Website: www.aceiot.ur.ac.rw
Mail: aceiot@ur.ac.rw

COLLEGE OF SCIENCE AND TECHNOLOGY

African Center of Excellence in Internet of Things *(ACEIoT)*

Research title:

IOT BASED BIOGAS STATUS MONITORING SYSTEM

Case Study: NGOMA DISTRICT

A dissertation submitted in partial fulfilment of the requirements for the degree of Masters in Internet of Thin Wireless Intelligent Sensors Networking (WISNET)

Submitted by

RUKUNDO Jean Claude

PG:220014156

December 2021

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PG:220014156

Supervised by

Dr. Damien HANYURWIMFURA

And

Dr. Christine NIYIZAMWIYITIRA

December 202

Declaration

I hereby declare that this research project report entitled "**IoT Based Biogas status monitoring system** " is presented for the award of Master's degree of science in Internet of Things – Embedded Computing Systems at the African Centre of Excellence in Internet of Things, University of Rwanda is my own work. It has never been presented or submitted in any other University or higher learning institution for similar award.

Student name and number

RUKUNDO Jean Claude

220014156

Date: December, 10, 2021

Certificate

This is to certify that the project work entitled "**IoT Based Biogas status monitoring system"** is a record of original work done by RUKUNDO Jean Claude with reference number: 220014156 in partial fulfillment of the requirements for the award of Masters in Internet of Things-Wireless intelligent sensor networking at the Africa Center of Excellence in Internet of Things, University of Rwanda during the academic year 2019-2021.

Main Supervisor **Co-Supervisor**

Dr. Damien HANYURWIMFURA **Dr. Christine NIYIZAMWIYITIRA**

Head of Masters and Trainings ACEIoT

Dr. James RWIGEMA

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I am deeply thankful to my supervisors **Dr. Damien** Hanyurwimfura and **Dr. Christine** Niyizamwiyitira for their empathy, help, suggestions, and encouragements that helped me all over this research journey and report redaction.

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May the Almighty God bless you all abundantly!

Abstract

Biogas is produced from biological process of mixed organic materials with the help of bacteria that facilitate the anaerobic digestion process. Biogas can be produced from manure agricultural waste or from other biomass resources available almost everywhere. Many developing countries especially in Africa depends on biomass for domestic energy needs which causes many issues related to socio-economics. In other hands, cattle manure can be used to generate cleaner and cheaper biogas as secondary energy source. To transform cattle manure into Biogas, a biogas digester has been built in several countries especially in Rwanda to reduce the use of woods and Charcoal as source of cooking energy. However, those Biogas digesters built does not have a monitoring system which result in malfunctioning and sometimes produce inefficient Biogas compared to what is should produce. The purpose of this study is to observe biogas production generated from different types of organic materials and measure other parameters that contribute to biogas production **.**This research aims to develop a Biogas status monitoring system. The developed system is equipped with sensors capable of measuring biogas status (Co2, Methane Gas, Temperature and PH) and the system process those data locally and then and send aggregated data to the cloud for further analytics. Biogas monitoring systems have been built and predictive model has been built in order to predict biogas yield based on the various Biogas feeding quantity and methods. The proposed predictive model has been evaluated with KNN, decision tree and random forest machine learning algorithms, and obtained results are promising.

Keywords: IoT, Biogas, KNN, Gradient boosting, MQTT, Decision tree

List of acronyms

ACEIoT: African Centre of Excellence in Internet of Things

API: Application Programming Interface

PH: Potential of hydrogen

Dr: Doctor

ESP: Espressif

GUI: Graphical User Interface

IDE: Integrated Development Environment

IoT: Internet of Things

MCU: Microcontroller Unit

CH4: Methane

Co2: Carbon Dioxide

MQTT: Message querying telemetry transport

IoT: Internet of things

PPM: Parts per million

Mongodb: Mongo database

PPM: Parts per million

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CHAPTER ONE: GENERAL INTRODUCTION

1.1 Overview and Background

Nowadays, there is an increase in renewable energy usage among world's population for environmental protection. Many countries had put in place policies regarding environmental protection which pushes people to use renewable energy as second source of energy. For this reason, Biogas energy has been adopted as alternative cooking energy. In Rwanda, the government has implemented a biogas construction program called National Domestic Biogas Program (NDBP). Main objective of the program was to put in place domestic biogas sector for commercial purpose in order to contribute to the improvement of rural families while reducing Woods and charcoal consumption. The target of the mentioned program was to build for 3,000 biogas digesters for rural households till 2011[1]. The program has been implemented jointly with Netherlands development organization NGO (SNV). However, there is a problem of continuous monitoring of biogas plant to maintain their health because some of them have already failed or malfunctioning.

Thus, the conversion of waste to energy is very useful as they allow a partial mitigation of the environmental control. Between the possible ways to convert waste to Energy is the, anaerobic digestion (AD) which is a green technology to transform solid or liquid organic wastes in biogas which in turn converted to beneficial energy[2].Anaerobic Digestion is the complex bio-chemical reaction process where micro-organism is converted in the absence of oxygen in the organic matter and in the mixture of gases which composed by carbon dioxide (CO_2), methane Gas(CH_4) and nitrogen (N_2). There other extra components found in that mixture like hydrogen sulphite, hydrogen, ammonia as oxygen and sometimes carbon monoxide[3].

The importance of internet of things (IoT) in the biogas digester is the innovative approach to address the barrier of biogas adoption and maintenance in rural areas. IoT is the technology that is used to connect unconnected existing physical devices or objects to the internet thus providing intelligent to think or react on given command or any situation that can happen. Internet of things technology uses several sensors like Global positioning system (GPS), radio frequency identifications (RFID), laser scanners, Infrared motion sensors and other types of sensors to connect anything to the internet. The data received from sensor are processed then communicated to the internet to enable location, monitoring, tracing and identification[4].

Internet of things is widely applied in various domains in daily life. It is used in environment protection systems , industry monitoring and preventive maintenance, process control in industries, food tracking , logistics and worldwide trading and many more fields [5]. In this research, we present a system which exploits this skill of IoT to monitor Biogas production status and provide real time feedback to end users and which can predict the biogas yield based on the inputs supplied to the digester.

1.2 Problem Statement

The primary energy consumption today in Rwanda comes mainly from biomass where most of it is used as direct cooking wood, as charcoal, as peat and finally as small crops residues. Biomass energy supply is not well harnessed and used in appropriate manner which causes many problems such as deforestation, land degradation, health and social problems and greenhouse gases emission. To minimize the negative impacts due to use of biomass as primary energy for cooking, the government has adopted Biogas as energy cooking alternatives. From different survey from biogas users some bio digesters built are not functioning properly which hinders the objectives of the program due to different reasons including lack of regular biogas monitoring, improper feeding deep, lack of training on biogas maintenance both for biogas users and technicians[6]. From this background, this research aims to put in place a biogas monitoring system in order to reduce the Biogas malfunctioning, to put in place real time monitoring and alert system.

1.3 Aim and Objectives

The aim of this study is design and implement an IoT based Biogas status monitoring system to monitor daily biogas status and alert user in case there is malfunction in biogas plant

1.3.1 General Objective

The overall objectives of this research is to develop biogas monitoring system which will automatically provide information on the biodigester status in order to provide support before malfunctioning of digester

1.3.2 Specific Objectives

The research specific objectives are to put in place biogas status monitoring system which will minimize or reduce the biogas malfunctioning due to improper feeding and improper biogas operations, helping end users in terms of getting necessary information about biogas status and it will be used for future prediction of biogas yields. In addition to that, the system will improve the current digester system to be a reliable source of energy by optimizing Bio gas production

To achieve our general objective, the following specific objectives will be considered;

- Design and implement an IoT based system to monitor the biogas digester in real-time and provide information whenever needed.
- Develop a biogas predictive model based on data taken from different parameters that determine biogas production (Temperature, Methane gas, carbon dioxide and PH)

1.4 Hypotheses of the research

In this research, two main hypotheses are taken to be considered in the evaluation of the proposed method. These are:

- The real time monitoring system of biogas reduces system failure and increase productivity.
- The biogas prediction model can help in best practice of biogas feeding and determination of expected biogas production based on organic materials used.

1.5 Scope of the Research

This research is limited with the scope of how IoT can be used to monitor biogas plant in real time and will be limited in Ngoma district where all test will be held.

1.6 Benefits of the research

Different stakeholders will benefits from this system in the following aspects:

1. Better utilization of organic material resources to produce more energy
2. Reduction of Biogas failure which will reduce the waste of other resources and time for end users
3. It will increase adoption rate once the system is successful
4. Poverty reduction and employment creation among youth in the implementation of this project

1.7 Organization of the Thesis

Chapter one: General introduction

This chapter describes the background of the study, the problem statement, and the objectives of the study, scope of the study, significance of the study, project interests and the organization of the study.

Chapter two: This chapter is mainly about basic theories and related literature review. It clarifies the works done by other researchers in Biogas production field, biogas status monitoring and related method that have been used in biogas production and monitoring.

Chapter Three: This chapter is mainly about research methodology. It emphasizes on the proposed methodology to monitor biogas digester with IoT with all corners covered. it also covers system prototype design process.

Chapter four: This chapter is mainly about project prototyping.

Chapter five: This chapter is about analysis of the dataset collected after prototyping using different machine learning algorithms and the results are presented.

Chapter Six: This chapter covers the conclusions, and recommendations for future researchers and future work.

CHAPTER TWO: LITERATURE REVIEW

2.1 **Introduction**

This chapter identifies the work done by other researchers and shows the missing elements in the design and implementation of new system to monitor biogas status in real time and facilitate end users to manage their biogas plant.

2.2 **Review of related works**

The proposed solution is to add system to existing bio- digesters that will monitor the health of biogas in real time and alert users when malfunctioning occurs and predict biogas production based on biogas data. For this case, edge computing and internet of things technology will be used to process data locally and also data will be sent to the cloud. Normally the malfunction of digesters may be caused by different reason but most of them are due to the improper feeding. the system will measure the biogas health parameters such as PH, Gas pressure,CO_2 and Methane gas produce in real time. Edge computing will be used in the system in order to process data locally close to end users and end users will have direct access to processed data. The aggregated data will be sent to cloud platform as backup and further analytics will be performed which will help in taking other decisions. In the related works have been done where they read sensor data from digestor and send them directly to the cloud for processing. The processing of data at edge layer will help end users to gain access directly to the data without depending on cloud. The amount of money required to send data every time to the cloud will be reduced because only aggregated data will only be sent to the cloud within a considerable time interval. The below literature has been used to understand my research and determine the key area of improvement.

V. Acharya[7] developed the biogas efficiency monitoring system where biogas data like temperature, pressure are measured with microcontroller and the data are sent to the remote database and the system provide alert to user. The gap in the system is that it does not cover all parameters needed to measure biogas health like $C0_2$ and Ph as they contribute to the anaerobic digestion process.

S.Africa,M.Engineering,and C. Author[8] developed a system for optimization of biogas production. They have also developed a model for biogas prediction based on biogas feeding methods and the model was simulated using MatLab. The overall system does not have the ability to monitor biogas at edge layer even in the cloud.

R.R.Pansari,S.R.Patil, and M.S.Khan[9]developed a biogas monitoring system for biogas plant. he used sensors to monitor biogas parameters and data are sent directly to the cloud using wifi chip connected to wireless network. This work also lacks the ability to process data locally.

P.Huo,F.Yang,H.Luo,M.Zhou, andY.Zhang[10]developed a wireless network for traditional biogas appliance to monitor the status of household equipment's that use biogas for cooking. The system shows the biogas usage amount and can detect the leakage in pipe and then alert users.The data collected are visualized locally and online. The system does not cover the parameters that show the status of biogas production process inside biogas container that can affect continuous biogas production.

M.Farhan,M.Pu, K.A.Sidek, and M.Mel[11]developed a biogas analyzer system for monitoring using IoT. The system uses Raspberry Pi for computing purpose. The device measures methane gas (CH4 and Carbon dioxide (C02) as main composition of the biogas . Data from biogas container are accessible locally and sent to remote server for remote access. Here the measurement is done only on gas container not in digester itself which means that there is no way to gather information about biogas status which can help us to predict the biogas production and needed maintenance.

2.3 **Summary of Gaps identified**

The above literature reviewed does not include the data processing at edge layer in order to solve identified issue caused by depending only on cloud data and allowing client to access data locally. Normally, a distributed edge computing devices on the network reduces downtime which ensures network availability. In that context, the bandwidth utilization is reduced by eliminating the necessity of repetitive request to the central or cloud server.

2.4 **Scientific Contribution**

The proposed system also will process data locally with minimal interaction with the cloud server. Once several requests to the central server are minimized, the operational expenses are minimized as well. Edge computing presents low latency as the data are processed at their source where immediate feedback or reaction is provided in real time. By using edge computing for this particular application, data will be close to end users where they are easily accessible anytime. The quality of services are granted in case of edge computing[12].

In this research, fog computing will be used for real time collection and reporting, while cloud computing will be used to keep data and make predictions.

2.5 **Conclusion**

In this chapter, an overview of the background of this research area is discussed. Related work is presented in this chapter. Similarities and contrasting features within conferences and journal papers are also discussed.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

The design of this proposed solution is divided in 3 main parts which are sensors segment, the data transmission segment and decision-making segment. The methodological approaches identified are made of both physical design which reflects hardware components section and logical design which also reflects the software components selection.

3.2 **Research approach**

This part provides the overview of the research approaches and all steps to follow in system development from gathering different ideas to final prototype and research results. The figure 3-1 indicates the research process from start to end.

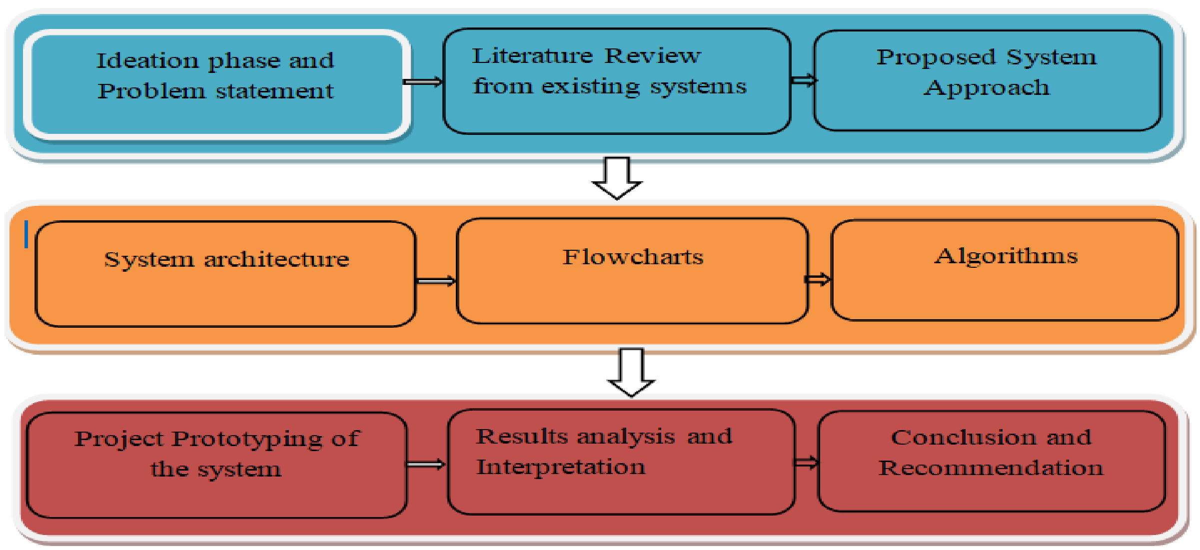


Figure 3.1 Research Approach

The idea behind this research is derived from conducting intensive literature review for the existing system and the problems identified.

3.3 Experimental Approach

During this research, the researcher will use experimental approach[13] whereby all necessary measurement has to be taken directly from sensors, analyzed and interpreted in order to see if they contribute to our hypothesis verification.

3.4 System Development Methodology

To implement the IoT based Biogas monitoring system, many technologies will be involved from the sensor design to the cloud. Hardware skills will be needed to interface sensors with microcontroller. Embedded systems programming skills will be required to process sensor data and communicate them from the fog device to the cloud server. Fog computing device will be made by raspberry pi running rasbian operating system. The processing scripts must be running on the raspberry pi working as server to process data and alert end user and then communicate with the cloud lately. All the process need to be iterative and repetitive in order to achieve the intended results.

3.5 Proposed system Design

As indicated in figure 3-2, the proposed system has four layers which are arranged from perception layer to application layer.

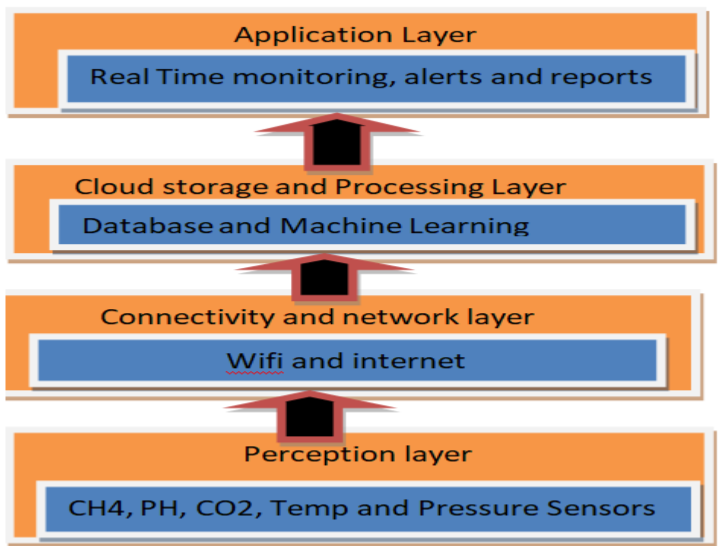


Figure 3.2 Proposed System layers

Those layers clearly show interactivity between all components of the entire system. Sensors are connected to the microcontroller at data acquisition layer or perception layer, and networking and communication components are located in the connectivity and network layer whereby all data collected are sent through the network to the processing layer. The management layer performs services like storing sensor data in database and machine learning models employed in the system.

The system will be having two parts: hardware and software. Hardware includes sensors that will be used to capture needed information from digestor (Gas pressure, Temperature, methane and PH). Microcontroller will receive and pre-process received sensor data and send fog device to process them locally. Fog device will be used for analytics, real time status and report to end user via sms. Web based interface will be provided for users with smart phones. The Fog device

will send aggregated data to the Cloud in given time interval to reduce bandwidth consumption.
The Biogas status monitoring system simple block diagram is made up with 3 parts as indicated by figure 3-3. It is make by Sensor node, fog computing device and cloud computing. Biogas monitoring system will be composed by 4 arts: Biogas Digester and Biogas Tank, Microcontroller that collect and process sensor data, edge computing device and Cloud computing for remote monitoring, analytics and reporting.

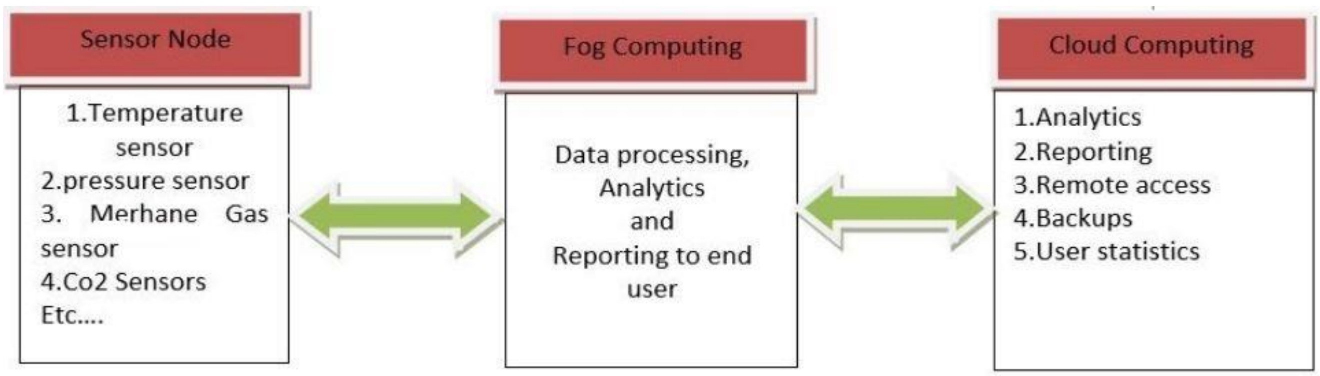


Figure 3.3 proposed system block diagram

The data received from biogas are processed by the microcontroller and send the data to the raspberry pi via Wi-Fi. The raspberry pi processes the data and provides feedback to end user via SMS whenever needed. Raspberry pi will also run a web server capable to provide information on dashboard when accessed via Smartphone or computer via local Wi-Fi router that connects microcontroller and Raspberry pi in order to exchange data. When one of the key parameters that is crucial for optimal biogas yield (Temperature, PH and methane Gas) drops below threshold, an alert will be sent to the end user directly so that he can investigate the cause and fix issue when it is possible. The report is also sent to the cloud for future reference.

As shown by figure 3-4, the system will be having two parts: hardware and software, hardware includes sensors that will be used to capture needed information from digestor (Gas pressure, Temperature, methane and PH). Microcontroller will receive and pre-process received sensor data and send fog device to process them locally. Fog device will be used for analytics, real time status and report to end user via SMS. Web based interface will be provided for users with smart phones. The fog device will send aggregated data to the cloud in given time interval to reduce bandwidth consumption.
The Biogas status monitoring system simple block diagram is made up with 3 parts: sensor node, fog computing device and cloud computing. Biogas monitoring system will be composed by 4 parts: Biogas Digester and Biogas Tank, Microcontroller that collect and process sensor data, edge computing device and cloud computing for remote monitoring, analytics and reporting.

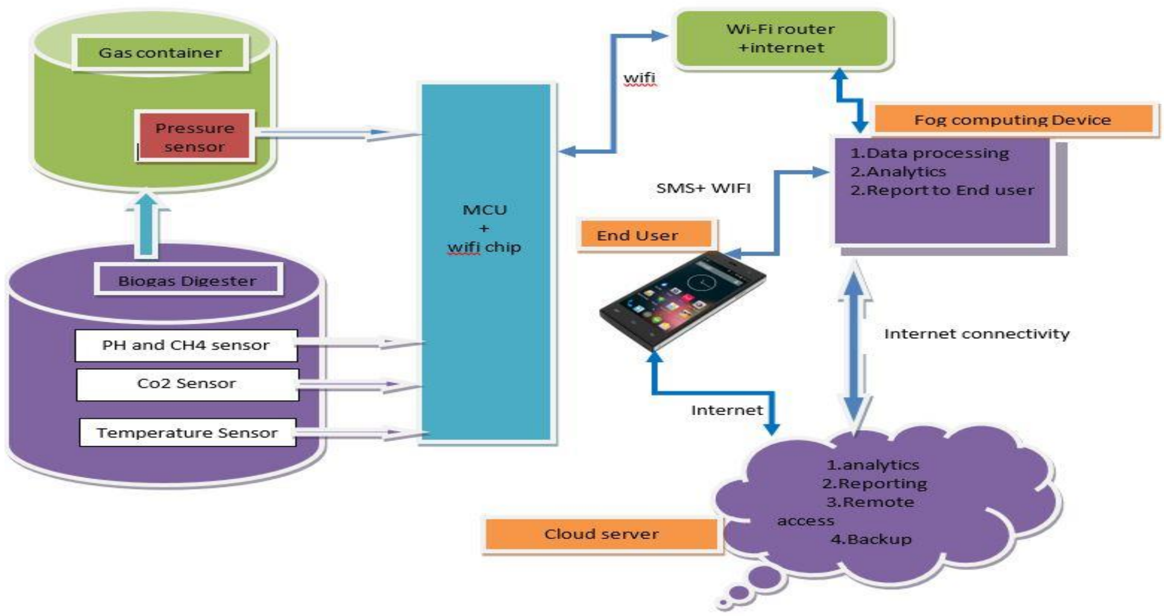


Figure 3.4 Detailed block diagram of the proposed system

The gas produced within digester is fed up in Biogas tank as shown by figure 3-4. The pressure sensor is inserted in the biogas tank to measure gas pressure inside the tank. The Biogas Digester is where chemical reactions happen in order to produce Biogas From animal waste. Parameters like carbon dioxyde, Ph, methane gas concentration inside the Digester affects the biogas production. For this reason, PH sensor, Carbon dioxide sensor and methane gas are placed inside biogas digester to collect those data. Data collected from Biogas digester and from Gas container are sent to the Fog device (Rasbery Pi will be used) to aggregate and analyze data in real time). Data from sensor will be sent to the fog device using wifi connectivity. Microcontroller will be having wifi chip that connects to the wifi modem to form local area network (LAN). Edge device and Fog device are all connected to the same LAN in order to exchange data.

3.6 Hardware components Selection

3.6.1 Microcontroller Selection

In this research, I will use two types of microcontrollers in the data acquisition and data processing process.

3.6.1.1 Raspberry pi 3 model B

Raspberry pi is credit card-sized PC one of the most successful computers ever made. with its ability to have an operating system , enough RAM and high processing speed[14] , the researcher have selected Raspberry pi to be used as fog device to process data locally before being sent to the cloud. It will work as web server and edge data processing element. The figure 3-5 is raspberry pi 3 model which is one of its versions available on market.

Figure 3.5 Raspberry pi 3 model

3.6.1.2 ESP32

The ESP32 as shown on figure 3-6 is micro controller designed and manufactured by Espressif Systems Company. Espressif is a company based in china in the province of Shanghai [15]. The ESP32 is self contained WiFi networking solution which offers a bridge from existing micro controllers to WiFi and it is capable of running self contained applications because its processing power and on-board memory .The researcher have selected this specific devices to be used for reading sensors because it equipped with 6 analog 12-bit analog to digital ports and its ability to have on-board wifi [15]which gives it ability to commutate easily with other wifi enabled devices. For our case, esp32 will collect sensor data and send them to local server that runs on top of raspberry pi.

Figure 3.6 ESP32 Microcontroller board

3.6.2 Sensors selection

3.6.2.1 Ph sensor

Analog pH meter V2 (figure 3-7) is analog sensor specifically designed for measuring the pH of a solution and reflect its acidity or alkalinity[16]. This sensor applied in various domains like such as such as, aquaculture, aquaponics and environmental water testing. This sensor will be used to determine the PH value of organic materials feed to the biogas digester. The ph value is the important parameter is the anaerobic digestion process. High concentration of Ph inhibits the CH4 production. It should be maintained on certain level in order to have a high methane production[17]. This sensor is powered with the voltage between 3.3V and 5.5v and it consumes 3mA when powered with 5V and 3mA when powered with 3.3V. This ph meter produces output voltage from 3.00V to 0.265V.the sensor has an accuracy of +- 0.2 with 10 years of life expectancy[16].

Equation to convert voltage to ph is given by:

PH = (-5.6548*voltage)+15.509

Figure 3.7 Analog pH meter V2

3.6.2.2 Carbon Dioxide sensor MQ-135

The MQ-135 sensor is one of series of MQ sensors that are used mainly for dangerous has detection methods.$C0_2$ is important parameter to be monitored in biogas plant. Biogas is a mixture of methane (CH4) and carbon dioxide ($C0_2$) along with along with other gases but methane and C02 has high percentages of concentration[18]. MQ gas sensing devices are analog components specifically designed to work with wide range microcontroller and microcontroller boards including arduino[19]. MQ-135 sensor is designed to detect NH3, N0x, alcohol, benzene, smoke, CO2 as well as many other dangerous gases available in our environment. The device has a sensitive layer which is used detects different gases basing on based conductivity. The device conductivity goes high with increase in gas concentration[19]. The gas sensitivity depends on both the temperature and the humidity. MQ-135 gas sensor has built-in heater that work with 5 V to create a needed environment for the sensor. The figure 3-8 is MQ-135 and it has 4 pins: A0, D0, GND, and VCC. VCC and GND pins used to power the sensor. A0 is the pin that provides outputs from 0 to 5V analog voltage based on the intensity of the gas the gas being detected.

Figure 3.8 MQ-134 Gas sensor

3.6.2.3 Temperature Sensor

In Biogas digester, Temperature is also a key parameter to be monitored. In relation to the biogas production rate in a given digester, internal temperature setting is one of the critical factors for an economical viable fermentation operation. Hence, temperature is a very important factor that affects anaerobic digestion because its influences on system heating requirements as well as methane production [20].in the study made by Ramaraj, Rameshprabu Unpaprom, Yuwalee[21] fermenters incubated at 35 °C produced the highest biogas (10377 ml) and highest methane yields were reached 64.47 %. In this study the sersearcher decided to use Ds18b20 Temperature sensor and it is indicated with figure 3-9. DS18B20 is waterproof temperature sensor that detects temperature change from -55 to 125°C (-67°F to +257°F). According to Nie, SongCheng, Yang-chunDai, Yuan [21], DS18B20 is suitable for measuring the temperature of conductor and ambient in dynamic capacity increase, and helpful to improve the accuracy of the calculation of capacity-increasing.

Figure 3.9 DS18B20 Temperature sensor

3.6.2.4 Methane Gas sensor

Biogas is a renewable energy source produced from the anaerobic digestion of organic waste. It is composed of a mixture of several gases, with a high predominance of carbon dioxide and methane. The composition of produced biogas can vary according to the used organic material as well as the biodigestion process, with methane corresponding to values between 20 and 80% and 20 to 60% for carbon dioxide[22] . The MQ-4 Gas sensor is in series of MQ-gas sensor series that are used to measure dangerous gases .The researcher decided to use MQ-4 (figure 3-10) gas sensor for its good response to the environment containing methane gas. MQ-4 sensor returns an analog reading that can range from 0 to 1023 which corresponds to a variation between 0 and 5 volts[22]. To obtain the concentration in ppm from the sensor reading some conversion method must be used.

Figure 3.10 MQ-4 methane gas sensor

3.6.2.5 Pressure sensor

Depending on the anaerobic digestion process, the produced gas has a given pressure. The pressure of produced gas can indicate the efficiency of feeding materials supplied to the biogas digester to produce biogas. When biogas pressure is monitored in real time, it can provide useful information and can be used to predict biogas production. Here, the researcher decided to use BMP180 pressure sensor (figure 3-11) to measure gas pressure inside digester for its efficacy and robustness. This sensor is the product of BOSCH and it is optimized to be used in mobile systems like PDAs and GPS navigation[23]. It has I2 C communication protocol whch facilitate the device integration with microcontroller systems. The sensor is based on piezoresistive technology which provides high accuracy and robustness. This sensor is able to take readings that range from 950 to 1050 hpa working at a temperature of 25˚C, providing the accuracy of 0.12 hpa [23].

Figure 3.11 BMP180 Pressure Sensor

3.7 Software Components Side

In this research, several software components will be used to achieve our target. This is the list of software that will be used:

3.7.1 Arduino IDE

Arduino IDE (integrated development environment) is the programming tool used to program different microcontrollers using C++ programming language. Arduino IDE is owned by arduino which open source hardware and software platform that is mainly based on easy-use of hardware and software in order to accelerate innovations[24]. Arduino community produces arduino different boards. I will use nodemcu board that it will be programmed using arduino IDE.

3.7.2 Nodejs and node-red

Nodejs is simply the event-driven asynchronous JavaScript runtime[25]. When using nodejs , you can write JavaScript code and being interpreted by operating system rather than the browser as it used to be in the recent years.

Node-RED is software based on flow development methods for visual programming. Node-red runs on top of nodejs. The tool was developed by IBM[26] with the purpose of wiring hardware devices together, online services and application program interfaces (API) and it is highly used in internet of things. Node-RED have web browser flow editor, which is used to write JavaScript functions in your program. The researcher selected node-red for its easy to use and its way to display and persist data and it runs perfectly in raspberry pi.

3.7.3 Mongodb database

Mongodb is non relational database that uses JSON-like documents with optional schemas for data modeling [27]. Considering its rich document model, efficient and powerful query functionality, scalabilable structure and architecture it easy to be integrated with leading Business Intelligence and analytics tools. For this research, mongodb will be used t store data from sensors and analytical tools will pull data from the database.

3.7.4 IoT Claud Platform

IoT platforms help companies to develop internet of things solutions quicker toward the the market by reducing software development time as well as expenses for IoT systems [28]. For this reason the researcher will use Adfruit cloud platform to store and analyze data from the edge device in order to get real time data from biogas anywhere anytime.

3.7.5 Data collection methods

During the prototyping of this system, the simple 10 liter plastic bucket with closing cap was used as biogas digester. The feeding process is done by taking cow manure and mixed with water .The used cow dung is indicated with figure 3-11. After feeding the plastic bucket, the closing cap is inserted well so that no gas leaks are observed and all gas produced remains inside the plastic bucket for the periods of 7 days and this process was repeated twice in order to collect all data needed.

Figure 3.12 Cow dung mixed with water

CHAPTER FOUR. SYSTEM PROTOTYPING

This chapter focuses on the system prototype model from the flowchart to the final protototype and it shows all components used and applied methodologies stated in previous chapter that contributed to the implementation of this prototype.

4.1 System flowchart

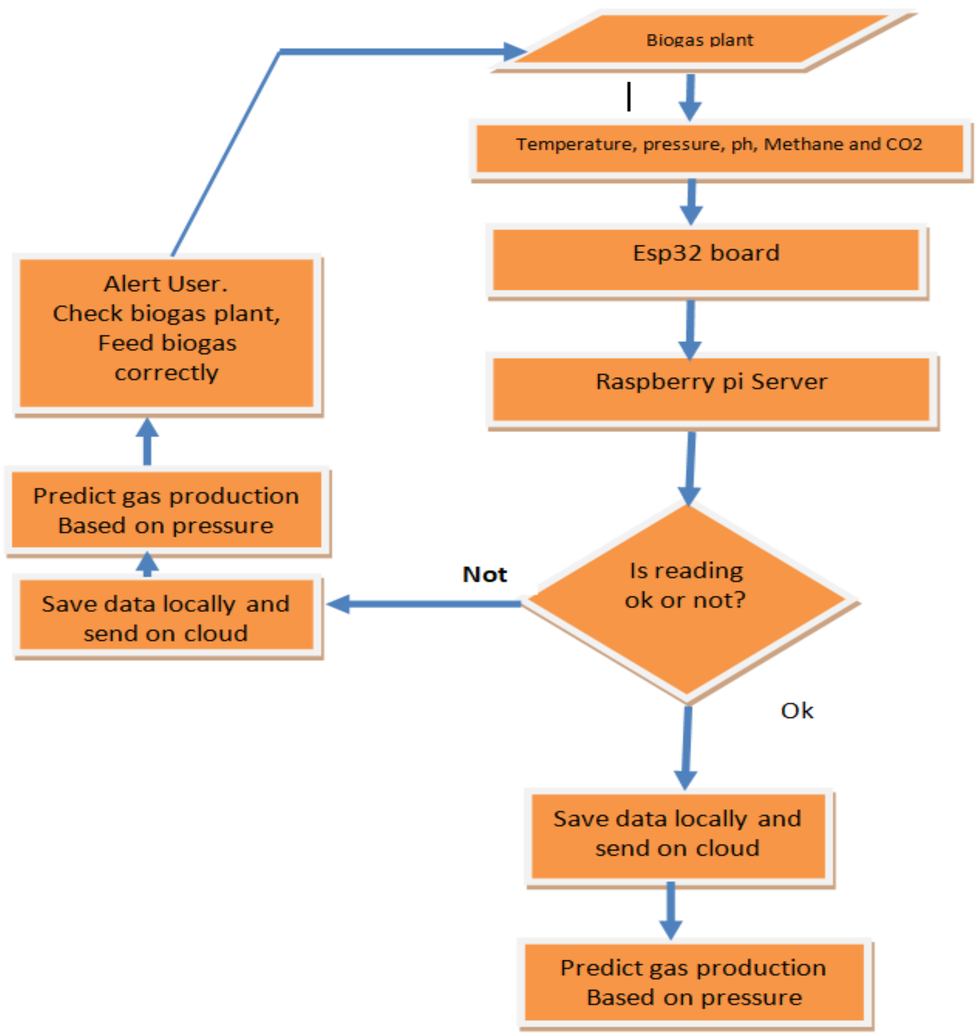


Figure 4.1 System Flow chart

The flowchart indicated in figure 4-1 shows the system functionality of biogas monitoring and prediction system. As indicated by the flowchart, the first input system is biogas plant, then Temperature, carbon dioxide (CO2), potential hydrogen (Ph) and methane (CH4) data are taken by ESP32 controller and readings are saved on local mongodb database and aggregated data are sent on cloud server. If reading on sensors are not in normal range, the system alerts the user and the user react accordingly.

The figure 4-1 shows a flowchart that cleanly shows method used to implement biogas monitoring with internet of things and edge computing. The figure 4-2 is the complete system architecture of the system. It shows that the first input system is biogas plant whereby sensors needed are installed in the biogas container. Those sensors are temperature sensor, pressure sensor, ph sensor, Carbon dioxide sensor, methane sensor. ESP32 development board is used to collect sensor data and send them to the raspberry pi via MQTT protocol for further processing. Raspberry pi received data and save them in mongodb database. Raspberry pi runs a node-red server that receives the incoming data, save them to the database and provide real time user dashboard for real time monitoring. The end user can access the dashboard by connecting to node-red server running on raspberry pi using only wifi connection. This help end user to access information without any other cost. Raspberry pi is set to send aggregate data to the adafruit MQTT cloud server after each 30 minutes and biogas user or any other allowed personnel can access cloud data any time.

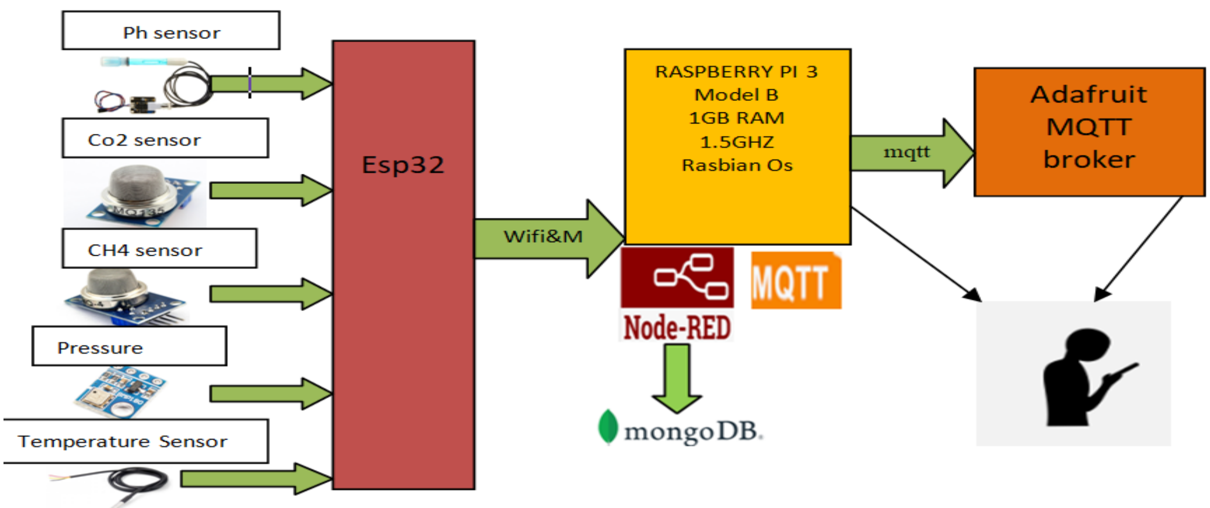


Figure 4.2 System deployment model

4.2 Prediction modeling process

a) Features Selection

The feature engineering is said to be one of among of the core techniques used to increase the chances of success while solving problems that requires machine learning [26]. As a part of feature engineering, feature learning is a machine learning technique that is used to derive new features in your dataset. As shown in figure 4-3, the main predictors used in this context are Temperature, carbon dioxide (CO_2), potential hydrogen (Ph), methane (CH_4), Volume of feeded

Columns (Double click to edit)

	Name	Type	Role	Values
1	CO2	N numeric	feature	
2	Methane	N numeric	feature	
3	**Pressure**	**N numeric**	**target**	
4	Temperature	N numeric	feature	
5	ph	N numeric	feature	

Figure 4.3 Predictors used for model training and evaluation

organic materials (Kg) while the gas pressure is considered as target. Those features are taken from the measurement produced by sensors inside biogas digester.

b) Model Training and evaluation

In this section the training inputs data considered are Temperature, carbon dioxide (CO_2), potential of hydrogen (Ph), methane (CH_4), Volume of feeded organic materials (Kg) and the pressure. The dataset used contains 1565 samples that include four features and one target variable called class. The figure 4-4 illustrates the process undertaken in order to have a predictive machine learning model.Before model training the dataset was divided into two datasets, training dataset and testing dataset. The training dataset contains 80% of original dataset, and the testing dataset contains 20% of the original dataset. The training dataset was applied to the machine learning algorithms in order to obtain desired predictive model. Testing dataset was used to verify if the predictive model does not under-fitting or over-fitting[29]. The over fitting occurs when the predictive model predicts well on the training data but does not do the same for new data or unseen data. The training and evaluation process has been done using

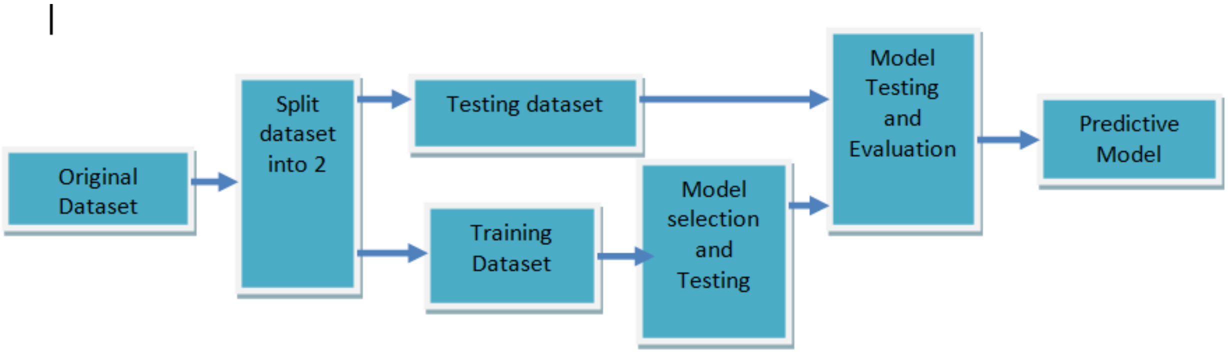


Figure 4.4 Machine Learning Training Evaluation Process

Jupiter notebook software package provided by anaconda distribution software.

After gathering and preparation of dataset to be used by Machine Learning Algorithms for prediction purpose, the models were trained on training data using several Machine Learning classification models: K-Nearest Neighbours (KNN), Random Forest, Gradient Boosting, Decision Trees and Neural network to model the relationship between Temperature, carbon dioxide (CO2), potential hydrogen (Ph), methane (CH4), Volume of feeded organic materials by using python code and available python packages used for data analysis. The python programming environment is used because it seems be a flexible and very popular language and makes many tools available as open source for the researcher from development to deployment [30][31]. Finally, the researcher has evaluated the generated Machine Learning predictive models and selected the one presenting the best predictive accuracy. The prediction accuracy is used to measure how well the generated predictive model is performing against unknown data by making comparison between a predicted value and an observed or known value. The higher prediction accuracy value indicates that the model is performing better[32][33].

4.3 System Interoperability

PH sensor is inserted directly in the mixture of organic materials fed to the biogas plant. It continuously read the ph value which changes with time after feeding is ended. The ph value is read by esp32 through its analog pin which has a great resolution of 12 bit analog to digital converter[15].

The MQ-135 sensor is the in the series of gas sensor which is very sensible to $C0_2$. The carbon dioxide produced by the mixture of organic material fed to the biogas plant is detected by the mq-135 sensor.

To measure the gases in PPM (part per million) the analog pin need to be used. The analog TTL is operated and operates at 3.3 volts and so can be used with most common microcontrollers. Here, the analog pin 0f MQ-135 sensor is connected to the analog pin of esp32.

The methane sensor MQ-4 is used to detect methane concentration. As indicated in the sensor description , it has analog output pin that produced analog signal which changes when the methane concentration changes in the biogas digester .the pin is also connected to the analog pin of esp32 development module. Its measurement is also converted in parts per million (ppm).

The pressure sensor used here is BMP180. it is connected to the microcontroller (esp32) using inter-integrated circuit (i2c) communication protocol and then shows the current pressure inside the biogas digester .

The Temperature sensor used is 18b20 which is waterproof temperature sensor. It is an accurate sensor and it is connected to the digital pin of esp32 in order to read the temperature inside the biogas plant.

After reading all sensor data identified above, all measurement are sent simultaneously to the raspberry pi via wifi using MQTTcommunication protocol each 5 minutes. The raspberry pi runs a node-red server that receives the incoming data, saves them to mongodb database running also on raspberry pi. The node-red server sends aggregated data to adafruit mqtt clod server each 10 minutes for remote monitoring purpose. The data received on raspberry pi are applied to the machine learning model trained in order to make predictions of expected gas pressure which is the key parameter that indicates the biogas production process. Node-red server also provides the user interface that is accessed by local user with the help of WIFI connection.

4.4 Sensor node design process and data acquisition

All sensors have been fixed on the bucket closing cap so that they take measument being above the mixture of the cow manure and water except the ph sensor which is inserted in the mixture. The figure 4-5 indicates the process of sensor installation on the biogas system.

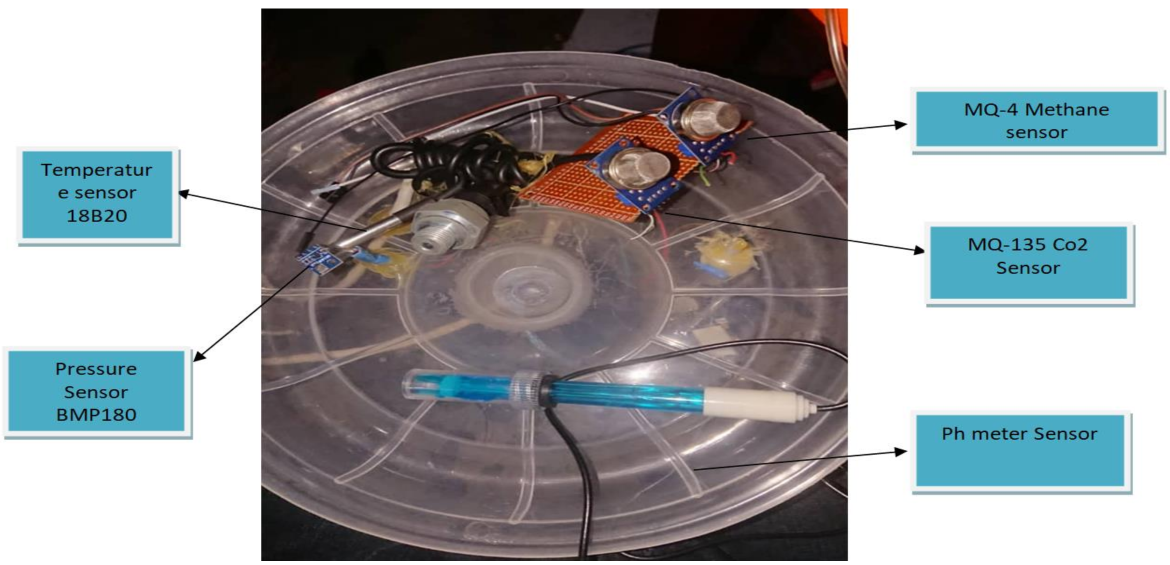


Figure 4.5 Sensor Installation process

The figure 4-6 demonstrate the process of receiving data sent by sensor node via MQTT protocol running on top of node-red server installed on raspberry pi where data are saved on mongodb database. Mongodb is selected for its ability to handle real time data[27]. The figure 4-6 demonstrates node-red flows that receives data from sensor node while figure 4-7 indicates data

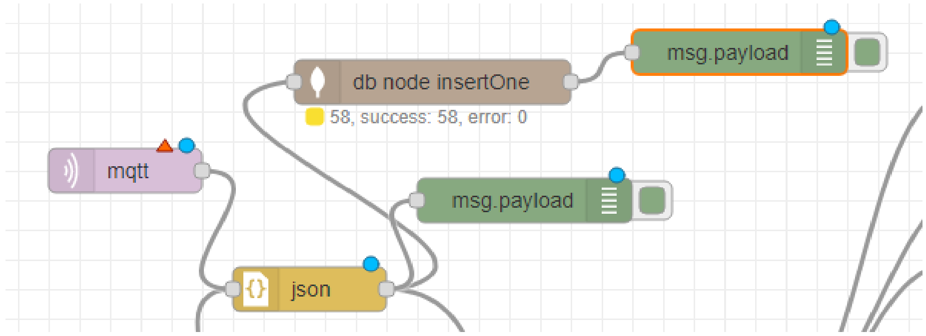


Figure 4.6 Node-red flow that receives data from esp32 and save to mongodb database

saved within mongobd collection. A collection in mongobd is considered as a table in traditional relational databases.

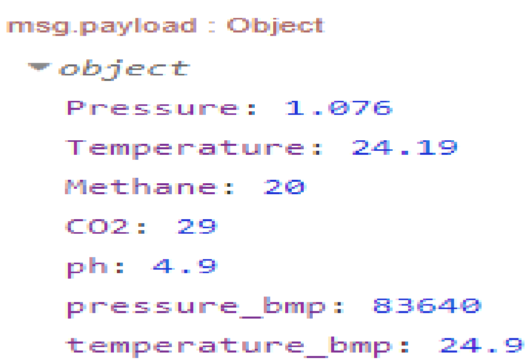


Figure 4.7 Data received by node-red server

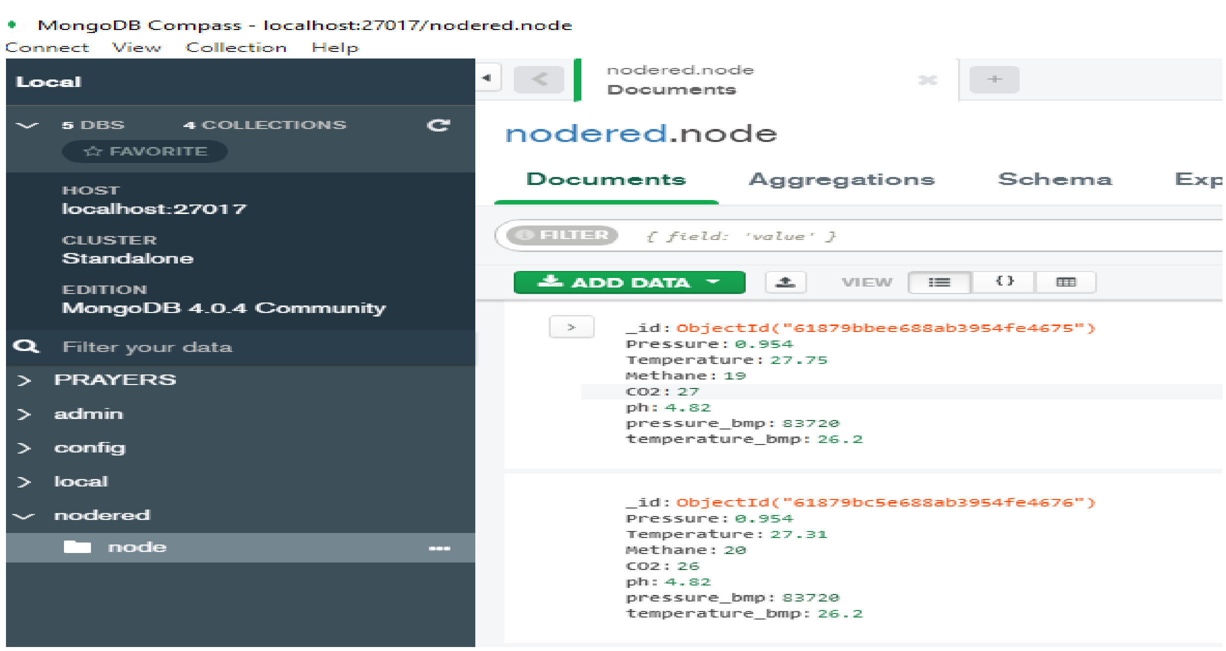


Figure 4.8 Sensor data stored in mongodb database

CHAPTER FIVE: BIOGAS MONITORING SYSTEM EVALUATION AND RESULTS DISCUSSIONS

5.1 Introduction

This chapter describes results found after system prototyping and testing phase of the biogas monitoring system. The chapter provides analysis on sensor data collected from all sensors and describes the relationship between the parameters used during data collection. It presents also data visualization and how real time alerts is implemented in order to alert end user biogas end user. Finally the machine learning model selected are trained and evaluated.

5.2 Data visualization and Dashboards

In order to visualize data in real time, dashboards have been designed using node-red user interface builder and all sensor sensor measurements are shown as indicated by the following figures. Those dashboards are accessed locally on the raspberry pi. You can connect to raspberry pi server using local WIFI network. The figure 5-1 shows the real time data sent from sensor node to node-red server cloud server while figure 5-2 shows real time data charts variation with time.

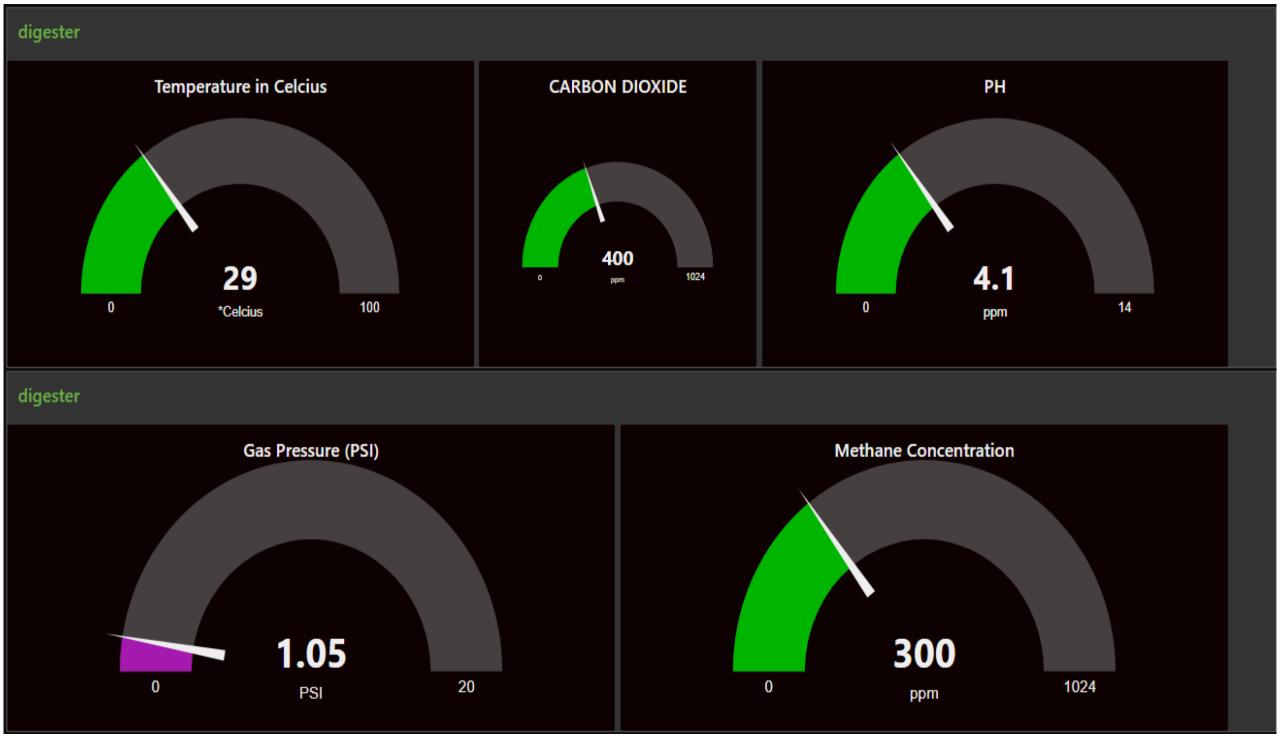


Figure 5.1 Dashboard for all data measurements with node-red server

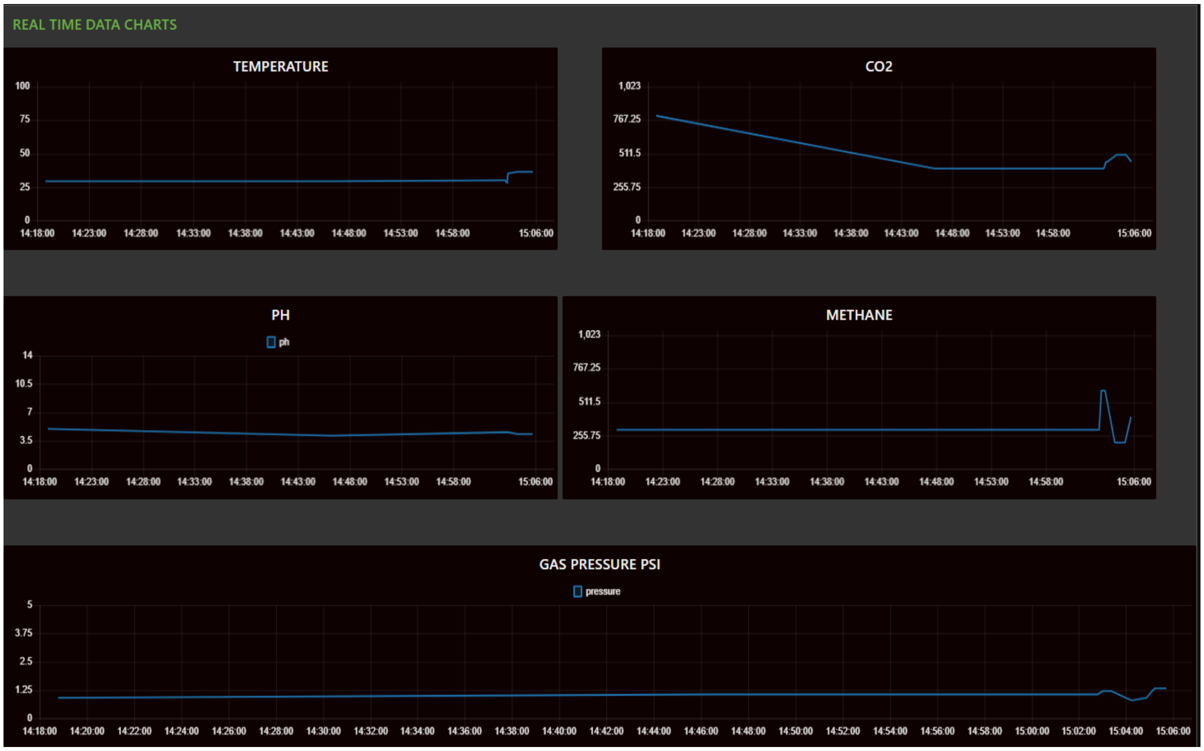


Figure 5.2 Real time data charts on node-red server

The sensor data collected on node-red server are also sent to the cloud server for remote monitoring. The figure 5-3 shows the real time data sent to Adafruit MQTT cloud server. Adafruit MQTT cloud server is used. It is having an MQTT broker service where you can publish and subscribe to sensor data anytime. It allows user to send the limit of 60 data points within a minutes under free account. If you want to send more than 60 data pint per minute, you have to upgrade to paid account. As shown in figure 5-4, the real time charts can indicate data variation within a period of hours, days or months.

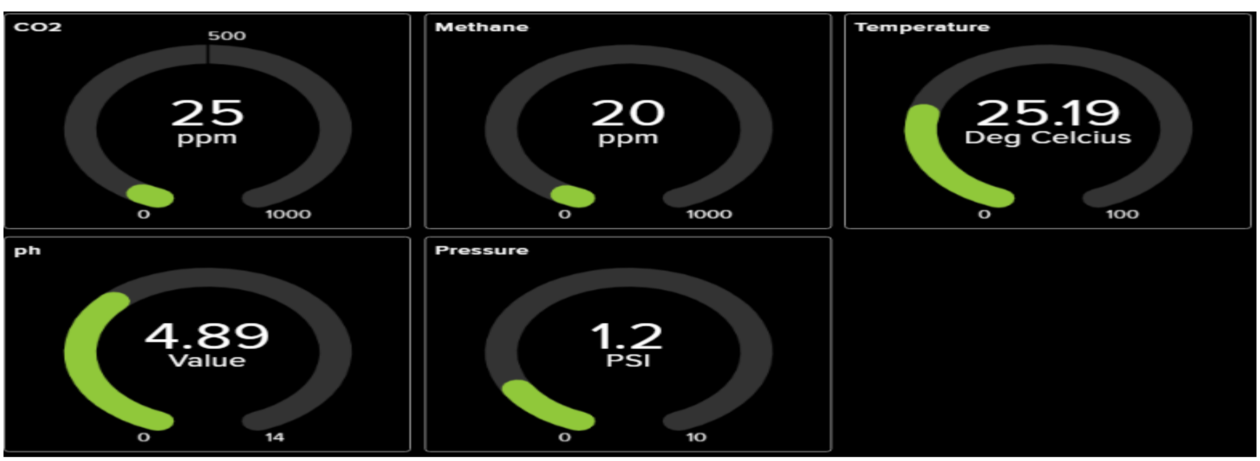


Figure 5.3 Real time biogas data monitoring via adafruit MQTT cloud server

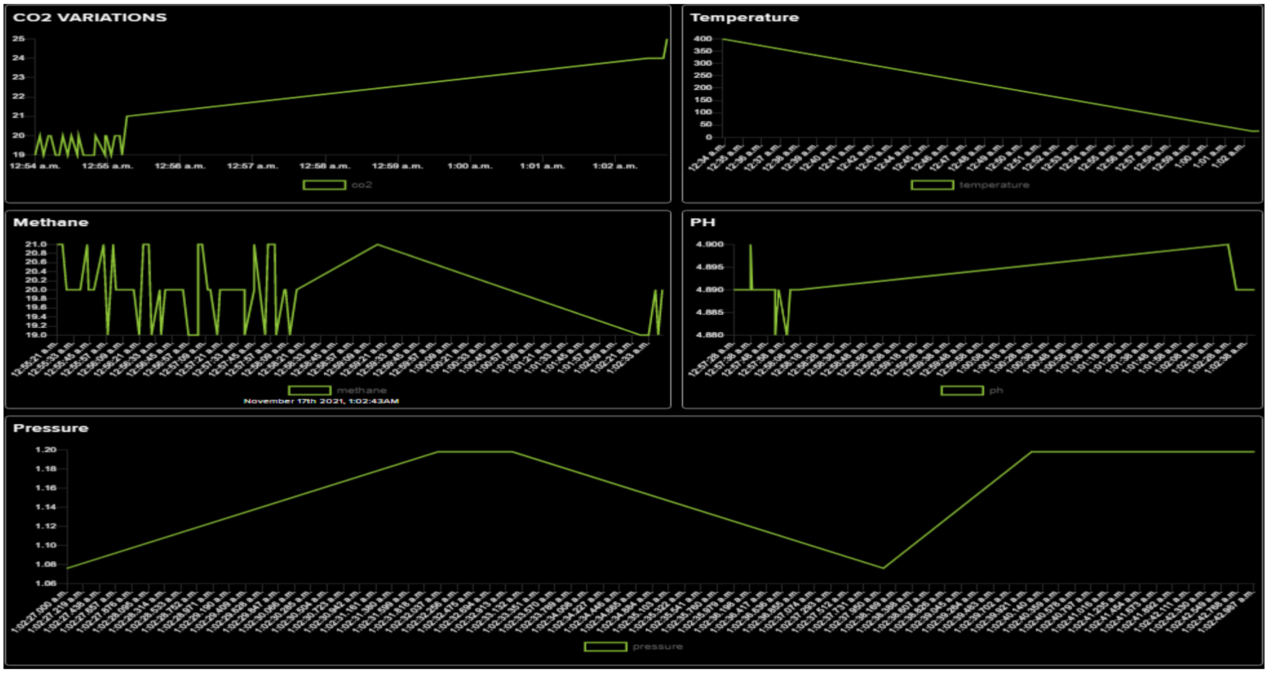
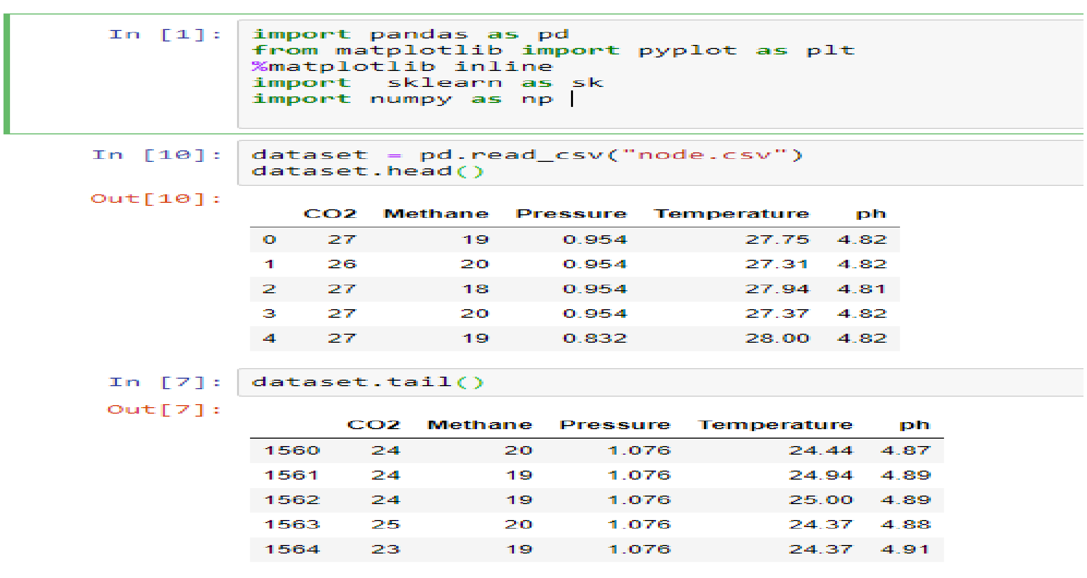


Figure 5.4 Graphs showing biogas digester data variation over time on adafruit cloud server

5.3 Machine Learning model training and evaluation

The training and evaluation process were implemented through python programming codes and python libraries. Diverse machine learning algorithms used were implemented using python and its libraries found in sklearn python package [44]. The training process and evaluation was done by importing the original dataset from CSV file by using data frame implemented with panda's python library module. The figure 5-5 is indicating the process of importing dataset and necessary python libraries used in data analysis .



In [1]:
```
import pandas as pd
from matplotlib import pyplot as plt
%matplotlib inline
import  sklearn as sk
import numpy as np
```

In [10]:
```
dataset = pd.read_csv("node.csv")
dataset.head()
```

Out[10]:

	CO2	Methane	Pressure	Temperature	ph
0	27	19	0.954	27.75	4.82
1	26	20	0.954	27.31	4.82
2	27	18	0.954	27.94	4.81
3	27	20	0.954	27.37	4.82
4	27	19	0.832	28.00	4.82

In [7]:
```
dataset.tail()
```

Out[7]:

	CO2	Methane	Pressure	Temperature	ph
1560	24	20	1.076	24.44	4.87
1561	24	19	1.076	24.94	4.89
1562	24	19	1.076	25.00	4.89
1563	25	20	1.076	24.37	4.88
1564	23	19	1.076	24.37	4.91

Figure 5.5 Importing dataset with jupyter notebook

The dataset used in model training and evaluation have four inputs features and one output or target variable. The model inputs include carbone dioxide, temperature, methane and potential of hydrogen. The model target is the pressure which is considered as the primarily indicator of biogas production inside the biogas digester. Dataset visualization is presented with figure 5-6.

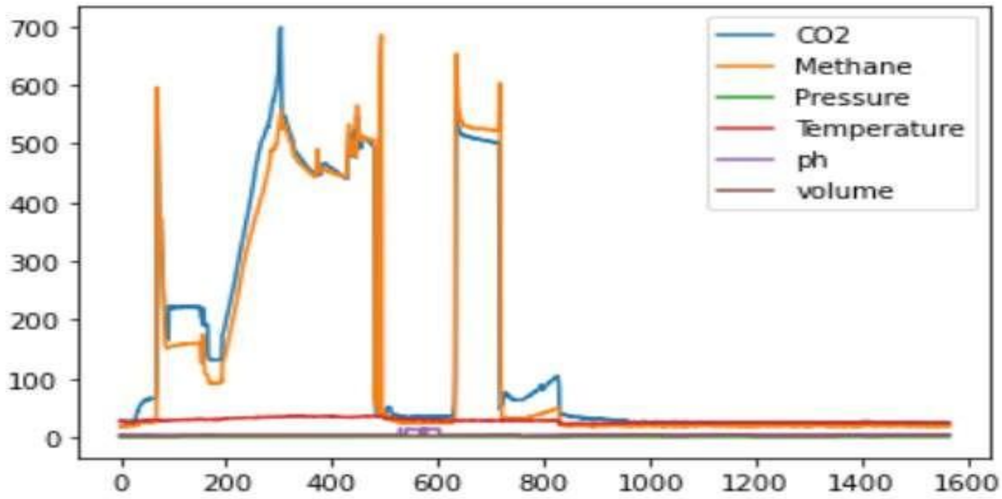


Figure 5.6 Data visualization with Matplotlib python package

prior to applying the inputs data to the desired machine learning algorithm, data normalization was performed for improving the prediction accuracy by decreasing the high differences between the model independent variables for allowing the model to generalize on the new or unseen data. The 80 and 20 percentages of the original dataset were used for training and for testing respectively.

The following is the summary of model training and evaluation process.

- **Dataset size**: 1565 samples
- **Training data size**: 1252 samples = 80% of dataset/for each model
- **Testing/evaluation data size**: 313 samples = 20% of dataset/for each model

- **Model features:** C02, Methane, volume, ph
- **Model target:** Pressure
- **Random state:** parameter considered during of selecting training and testing data

The results appeared in the figure 5-7 were generated K-Nearest Neighbors machine learning algorithms during of model's training and evaluation process. As seen in the figure 5-7, the predictive accuracy was taken as the machine learning evaluation metric to assess the performance of the predictive model. It is clear to figure out that the predictive accuracy is improved as the number of iterations increase progressively for both training and testing data. The accuracy obtained tend to be near 70 % .

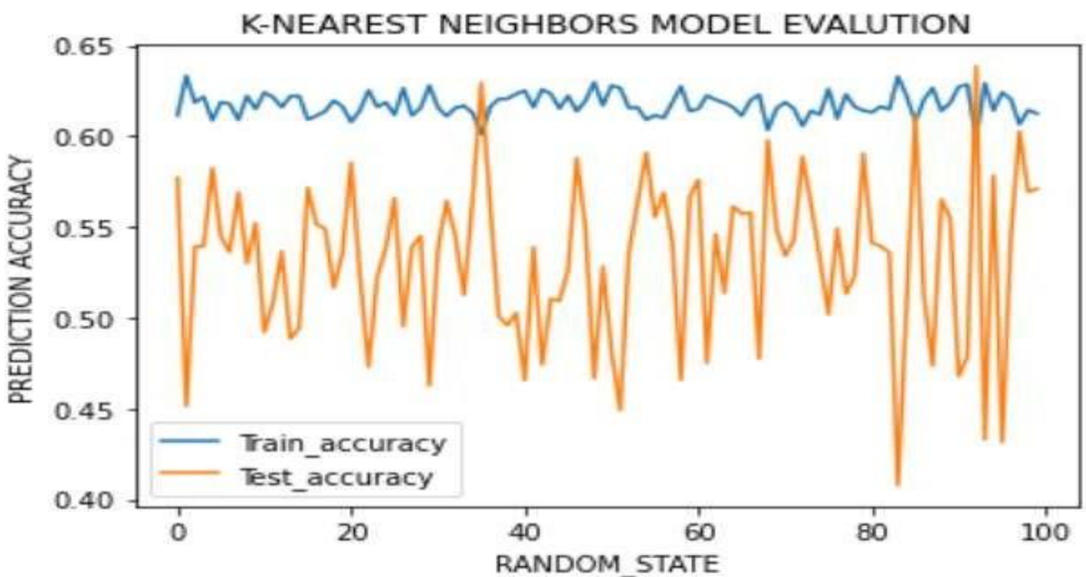


Figure 5.7 KNN model evaluation

The accuracy tends to be lower to 70% when we use decision tree machine learning algorithm.

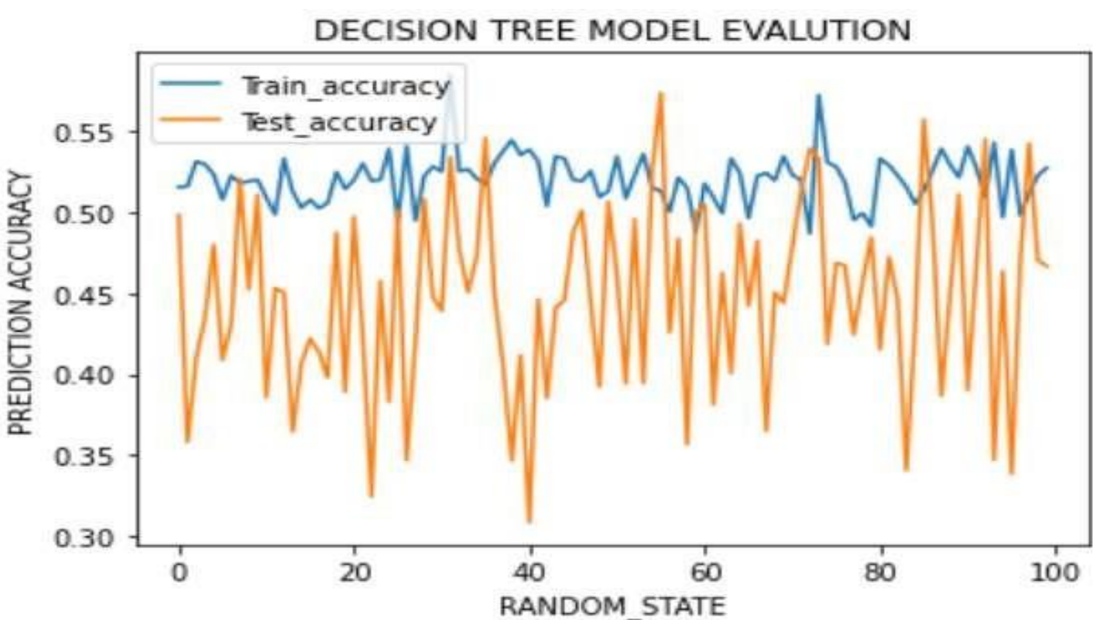


Figure 5.8 Decision tree model evaluation

When gradient boosting machine learning model is used as shown by figure 5-8, both the training and testing accuracy became roughly around 65 %.

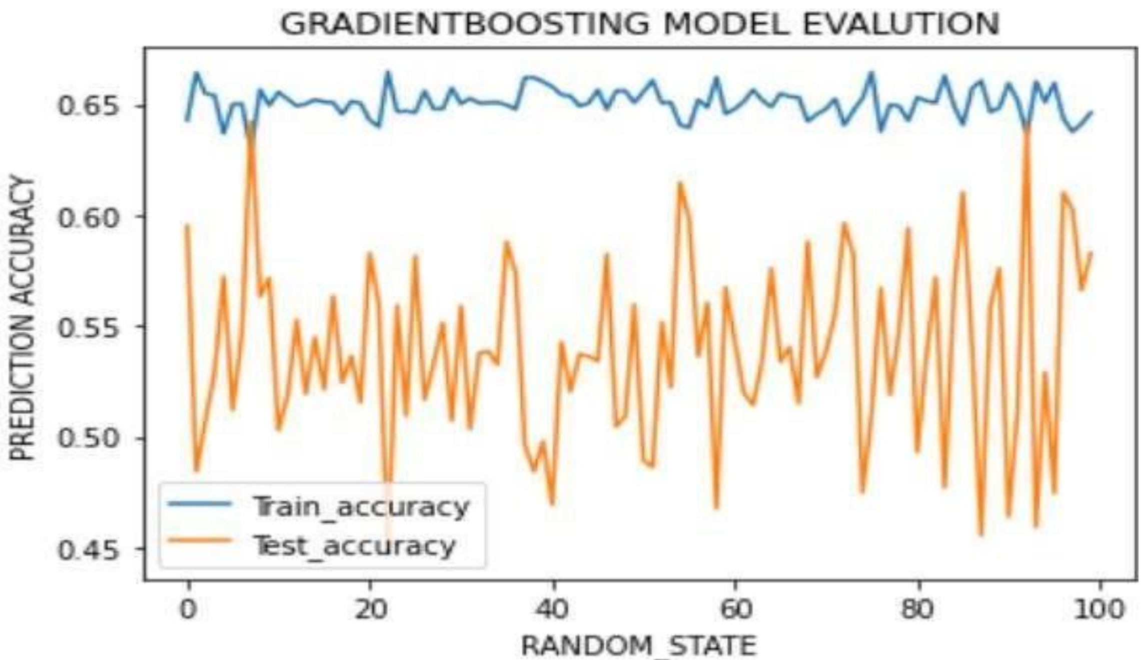


Figure 5.9 Gradient boosting Model evaluation

As shown in figure 5-9, Pressure was predicted well using the above machine learning algorithms used in this research. The figures 5-10, 5-11, and 5-12 shows random selected testing dataset with selected machine learning model and their corresponding biogas prediction results which seems to be accurate.

	kNN	Pressure	CO2	Methane	Temperature	ph	volume
99	0.905	0.832	220	155	29.12	3.98	2
73	1.100	0.832	449	465	29.25	4.15	2
101	0.930	0.832	221	156	29.25	3.95	2
59	0.905	0.832	65	26	29.31	4.39	2
106	0.930	0.832	220	156	29.37	3.98	2
62	0.905	0.832	66	27	29.50	4.31	2
61	0.905	0.832	66	26	29.56	4.30	2
69	1.100	0.832	81	34	29.69	4.20	2
123	0.978	0.832	222	160	30.06	3.98	3
153	0.905	0.832	214	149	30.25	4.00	3
168	1.003	0.832	135	97	30.25	4.75	3
145	0.930	0.832	221	160	30.75	3.98	3
150	0.930	0.832	223	161	30.94	3.98	3
845	0.978	0.954	37	20	22.87	4.88	2
851	1.027	0.954	37	20	22.87	4.89	3
853	1.052	0.954	36	19	22.87	4.87	3
859	1.052	0.954	35	20	23.00	4.89	3
873	0.905	0.954	34	19	23.00	4.87	3
871	1.003	0.954	35	21	23.06	4.87	3
874	0.930	0.954	33	20	23.12	4.89	3
890	1.052	0.954	32	20	23.19	4.90	3
841	0.978	0.954	38	19	23.25	4.89	2
896	0.978	0.954	31	21	23.31	4.88	3
906	0.978	0.954	31	21	23.31	4.88	3
831	1.052	0.954	41	20	23.37	4.88	2

Model	MSE	RMSE	MAE	R2
kNN	0.006	0.078	0.062	0.628

Figure 5-.10 Pressure prediction with KNN

	Gradient Boosting	Pressure	CO2	Methane	Temperature	ph	volume
58	0.968	0.954	35	21	23.06	4.87	3
59	0.922	0.954	33	20	23.12	4.89	3
60	0.922	0.954	32	20	23.19	4.90	3
61	0.922	0.954	38	19	23.25	4.89	2
62	0.922	0.954	31	21	23.31	4.88	3
63	0.962	0.954	31	21	23.31	4.88	3
64	0.962	0.954	41	20	23.37	4.88	2
65	0.962	0.954	31	20	23.37	4.89	3
66	1.013	0.954	39	20	23.44	4.89	2
67	0.962	0.954	38	21	23.44	4.89	2
68	0.988	0.954	36	21	23.44	4.89	3
69	1.005	0.954	30	20	23.44	4.88	3
70	1.028	0.954	36	19	23.50	4.89	2
71	1.122	0.954	33	20	23.56	4.88	3
72	1.134	0.954	34	21	23.62	4.87	3
73	0.956	0.954	34	19	23.62	4.89	3
74	0.954	0.954	34	20	23.62	4.89	3
75	0.997	0.954	32	20	23.62	4.90	3
76	0.991	0.954	35	20	23.69	4.89	3
77	0.995	0.954	33	21	23.69	4.88	3
78	0.982	0.954	29	20	23.69	4.89	3
79	0.991	0.954	34	20	23.75	4.88	3
80	0.991	0.954	32	19	23.75	4.89	3
81	0.991	0.954	32	21	23.81	4.88	3
82	0.986	0.954	32	19	23.81	4.88	3

Model	MSE	RMSE	MAE	R2
Gradient Boosting	0.006	0.077	0.062	0.638

Figure 5.11 Pressure Prediction with Gradient Boosting

	Tree	Pressure	CO2	Methane	Temperature	ph	volume
1	0.954	0.954	27	19	27.75	4.82	2
2	0.832	0.954	26	20	27.31	4.82	2
3	0.893	0.954	27	18	27.94	4.81	2
4	0.954	0.954	27	20	27.37	4.82	2
5	0.873	0.832	27	19	28.00	4.82	2
6	0.873	0.832	27	19	28.06	4.82	2
7	0.893	0.832	27	19	27.94	4.82	2
8	0.873	0.954	27	19	28.06	4.82	2
9	0.832	0.832	26	18	27.94	4.81	2
10	0.832	0.832	27	19	28.19	4.80	2
11	0.954	0.954	27	20	27.62	4.80	2
12	0.832	0.832	25	19	24.44	4.83	2
13	0.893	0.832	27	19	25.12	4.82	2
14	0.893	0.954	28	19	25.19	4.82	2
15	0.893	0.832	28	19	25.25	4.82	2
16	0.893	0.832	28	20	25.12	4.81	2
17	0.770	0.832	28	19	25.19	4.92	2
18	0.873	0.832	27	19	25.31	5.00	2
19	0.873	0.832	27	19	25.31	5.03	2
20	0.954	0.954	28	20	24.81	5.06	2
21	0.954	0.832	27	20	25.31	5.06	2
22	0.954	0.832	27	19	25.44	5.14	2
23	0.954	0.954	27	19	24.81	5.08	2
24	0.770	0.709	27	19	24.94	5.01	2
25	0.873	0.954	28	19	25.50	4.99	2
26	1.015	0.954	28	19	25.62	4.95	2

Model	MSE	RMSE	MAE	R2
Tree	0.004	0.065	0.045	0.740

Figure 5.12 Pressure prediction with decision tree

5.4 Results discussion

After making the biogas monitoring system and making possible analysis of data collected on biogas digester, we have achieved our objectives which were to put in place biogas monitoring system for preventive maintenance and making a biogas prediction model for predicting biogas production based on inputs feedings. The prototype made contains sensors which provide data inside biogas digester where data collected are analyzed at the edge and aggregated data are sent to the cloud for storage and for future analysis. The analysis of data collected on biogas using selected machine learning models indicated the dependency between features used and contribution of each future in the production of biogas. The model has been made and the prediction accuracy was around 70% which is a promising results.

CHAPTER SIX: CONCLUSION, RECOMMENDATION AND FUTURE WORK

6.1 Conclusion

This research aimed to make the biogas monitoring system and making biogas prediction model to predict biogas production based on inputs feedings with organic materials. The monitoring system have been implanted successfully where all key biogas parameters involved in biogas production (temperature, methane gas, pressure, ph) are monitored and the data can be accessed either on the edge or in the cloud where biogas end user or any other authorized agent can access biogas data and react accordingly when necessary for preventive maintenance . After that, biogas parameters (Temperature, methane gas, pressure) have been analyzed using Machine Learning algorithms in order to predict biogas production based on data produced and feeding of organic materials used. The outcome of the current research shows that the biogas production in biogas container could be predicted with high accuracy (between 65% and 70%) by using K-nearest neighbors (K-NN), gradient boosting and Decision tree Machine Learning Algorithms respectively comparing with the other algorithms tested through this research.

6.2 Recommendations

I recommend the decision makers to help in developing a complete biogas digester and apply this IoT technology in order to optimize the biogas production in rural to reduce the use of biomass and it will contribute in environmental protection. I also recommend decision makers to work with available stakeholders in order to convince rural population to adopt biogas technology for their well being.

6.3 Future work

For the future work, we expect to employ some advanced machine learning models like time series models (Recurrent Neural Networks) to predict the biogas production rate because of the complexities of anaerobic digestion that occurs inside biogas digester to produce biogas [8]. In this research, only one organic material has been considered (cow dung and water). The next researcher could do deep analysis of different feeding materials available as they do not contain the same amount of biogas and the dataset could be taken in order of several months or years which could help the accuracy of the prediction by the machine learning algorithm.

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