current consumption of the radio unit and as we recorded for 24 hours for each location, we are considering the average current for each location so, Cr, the radio unit can have found using the following formula

$$Cr = \frac{\sum_{n}^{K} o^{i}}{k} \tag{7}$$

Where:
Cr is the average radio consumption current at a particular location, k number of measurements, and I the instantaneous current.
During our experiment, we use to record data for 24 hours with a waiting time of 500 ms, then we made 172800 measurements for the whole day. Then referring to the eq. 7, $k = 172800$ and from table 13, we have Pr from six different locations.

Average currents in six different locations are summarized below:
Current for Location 1 = 0.016A
Current for Location 2 = 0.017A
Current for Location 3 = 0.008A
Current for Location 4 = 0.012A
Current for Location 5= 0.013A
Current for Location 6 = 0.011A

5.4.3.2.Battery Life Prediction Model for SIM800L Sensor Node

While planning for the development of an IoT network it is necessary to estimate the duration of each network node so that the time on which the battery will be replaced shall be known. It has been found that the GPRS sensor node consumes more power when it is located in a location with bad signal quality and consumes low power when it is located in a location with good signal quality. In this section, we are trying to find a mathematical relationship between the current consumption for a GPRS sensor node at a particular location with the received signal quality.

From Figure 38, the relationship between the current and RSSI seems to exponentially decay. So, it can be written using the following equation. In this case, the current consumption is the independent variable while the signal quality RSSI is the predictive variable or independent variable and this can be expressed by the following equation:

$$Y = Ae^{r\sigma} \tag{8}$$

Where:
Y: The average current consumption
A: an initial value and have to be greater than zero
r: a decal rate and have to be negative
σ: the signal quality or RSSI

The analytical solution for the eq. (8) can be written as:

$$y = a + \frac{b}{\sigma} + c * \ln(\sigma) \tag{9}$$

In trying to find a mathematical relationship between the current consumption of a GPRS sensor node with respect to the location where it is placed, we used Python APM (advanced Process Monitor) through its interface GEKKO which is a Python library for machine learning and optimization of mixed-integer and differential equations. We found the solution for Equation (9) as:

a = 0.085966482761
b =0.19094884551
c =0.020681155519

In the end, we tried to calculate the coefficient of determination R^2 to see how our measured data fit our model and the value of R^2 was found to be 0.9231243723176469 which is tending to be a unit. This shows that our model is somehow accurate. So, Equation (6) can be written as:

$$y = 0.085966482761 - \frac{0.19094884551}{\sigma} - 0.020681155519 * \ln(\sigma) \tag{10}$$

By combining equation (10) and equation (5) and considering that $y = Cr$(the average current consumed by the radio unit, equation (5) can be written as:

$$Bl = \frac{Bc}{Cs + Cmr + 0.0855966482761 - \frac{0.1909488455}{\sigma} - 0.020681155519 * \ln(\sigma)} \tag{11}$$

Where:

Bl: Battery life in Hours
Bc: battery capacity in mAh
α: the received Signal Stheignth Information RSSI in dB
Cs, Cmr: the current consumption for sensor circuitry and microcontroller respectively

Considering that the current consumption for the sensory circuitry and the current consumed by the microcontroller is known, Equation (11) can be considered as our mathematical model which can even help in estimating how long a GPRS sensor node with SIM800L will live at a particular location with known signal quality. The representation of the above equation is shown in Figure 39 below.

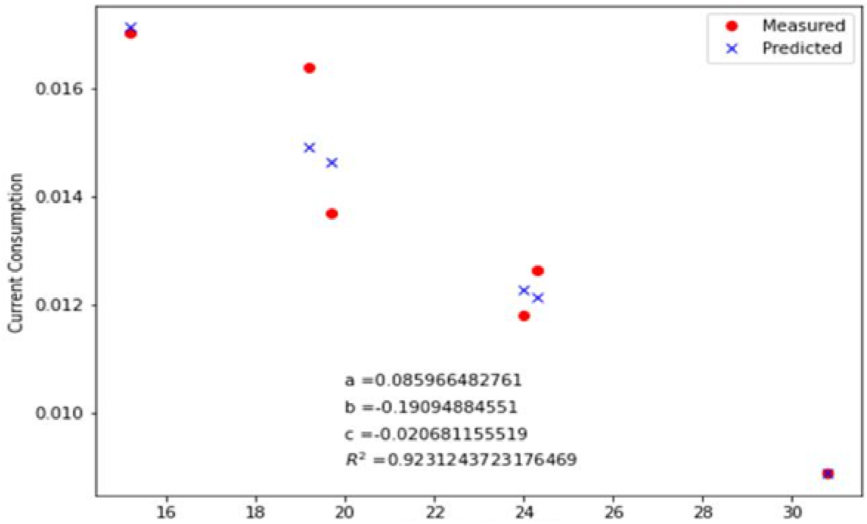

Figure 39: Mathematical Model

5.5.Summary and Limitation

The results from our experiments show the GSM/GPRS sensor node consumes current in the mA range; this current is not small in WSN or IoT applications. However, in an area like Kigali, Rwanda a country with a lot of hills where the geographical structure does not allow line of sight communication, building a network using low-power sensor nodes like Lora or Sigfox will cost a lot due to a lot of gateways. So, in applications where the line of sight is difficult to achieve and where the GSM network is already in place, GPRS sensor nodes can be used and the cost of building a network will not be expensive as the GSM network is already in place. The quantitative model developed in this paper will help sensor nodes supplied with batteries as it is possible to know how long a battery will last if the information about the signal quality is known and this will finally help to predict when a battery can be replaced. This work has been completed using the GSM module. However, we recommend for future work that a model like the one found in Equation (11) can be found for other modules such as LoRa and Sigfox using the same procedures.

This research outcome will help to predict GPRS sensor node life, replacement intervals, and dynamic handover which will in turn provide uninterrupted data service. This model can be deployed in various remote WSN and IoT-based applications like forests, volcanoes, etc. Our research has shown convincing results like when there is a reduction of −30 dBm in RSSI, the current consumption of the radio unit of the node will double. This research work has been conducted during the time of Covid-19, at this time we were in total lockdown, this made us collect information about RSSI and their corresponding power consumption in a single multi-story building. This study could be improved if data from hill areas are also collected.

Chapter 6: Prologue to Third Article

6.1. Article Details

A Data-Driven Predictive Machine Learning Model for Efficiently Storing Temperature-Sensitive Medical Products, Such as Vaccines: Case Study: Pharmacies in Rwanda.

Habiyaremye.J, Zennaro.M ,Mikeka.C, Masabo.E, Jayavel.K, Santhi.K Journal of healthcare engineering. 2021. 9990552. https://doi.org/10.1155/2021/9990552.

Personal contribution: The idea of experimental development of a Data-Driven Predictive Machine Learning Model for Efficiently Storing Temperature-Sensitive Medical Products, Such as Vaccines was my initiative. Tuning it for monitoring the frequency of opening the fridge was initiated and guided by Zennaro. M. I implemented the hardware and software related to the developed fridge. I did most of the writing with the guidance of Zennaro. M, Mikeka.C, Kumaran,S , and Jayavel.

6.2.Context

In Rwanda, each pharmacy has a refrigerator for keeping temperature-sensitive medical products. During medicine selling, a pharmacist will frequently open and close the refrigerator while picking up needed medicine. This activity will make some fluctuation in temperature. In this article, we proposed an IoT smart fridge with which it is possible to monitor the impact of frequently opening and closing the fridge to its internal temperature.

6.3.Contribution

The general contribution of this article is the developed machine learning model. This model can be used for internet of things-based refrigerators that are storing temperature-sensitive products. The developed model has been found to have an accuracy of 77 %. This model is based on a multivariate linear regression algorithm.

6.4.Recent Development

The linear regression model specifically multivariate regression has been used by many researchers. This machine learning algorithm is commonly used when there are tasks that have some prediction requirements. It is in the same way that we have chosen it for our application of controlling and monitoring the pharmaceutical products' cold chain.

Chapter 7: A Data-Driven Predictive Machine Learning Model for Efficiently Storing Temperature-Sensitive Medical products, such as Vaccines: Case Study: Pharmacies in Rwanda

7.1. Introduction

In Rwanda, medicines and even some types of vaccines are being sold in pharmacies. Medical products are stored based on their storage conditions, such as temperature, light, and humidity[103]. Some medicines are stored at room temperature, in a freezer, or refrigerator. Vaccines are mainly used to be kept at a temperature between 2 and 8 degrees Celcius[104]. When a client or patient approaches a pharmacy seeking a vaccine or another medical product that is kept in the fridge, someone who is managing the pharmacy will open the fridge to pick up the requested product. When the fridge is opened, the outside hot air will enter the fridge, making the inner side of the fridge gains temperature and lose coldness[105]. If the frequency of opening and closing of the fridge increases, the inner temperature might go beyond the acceptable storage range, and this may lead to the inefficacy of the stored medical products[106].

In this work, we proposed a predictive model that can be embedded in a fridge with multiple chambers to keep displaying the remaining time slot for every chamber to reach the cut-off temperature (the upper-temperature range). In this work, we assumed that the fridge contains only products with identical storage conditions. This model uses historical data about how long it takes for the temperature to go beyond the acceptable range when the fridge is opened, the initial inner temperature of the fridge at the time of opening, the outside temperature at the opening time, and the time of the day at which the fridge got opened. To get training data for our model, we have developed a fridge using Peltier cooler kits, a microcontroller, temperature sensors, and magnetic switches.

Data generated from the fridge were sent to a remote database through GPRS protocol. We randomly opened the fridge simulating the way the fridge is being opened while picking up medicines in pharmacies, but that time we opened the fridge and waited for the inner temperature to rise and reach the maximum allowed storage temperature for the medicine under consideration, then we recorded the initial opening temperature (the temperature at opening time), the outside temperature, the time taken for the temperature to reach the maximum allowed temperature, and the time of the day at which the fridge got opened. Data were manually fetched from the database and then used for model training and other analysis. Our contribution was to propose a machine learning model which is based on linear regression with multiple variables that can be embedded in a fridge (multi chambers fridge) to make it enough intelligent for monitoring the opening and closing of the door for proper storage of temperature-sensitive products such as vaccines.

7.2.Related work

This section summarizes some works related to smart fridges. A lot of researchers proposed fridges that can be remotely monitored with the help of the Internet of things, a fridge that can help in monitoring the expiration date of refrigerated products, and others proposed fridges that can help in the management of food wastage. Livingston[107] proposed a smart home fridge (that keeps vaccines) that is programmed in a way that it will keep monitoring the action of opening and closing the door to check if the patient is regularly taking medicines, considering that he/she is taking medicine at regularly known intervals of time. If the fridge is not opened at the corresponding time, it will send some notification to the doctor or a family member. The article [108] details an IoT-based fridge where it can be seen from a remote area if vaccines are stored at the right temperature. The article in[109] talks about an intelligent fridge that gives alerts when there was a power failure, fridge failure, or even when the door was left open. Weka[110] solutions developed an IoT platform (Azure IoT Platform) that collects data from sensors from the vaccine fridge in a real-time manner and this fridge is working on Raspberry Pi 2. Works of [111], [112] proposed a smart fridge from which it is possible to get information about products remaining inside and it is possible to know the status of its door with the help of RFID technology[113]. The research work in [114] proposes a medical fridge to improve the healthcare system by using the barcode reader system. The system scans the barcode for each medicine to keep tracking the expiration date. It also has a camera to keep monitoring the fridge content and this can be done from remote locations. Articles in [115], [116]–[118] worked on a refrigerator that is based on IoT for remotely monitoring different parameters in real-time mode. Articles in [119], [120] proposed different methods related to the smart refrigerator for avoiding food wastage in a fridge. When it comes to remote control or monitoring of patient-related items through the Internet, security must be taken under consideration even if it is not directly related to the current work, but we have decided to incorporate the security aspect as part of our future works. In the following works, the authors elaborated on different important security aspects that can be used in IoT systems.

The work in [121] proposed security aspects that can be considered in the term of the Internet of Medical)Things (IoMT); this can be used in our medical fridge too. In the article [122], a blockchain-based security mechanism is explained, though the application is used for verification in a smart city context. This also serves as an inspiration to add security aspects to our medical fridge in terms of blockchain-enabled technology. The work in [123] discussed the concept of a Cache Distributed System, with the help of two servers, one Cloud server, and an Edge Server. This emphasizes the importance of incorporating 6G in cases that involve big data. This can also be applied in our case as well. On the fridge side, some authentication can also be added so that it could be accessed by only individuals for better and safer handling. The work in[124] gives some details on how security can be achieved by fingerprint images with an optimal compression ratio. To the best of our knowledge, this is the only research work that proposes a machine learning model to be embedded in a medical multi-chambers fridge to help pharmacists to achieve an efficient way of storing medical products by predicting the remaining time for a particular chamber to go beyond the accepted storage temperature.

7.3.Proposed model

To efficiently manage the storage of medicines, especially temperature-sensitive products, such as vaccines. We propose a multiple chamber fridge with an embedded controller that can run a predictive machine learning model. The proposed model is shown in Figure 40.

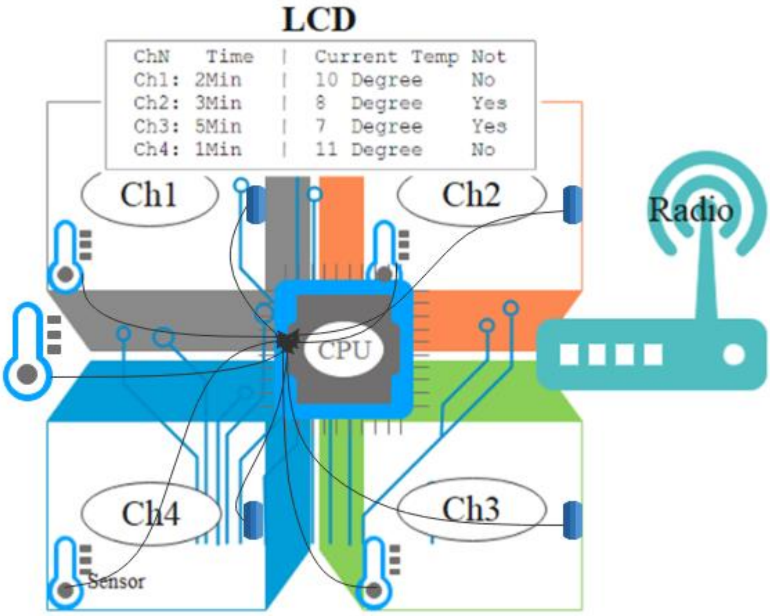

Figure 40: Proposed fridge

From the above figure, the proposed fridge has multiple rooms (four in our case). Each room has an inside temperature sensor to keep monitoring the temperature, a door magnetic sensor to get information about the door condition (closed or opened), and an outside temperature sensor (common for all rooms). The fridge has also a screen from which a user can see different room conditions including the current room temperature, the room door status, and the time remaining for each room to get the cut-off temperature (the maximum allowed temperature). Apart from that, the fridge has a GSM modem that is transmitting data to a remote database for remote monitoring or for saving data for further research.

From our experiments, we found that the time to cut-off temperature depends on:

1. The initial room temperature (the temperature at the opening time). If this temperature is high (approaching the cut-off temperature), the time to cut-off temperature will be short.
2. The time of the day. Particularly, in Rwanda, the temperature will increase with time especially when we have a sunny day. During the morning time, it is somehow cold and the temperature rises over time and starts reducing by evening time. This temperature change will have some impact on the inner fridge temperature due to heat transfer through fridge walls.
3. The outside air temperature.

In addition to the above parameters, it is clear that this time slot depends even on the angle at which the fridge is being opened and the outside atmospheric pressure. However, in our experiments, we have ignored the impact of atmospheric pressure, and we have kept the opening angle constant. We propose that when the pharmacist wants to pick a vaccine, he/she will first take a look at the display to check which room has a long time. If the time to cut off temperature is found to be short, the pharmacist can even wait for some time. The process can be explained with the flowchart of Figure 41.

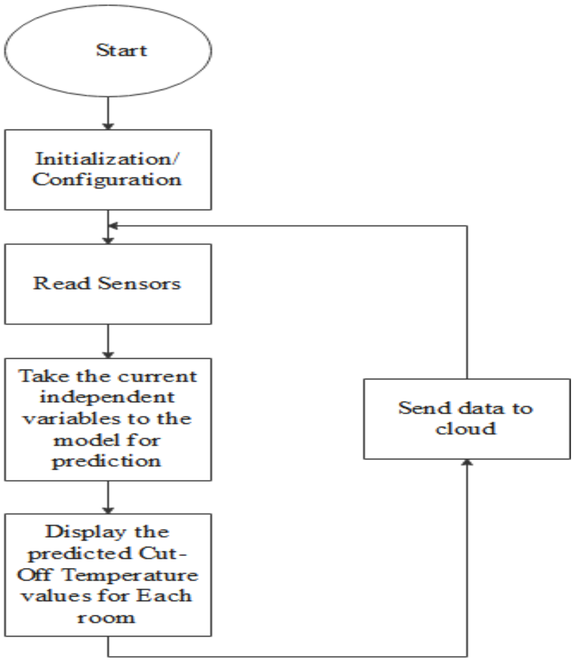

Figure 41:Proposed model flow chart

7.4.Materials and Methods

During our research work, we tried to generate data to be used for model training. The following section gives all details about how we got the data that have been used.

7.4.1.Single room fridge development

To generate data, we built a four-chamber fridge, Figure 42, and from this fridge, we did our study on one of the chamber this fridge (the main chamber).

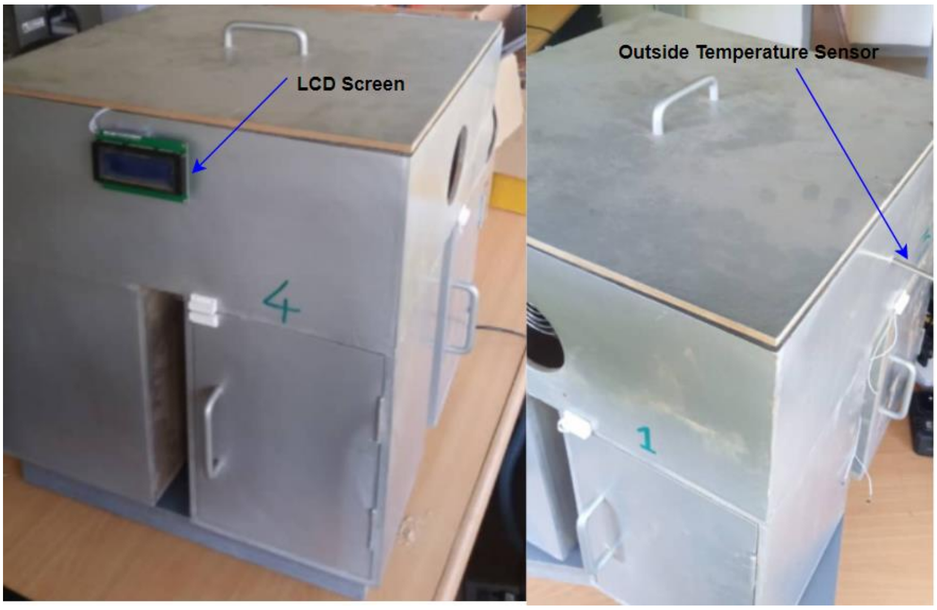

Figure 42: The Developed Four Chamber fridge

The cooling system for this fridge is made of thermoelectric coolers[125] [126]. Each of the four rooms in our fridge has an inside temperature sensor and a door magnetic switch to know if a particular room is open or closed. Apart from this, there is an outside temperature sensor to get information about the outside environment temperature. The details about the fridge construction are shown in Figure 43.

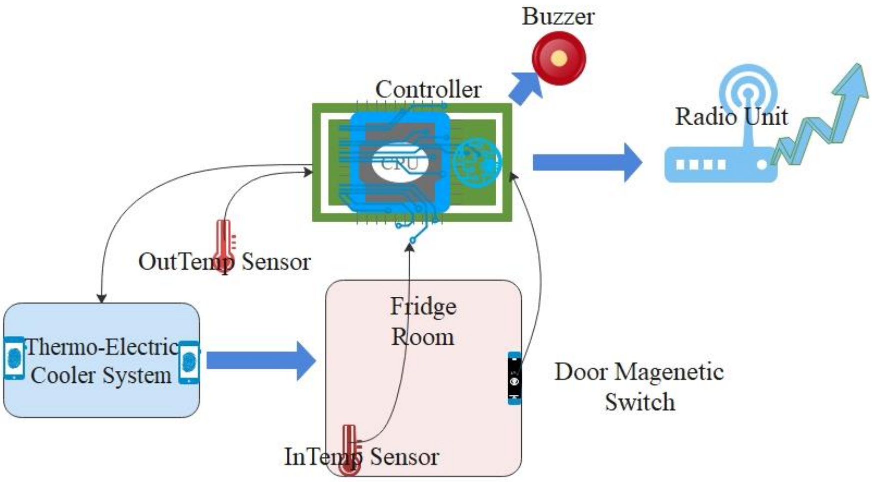

Figure 43: Data generation system diagram

7.4.2.Fridge Components

To generate data to be used for model training, an electronically controlled fridge that is made from thermoelectric technology was developed. The fridge has two main components:

7.4.2.1.Thermo-electric cooler system

This is the part that generates cooling. It is made of a combination of two fans, a heat sink, and a TEC device. In short, when a TEC device is supplied by a DC voltage, one side will be hot while another one will be cold. To bring the generated low temperature to our room/chamber, we used one fan and another fan was used to take out the generated high temperature. The cooling room is made up of two TEC kits, one on the left side and another is on the right side. Details can be seen in Figure 44.

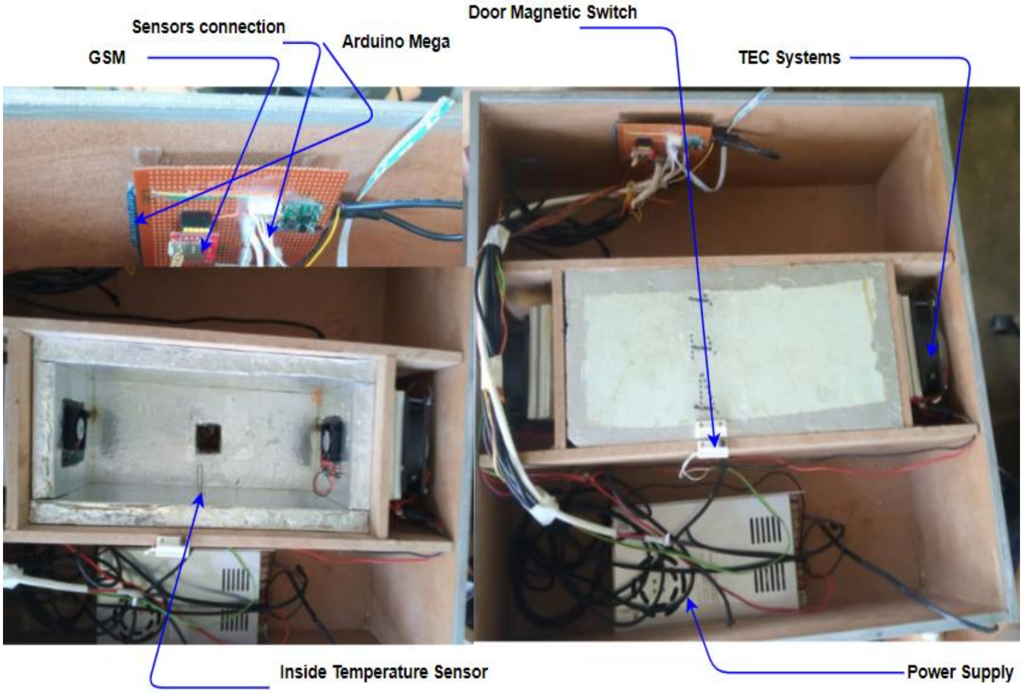

Figure 44: Fridge components & data generation details

7.4.2.2.Controller and radio unit

The cooling system (TEC Systems) and fridge systems are controlled by Arduino Mega (Arduino, Turin, Italy) through temperature and door magnetic sensors. The radio unit is made by a SIM800L (SimCom, Shangai, China) which is transmitting data to a remote database through GPRS protocol from where data are manually downloaded in CSV format for model training purposes. The controller was programmed to read sensors (temperature and door magnetic switch) and count the time passed when a particular door is opened and finally send this data to the GSM modem.

7.4.3.Data generation

As our target was to know the impact of opening and closing the fridge while picking some medicines, the data generated from this fridge were sent to a remote database for storage as this was our easiest method of saving data. This work is a small portion of the other research work which is under progress where we monitor and control a four-chamber fridge with the help of the Internet of Things. However, in this work, we only work with data from a single room, Figure 45 gives details on how data are generated and transmitted to the remote database.We simulated the process of opening and closing the medical fridge by the pharmacist while picking medicines. The constructed fridge was able to reduce the fridge room temperature up to 9 Celcius degrees.

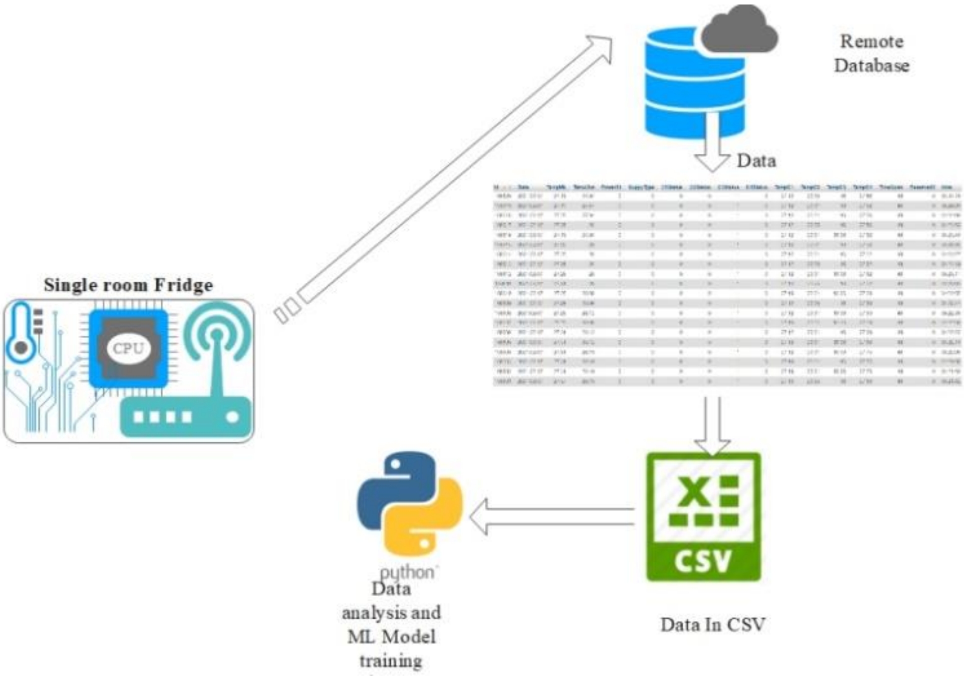

Figure 45: Data generation process

To achieve our simulation, we considered a temperature range of 10-18 degrees. We could take a normal vaccine range (2-8 Celcius degrees), however, our cooling system could not help) and used to randomly open and wait for the chamber temperature to hit up range (18 Celcius degrees), if the upper acceptable temperature is reached, the buzzer used to ring, then we used to close the door and wait for some random time and repeat the operation. The figure of Figure 46 shows the flowchart that indicates the way we generated data.

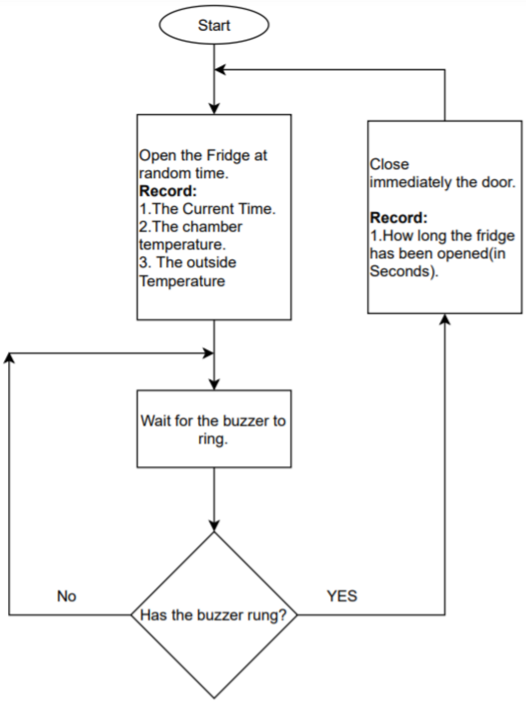

Figure 46: Training mode data generation flow chart

Generally, we send the status of the door (open or closed), the chamber temperature, the outside temperature, how long the chamber has been opened (in the case is opened), and the time stamp.

7.4.5.Model training

To find a relationship between independent variables (outside temperature, inside chamber temperature, and the time of the day) and the dependent variables (the time to be taken to reach the upper acceptable temperature), we used linear regression with multiple variables also known as multivariate regression. The following figure, Figure 47, shows the relationship between different parameters used in our model: The outside temperature (OuTemp), inside temperature (InTemp), the time day (Day_Time), and the time during which the fridge has been opened for reaching the cut-off temperature (Time_Opened_Min).

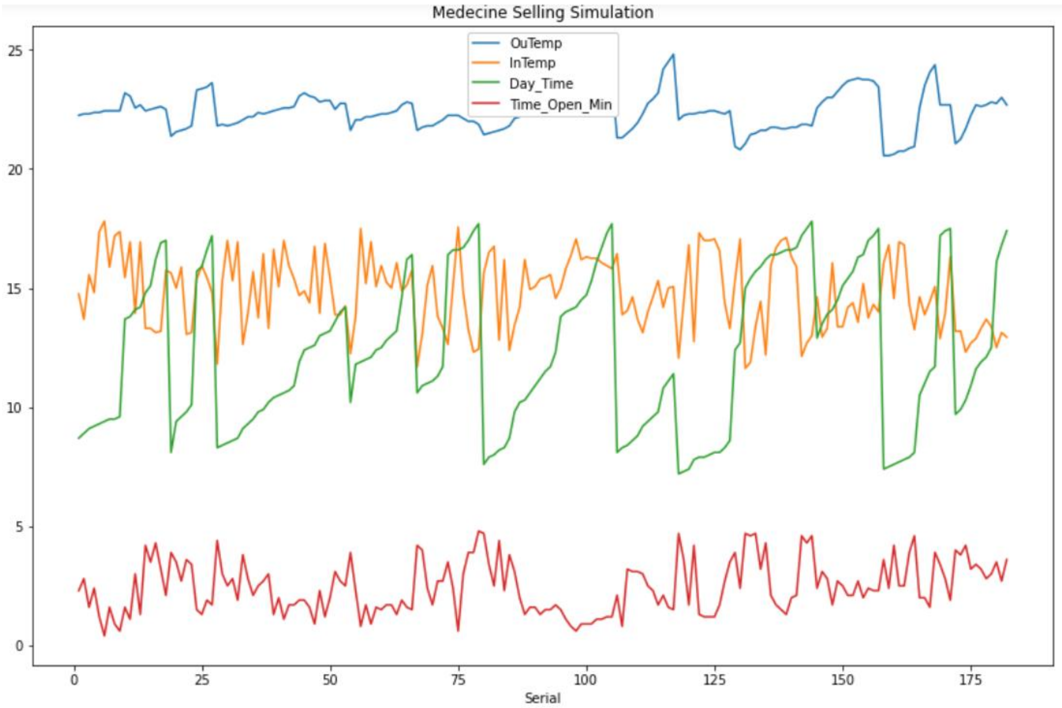

Figure 47: Relationship between variables under consideration

The inside temperature, outside temperature, and daytime are taken as independent variables, and the time required for the room temperature to reach the cut-off temperature is taken as the dependent variable. Variables to predict the time to cut-off temperature are explained in Table 14 and the statistics details of the variables are shown in Table 15.

Table 14: Explanatory variables considered in the regression model

Variables	**Description**	**Units**
OuTemp	The outside temperature at opening time	[° C]
InTemp	The inside room temperature at opening time	[° C]
DayTime	The daytime at the time of fridge opening	[Hours]

Table 15: Descriptive statistics of independent variables

Independent Variables	TempOut[° C]	InTemp [° C]	Day_Hour
Mean	22.4	14.9	12.24
Std	0.79	1.52	3.24
Min	20.56	11.63	7.2
Max	24.8	17.81	17.8

The linear regression with multiples features equation can be written as:

$$T_{cut-off} = m_1 * OuTemp + m_2 * InTemp + m_3 * DayTime + \beta \tag{12}$$

Where:
$T_{cut-off}$: the time required for the room temperature to hit the upper-temperature range.
OuTemp: The outside temperature.
InTemp: Inside temperature.
DayTime: daytime.
m_n : Coefficient.
β: the intercept.

7.4.6.Data preprocessing

While sending data to a remote server, the server was used to provide a timestamp in HH:MM: SS XM format means a 12H system, to easily use a timestamp in our model, we converted it to HH:MM: SS means a 24H system. Our target was to count a day from the 1st hour to the 24th hour and consider that hours of a day can impact the model differently. The following tables indicate only ten rows of our dataset. Apart from the timestamp, the period in which the fridge got opened has been considered in minutes. Details about how the data have been converted before being used for model training are shown in Table 16 and Table 17.

Table 16: Initial data: Before preprocessing

OuTemp [° C]	InTemp [° C]	Time_Open[Sec]	Time_Stamp
22.25	14.75	136	8:39:10
22.31	13.69	168	8:54:45
22.31	15.56	95	9:03:33
22.37	14.81	144	9:14:32
22.37	17.37	71	9:19:08
22.44	17.81	22	9:21:19
22.44	15.88	95	9:27:00
22.44	17.19	54	9:31:28

22.44	17.37	38	9:35:16
23.19	15.44	95	1:41:38

Table 17: Final data. After preprocessing

OuTemp [° C]	InTemp [° C]	Time_Open [Sec]	Time_Open [Min]	Time [12H]	Time [24H]	Day_ Hour
22.25	14.75	136	2.3	8:39:10	8:39:10	8.7
22.31	13.69	168	2.8	8:54:45	8:54:45	8.9
22.31	15.56	95	1.6	9:03:33	9:03:33	9.1
22.37	14.81	144	2.4	9:14:32	9:14:32	9.2
22.37	17.37	71	1.2	9:19:08	9:19:08	9.3
22.44	17.81	22	0.4	9:21:19	9:21:19	9.4
22.44	15.88	95	1.6	9:27:00	9:27:00	9.5
22.44	17.19	54	0.9	9:31:28	9:31:28	9.5
22.44	17.37	38	0.6	9:35:16	9:35:16	9.6
23.19	15.44	95	1.6	1:41:38	13:41:38	13.7

7.5. Results and Discussion

During our experiment, we recorded the data for 3 months. However, we simulated the selling process for 12 days. Figure 48 gives details about the different results. From these figures, we can easily see that the process of opening and closing a fridge has a big impact on the chamber temperature.

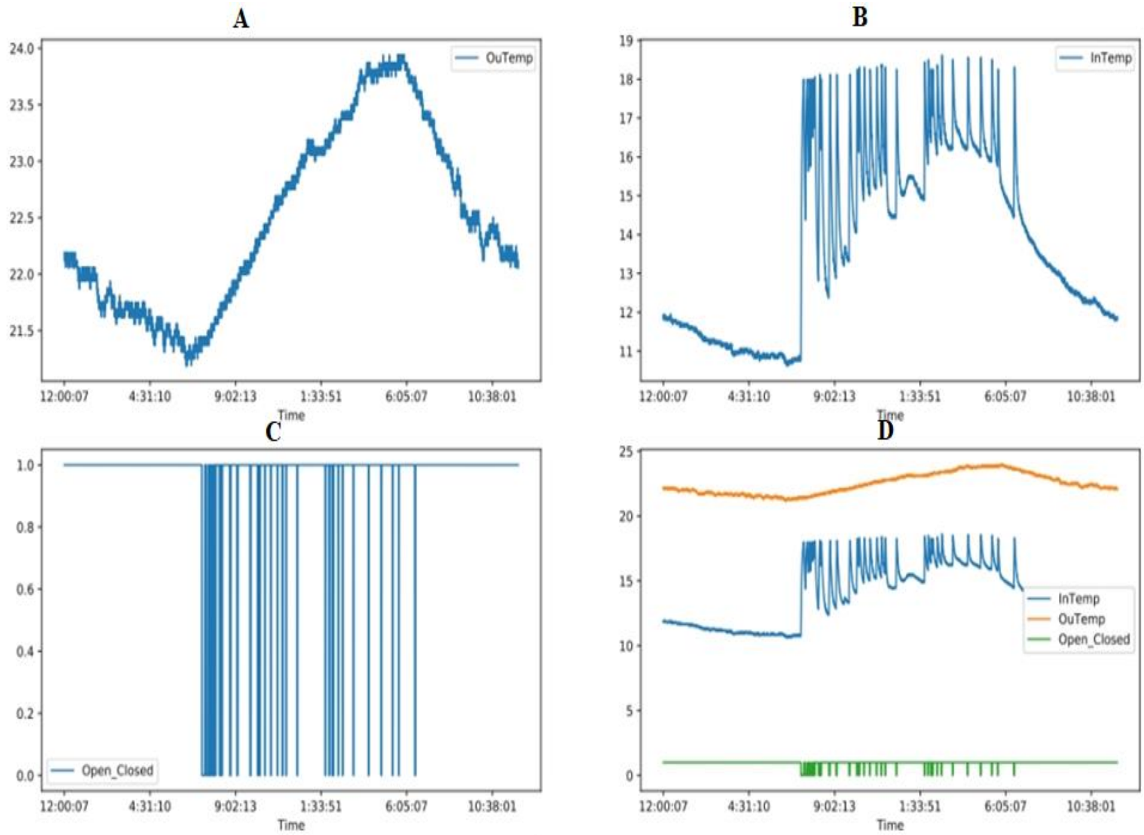

Figure 48:Experimental results outside, inside of the fridge when open and closed

From the above Figure 48 , A: the outside temperature variation due to climate, B: the inside temperature variation due to opening and closing. C: opening and closing (Closed= 1, Open =0). C: Consolidated graph. As depicted, the process happened only during the daytime and it is also seen that during the daytime, the temperature (for both inside and outside) increases while the temperature reduces during nighttime.

This explains that the daytime has an impact on the temperature too. The above details show that the fridge's inside temperature varies when the fridge is being opened. From the same graphs, we can also see that the outside temperature will vary based on the time of the day. During the daytime even if the door is closed, we can observe some increase in inside temperature which is due to heat exchange between the outside medium and the inside medium. This is graphically demonstrated in the following Figure 49.

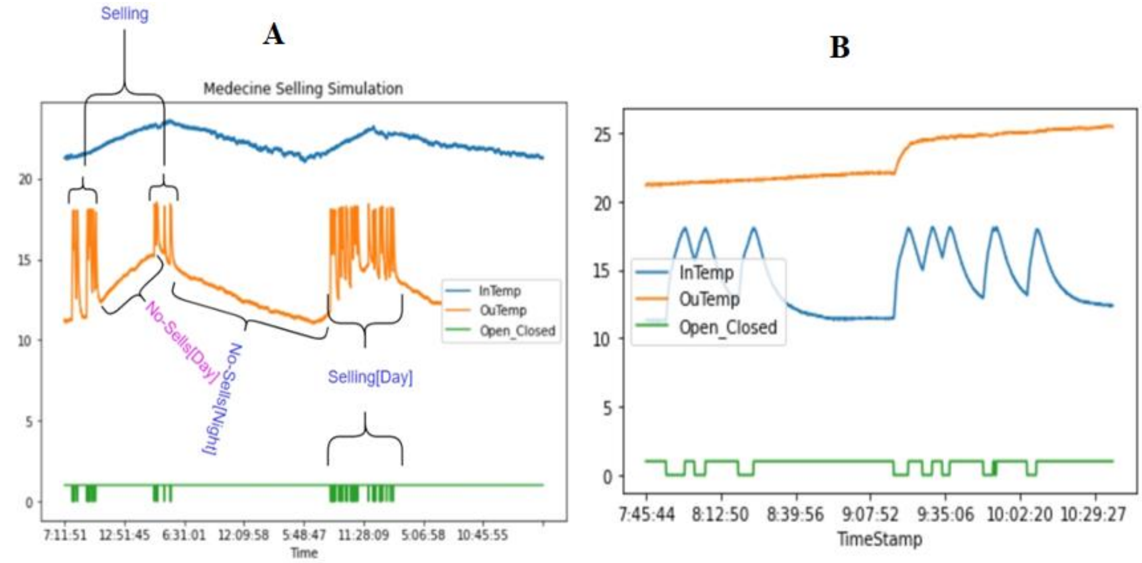

Figure 49: Analysis of the whole day results

Figure Figure 49 shows one-day simulation results (A) and analysis during a portion of two hours (B). The fridge's room temperature depends on how frequently is being opened, the time of the day, and the outside temperature. And the period for the inside temperature to reach the upper-temperature limit depends on the initial temperature at the opening time, the time of the day, and the outside temperature.

7.5.1. Model results and prediction accuracy.

In this section, we have different results which show that our model is accurate. Figure 50 indicates how each predictor variable is related to the target variable.

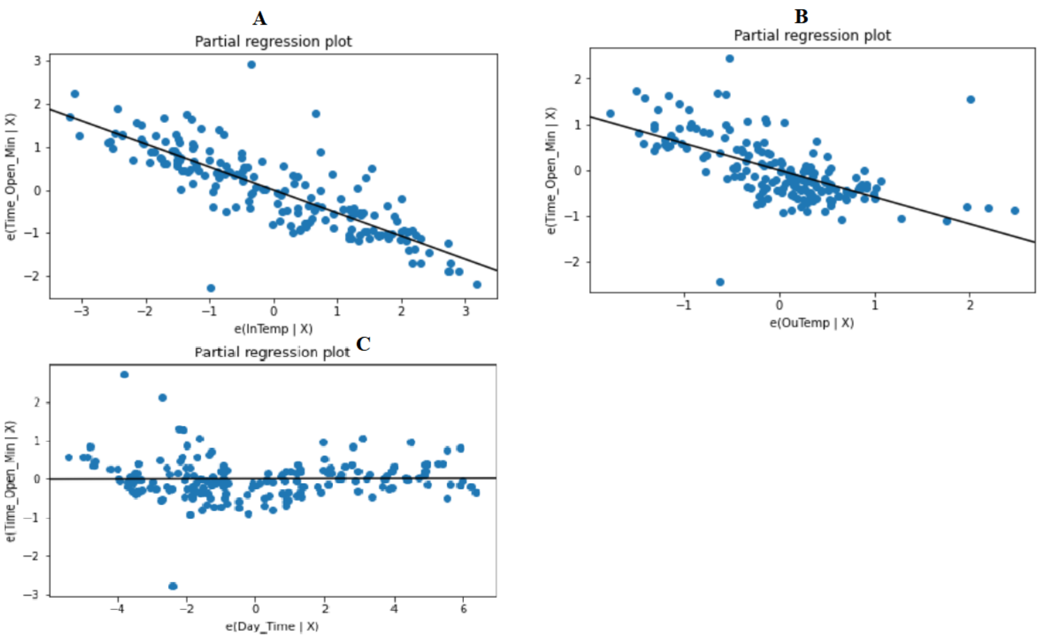

Figure 50: The contribution of independent variables

From the above figure 50 by looking on the independent variables contribution, where on A Relationship between the dependent variable and the chamber temperature. B: Relationship between the dependent variable and the outside temperature. C: Relationship between the dependent variable and the daytime, we conclude that the chamber temperature and the outside temperature have more contribution to the model than the daytime. Looking at results from Figure 51 (of residuals plots), points are randomly dispersed around the x-axis. Where A is residuals versus the chamber temperature. B, residuals versus the outside temperature and C: residuals versus the daytime. This indicates that heteroscedasticity is not an issue with predictor variables[127] [128], [129]. Then our model is appropriate and the results from the analysis can be taken as valid.

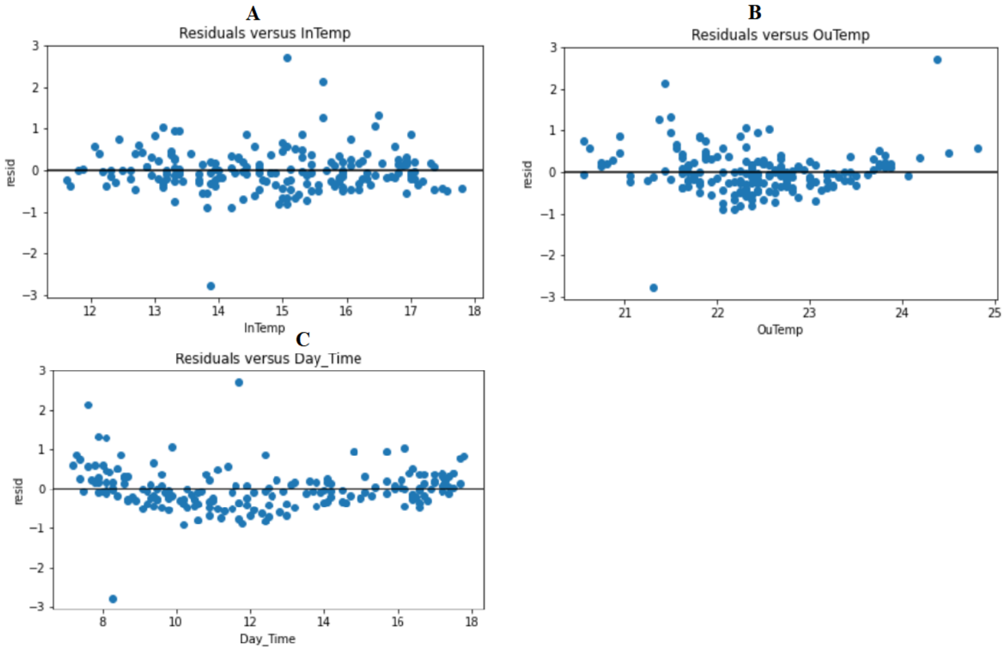

Figure 51: Model residuals analysis

Table 18. shows some numerical results for checking the accuracy of our model. From this table, we can see that the coefficient of determination is equal to 0.767. Thus, the model is not less effective and efficient.

Table 18: Regression model results

	coef	std err	t	P>|t|
Intercept	23.405	1.199	19.520	0.000
InTemp	-0.5328	0.027	-20.093	0.000
OuTemp	-0.5838	0.055	-10.558	0.000
Day_Hour	0.0016	0.014	0.120	0.905

Table 19: More about regression model results

Parameter	**Value**
R-squared	0.767
Adj. R-squared	0.763
F-statistic	195.2
Prob (F-statistic)	4.90 e-56

Log-Likelihood	-142.47
AIC	292.9
BIC	305.8

From above Table 19, m_1= -0.58, m_2 = -0.53, m_3= 0.0016, β= 23.4. Then Equation 12 can be rewritten as:

$$T_{\mathrm{cut-off}} = -0.58 * \mathrm{OuTemp} - 0.53 * \mathrm{InTemp} + 0.0016\mathrm{DayTime} + 23.4 \quad (13)$$

Considering the above coefficient of Table 13 and model results, we can say that:

1. When the outside temperature increases, it will take a short period for the inside temperature to reach the cut-off temperature.
2. It is even the same for the inside temperature (at the opening time) if it is higher, it will also take a short period for reaching the cut-off temperature.
3. Considering the P-values of dependent variables, the inside temperature and the outside temperature contribute more to the prediction compared to the daytime.

During our research work, we initially considered a deep Neural Network algorithm, but in the end, we found that the regression model works better than the Neural Network. The following Table 20 summarizes the results from the two algorithms. Column 2 of Table 20 (the linear regression predicted values) can even be verified using Equation 13.

Table 20: Comparison between Neural Network and Linear regression on our datasets

True Value[Min]	Predicted_Linear_Reg	Predicted_DNN
2.3	2.5	2.6
2.8	3.1	3.1
1.6	2.1	2.0
2.4	2.4	2.4
1.2	1.1	2.0
0.4	0.8	2.0
1.6	1.8	1.9
0.9	1.1	2.0
0.6	1.0	2.0
1.6	1.6	2.1
1.1	0.9	2.0
3	2.8	2.5
1.3	1.1	2.1
4.2	3.2	2.3
3.5	3.2	2.4
4.3	3.2	2.7
3.2	3.2	2.9

7.6. Summary Limitation

In this work, a machine learning method to predict the remaining period for the temperature inside a fridge to go beyond the acceptable range has been developed. The proposed model will keep monitoring the impact of opening and closing the fridge while picking some products. Results from our analysis show that the model was accurate at 0.77, which means that 77% of the total variation in time to cut-off temperature is explained by the regression. P values for both the inside temperature and outside temperature are below 0.05, and then it can be concluded that those two parameters have considerable contributions to the prediction of the time required for the chamber temperature to reach the upper acceptable range.

The experiment showed that when the outside temperature increases by one-degree Celcius, the time to cut-off temperature is reduced by 0.58 minutes. When the inside temperature is kept constant and when the chamber temperature increases by one-degree Celcius, the time to cut-off temperature is reduced by 0.53 minutes when the outside temperature is kept constant. The proposed model is useful for pharmacies that sell medical products (case of Rwanda). We also proposed that to efficiently store temperature-sensitive medical products, the proposed model must be used in a multiple chambers fridge with a screen from where the remaining period for cut-off temperature will be displayed. In this case, someone in charge, before opening the fridge, will check and open the chamber that indicates a longer period. The Internet of Things can also be integrated into the proposed solution for remote monitoring and control purposes

In this work, through experiment, we recorded the data for 3 months and we simulated the selling process for 12 days. It is obvious that if the sample size is increased, the accuracy will be optimized too. Apart from this, the developed prototype was made from timbers. This made some difficulties when it comes to heat isolation. We think there was some uncontrolled heat leakage and we think that if the prototype could be made of aluminum metal with good heat isolators, this would improve again the accuracy of the developed model. During the construction of the fridge, only one temperature was used, and was randomly placed inside the room. We think following the principle of thermodynamics, the temperature is not equally distributed. Therefore, if more than one sensor is systematically placed inside the room, the temperature will be captured efficiently and this provides more accuracy in the proposed model. It is also clear that the angle at which the fridge is being opened, the volume of the room, and the current atmospheric pressure have some impact on the developed model. This has been ignored, but if it is considered it can make the model accurate.

Chapter 8: Conclusion and Future Research direction

For our first work, 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 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. The results from experiments for our second work show that the GSM/GPRS sensor node consumes current in the mA range; this current is not small in WSN or IoT applications. However, in an area like Kigali, Rwanda a country with a lot of hills where the geographical structure does not allow line of sight communication, building a network using low power sensor nodes like Lora or Sigfox will cost a lot due to a lot of gateways. So, in applications where the line of sight is difficult to achieve and where the GSM network is already in place, GPRS sensor nodes can be used and the cost of building a network will not be expensive as the GSM network is already in place. The quantitative model developed in this work will help sensor nodes supplied with batteries as it is possible to know how long a battery will last if the information about the signal quality is known and this will finally help to predict when a battery can be replaced. This work has been completed using GSM module. However, we recommend for future work that a model like the one found in Equation (11) can be found for other modules such as LoRa and Sigfox using the same procedures.

In our third work, a machine learning method to predict the remaining time period for the temperature inside a fridge to go beyond the acceptable range has been developed. The developed model must be embedded in the fridge that has a controller with enough resources to run a machine learning model. The proposed model will keep monitoring the impact of opening and closing the fridge while picking some products. Results from our second work analysis show that the model was accurate at 0.77, which means that 77% of the total variation in time to cut-off temperature is explained by the regression. P-values for both the inside temperature and outside temperature are below 0.05, then it can be concluded that those two parameters have considerable contributions to the prediction of the time required for the chamber temperature to reach the upper acceptable range. The experiment showed that when the outside temperature increases by one degree Celcius, the time to cut-off temperature is reduced by 0.58 minutes. When the inside temperature is kept constant and when the chamber temperature increases by one degree Celcius, the time to cut-off temperature is reduced by 0.53 minutes when the outside temperature is kept constant. The proposed model is useful for pharmacies that sell medical products (case of Rwanda). We also proposed that to efficiently store temperature-sensitive medical products, the proposed model has to be used in a multiple chambers fridge with a screen from where the remaining period for cut-off temperature will be displayed. In this case, someone in charge, before opening the fridge, will check and open the chamber that indicates a longer period. The internet of things can also be integrated into the proposed solution for remote monitoring and control. 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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