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# FOOD SAFETY FORECASTING USING INTERNET OF THINGS AND MACHINE LEARNING

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## ABSTRACT

Food sector is a significant part of the economy but it faces challenges with food spoilage, especially in meat, fruits, and vegetables. This issue involves food items, especially meat, fruits, and vegetables, going stale and often reaching consumers unnoticed. Additionally, during food chain there may be instances where the food may still be within the proposed shelf life but may be spoilt before it gets to the consumer, therefore, it is important to test them and envisage when it will be inedible. This paper presents a predictive model which is used to forecast when the fruits will be inedible via the use of time series data generated from internet of things (IoT) based device. The IoT device developed in this research is used to monitor the decline of the freshness of the fruit to the state of inedibility. This device measures parameters such as alcohol, and ammonia around the fruit, as such large amounts of real-time data are generated. A web server is used for the storage of data values sensed in real time and also for the analysis of results. Long Short-Term Memory (LSTM) predictive model is

## Introduction

Food safety is the condition that ensures that all people have access physically and economically to safe and nutritious food that meets their needs for healthy living (Yu *et al*., 2022). According to Hebbar, (2020), in ensuring food security, food safety which includes a healthy and quality food supply must be considered more important to ensure the safety of consumers (Hebbar, 2020). This, therefore, suggests that food may be available but, remains unsafe to be consumed (Ajay Menon *et al*., 2020). Aside from diseases and death, unsafe food could result to economic waste and therefore, the need for consistent real-time monitoring of food quality and its safe health status.

used to forecast the time the fruit will be inedible via the use of time series data harvested from the cloud. The implementation of this technology enhances traceability, minimizes food wastage, and, most importantly, protects consumers from foodborne illnesses.

**Keywords:** Food safety, IoT, Machine learning.

This will aid the removal of harmful food from the food chain. Furthermore, results indicating safe state of food after a test must be accessible by everyone remotely without any limitations. However, all this will ensure the safety of consumers. To achieve this, the Internet of Things becomes an obvious technique. This technology ensures the availability of information anywhere at any time via the use of a protocol called Internet Protocol (IP).

During the food chain there may be instances where the food may still be within the proposed shelf life but may be spoilt before it gets to the consumer. It is important to test them and envisage when it will be inedible. This will help workers in the food chain to isolate such spoilt food from the rest if they can't make it through the food chain. In other words, Long Short -Term Memory (LSTM) predictive model will be used to forecast the time the tomatoes will be inedible via the use of time series data generated via the use of internet of things (IoT) based device.

This will be achieved via the use of IoT device which will measure parameters like oxygen level, alcohol and ammonia around the fruit. The device developed in this research is used to monitor the decline of the freshness of the fruit to the state of inedibility. The data generated will be used to forecasted the date of rancidity before it happens so as to determine if the food can continue in the food chain.

## Related works

Authors in Yu et al. (2022) reviewed the different technologies used to ensure the safety of food. One of the ways in which contaminants are detected includes the laboratory-based test which does not involve any sophisticated devices. However, the limitation is that it can't be used in on some cite such as the market .to overcome this limitation, the author in the review, classified the sensor that can also be used on site. These sensors are called portable devices which includes portable spectrometer such as infrared food safety thermometer and nuclear magnetic spectrometer, array sensors which mimics the human sensory organs of smell and taste, lab on chip and smart phone-based analysis. Among all these portable devices, the spectrometers have the capability to analyze the safety of food without destroying them. The limitation is that such result could be compromised since it does not have real time storage. Furthermore, the detection done in the study is at the point of in-edibility.

Chandran & Lias, (2021) presented a system to aid the management of the quality of banana. In the investigation of how best to keep food in the home, the specimen (banana) was observed under 72 hours at different environmental conditions.so as to ascertain its edibility condition. To achieve this, DHT11 was used to measure environmental temperature and humidity. Furthermore, MQ3 sensor, interfaced to a controller, was used to measure the alcohol content generated by the banana as it goes bad. At the end of the research, it was observed that the banana observed in cooler temperature stayed longer than the 72hours before getting bad.

In a presentation by (Hebbar, 2020), spoilt food was detected automatically using the sensors which senses the gases that are produced from the food. Also, machine learning was used to predict when the food is spoilt. This was aimed at the fast retrieval of spoilt food transported on a conveyor belt in industries. To achieve this, a Node MCU was used to process the sensing done by the sensors. Afterwards, the device sounds a buzzer to create attention and furthermore, the data is stored in the cloud. The sensors used in this presentation is oxygen sensor and ammonia sensor. This is because the acting of bacterial on a food will limit the oxygen around as more ammonia will be produced. The limitation of the study is that it did not take into account forecasting so as to ensure limit waste before rancidity.

## Methodology

The materials used to achieve this design are the following

i. MQ3 alcohol sensor ii. ADS1115 iii. .MQ137 ammonia sensor. iv. Arduino Uno

v. Node MCU vi. 12V Battery vii. LM2596 Buck converter module.

## Software used

The software used in this research is subdivided into firmware and analytical software. The firmware which runs in the controller (Node-MCU) is written in


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C++. This is written and compiled using Arduino Integrated Development Environment (IDE). The analysis is done using Python. This whole data analysis and the deep learning algorithm are achieved on Anaconda IDE.

### Cloud Service

The cloud server used is Think Speak. The reason for the selection of this server among all other servers is because it is simple to use, and can represent data in different formats like CSV and Jason. Furthermore, the platform also could create visual widgets and graphical representations of data within a period.

### Architecture of the system

The system as shown in Figure 1 is subdivided into several subunits. One of the units is the power unit. This unit is connected to every part of the system to power the system. the power unit is designed to output 5V which is used by all the various units in the system. the sensors used in this design is the alcohol sensor, and the ammonia sensor. All these are connected to the controller unit. The controller unit is the center of the whole system. the controller unit is responsible for the processing of signals outputted from all sensors converting it to equivalent data. Also, the controller which consists of a WIFI connects to a wireless router to relay computed data to the cloud.

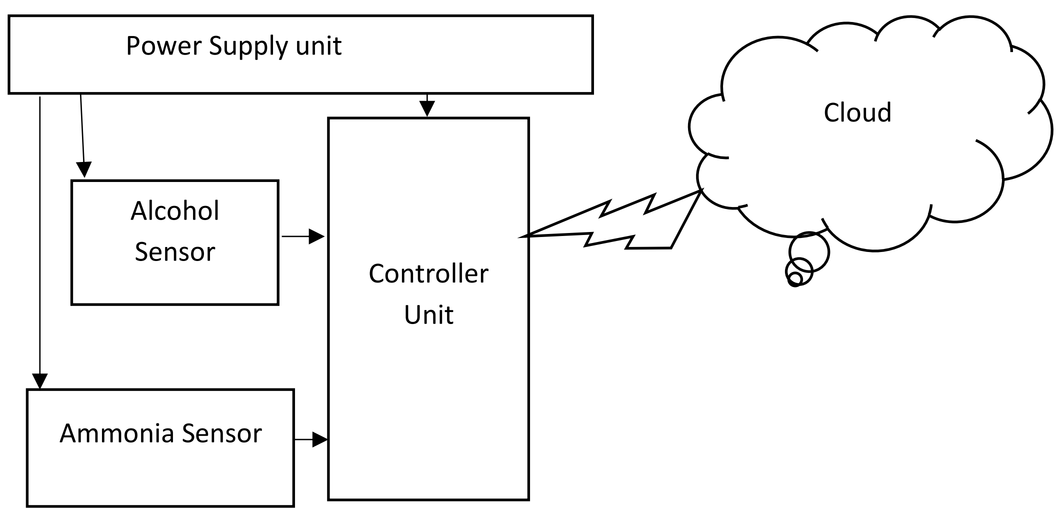


Figure 1. Block Diagram illustrating the architecture of the system

### Power Supply Unit

As shown in Figure 2, the power unit consists of four LM2596 buck converters and a 12V 7AH battery. The buck converter labeled U1 is used to power the controller. The other buck converter labeled U2, U3, and U4 is used to power the sensors. This will help to power the gas sensors which consume a minimum of 0.75W. All of the converters are adjusted to deliver 5V to the circuit. This will consume a total of 3A.

### Controller Unit

The controller unit as shown in Figure 2, is made up of Arduino Uno and Node MCU. The Arduino Uno is used for the conversion of electrical signals obtained from the sensors into interpretable numeric data showing the concentration of the gases produced as a result of the degrading freshness of tomatoes. These data are then sent to the Node MCU which via WIFI sends it to the cloud.

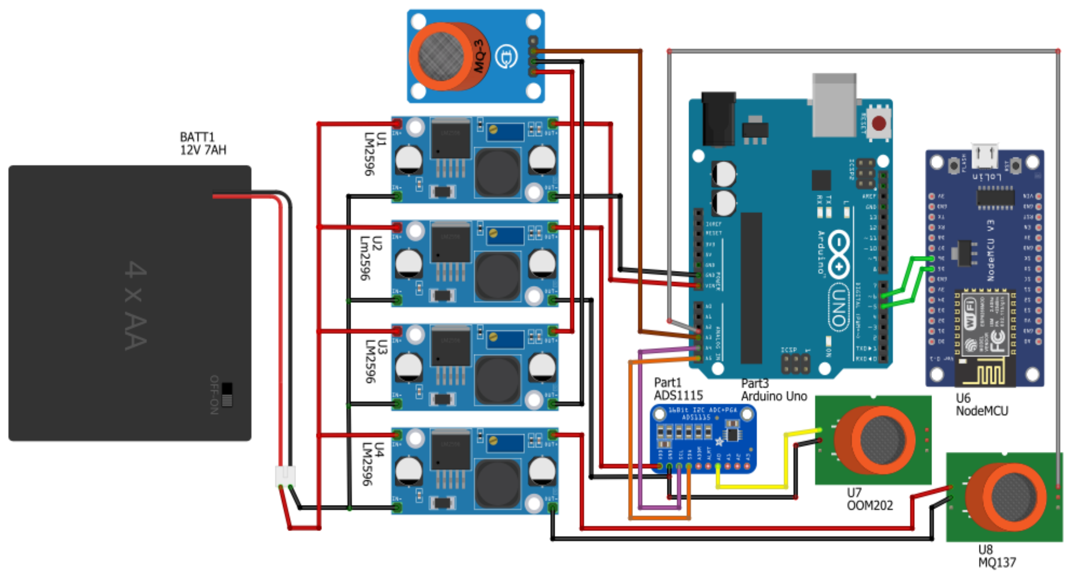


Figure 2. complete circuit diagram of the system.

### Mode of Operation

All gas sensors used were chosen based on the behavior of tomatoes. Generally, the oxygen around this fruit is expected to be high when it is fresh. As the fruit degrades in freshness, the oxygen around the fruit decreases. Afterwards, the fruit starts the fermentation process which generates alcohol that is detected by the alcohol sensor. At the point when the tomatoes are rancid, the fruit generates a foul smell which is detected by the ammonia sensor. All these are gases are represented in their concentration in parts per million (ppm). The values generated by the controller representing the concentration of these gases are sent to the cloud for storage. After 48 hours of data collection, the data is then harvested and used to train the LSTM algorithm. This will then be used for forecasting the state of the tomatoes for the next 48 hours. The conditions at which this is done are atmospheric conditions.

### Experimental Setup

The sensors are fastened to a clean transparent container with lead. The fresh tomatoes will be placed in this container and covered. This setup will be left for 48 hours. Afterward, the data harvested will be used for forecasting

### Data generated

The data generated from the experiment performed includes three features, these are, date time stamp, alcohol gas concentration, and ammonia gas concentration as shown in figure 3. Being sequence data, it is used to train the LSTM model, and a forecast is made to generate future sequences which represent these concentrations

| created_a | entry_id | Alchohol | Ammonia |
|---|---|---|---|
| 2023-06-2! | 1 | 235 | 567 |
| 2023-06-2! | 2 | 237 | 568 |
| 2023-06-2! | 3 | 237 | 567 |
| 2023-06-2! | 4 | 239 | 566 |
| 2023-06-2! | 5 | 238 | 567 |
| 2023-06-2! | 6 | 238 | 568 |
| 2023-06-2! | 7 | 240 | 569 |
| 2023-06-2! | 8 | 242 | 571 |
| 2023-06-2! | 9 | 244 | 576 |
| 2023-06-2! | 10 | 247 | 578 |
| 2023-06-2! | 11 | 258 | 587 |
| 2023-06-2! | 12 | 271 | 597 |
| 2023-06-2! | 13 | 275 | 604 |
| 2023-06-2! | 14 | 282 | 618 |
| 2023-06-2! | 15 | 284 | 630 |
| 2023-06-2! | 16 | 292 | 642 |
| 2023-06-2! | 17 | 296 | 657 |
| 2023-06-2! | 18 | 302 | 675 |
| 2023-06-2! | 19 | 306 | 673 |
| 2023-06-2! | 20 | 301 | 659 |

Figure 3 An image of the portion of data sheet

**LSTM is a tool for Forecasting the state of tomatoes.**
Among other forms of forecasting methods, LSTM was chosen because it can forget irrelevant data and hold on to relevant ones. In other words, it aids the extraction and retention of important data in series of the past (Nguyen et al., 2021). This is achieved via the use of three gates which are the forget gate, input gate, and output gate (Muzaffar & Afshari, 2019).

## RESULTS AND DISCUSSION

The developed node is evaluated using data loss as a metric. Afterwards, the data collected which is used to train the LSTM model is used to forecast when the tomatoes are likely to go rancid. This model is evaluated using the root mean square value.

### Evaluation of the node

The node developed as shown in Figure 4.1 was expected to upload data every 15 seconds. The experiment which involved data logging started on the 30th seconds of 1:12 pm on 29th of June 2023 to the 24th seconds of 11:55 am on the 2nd of July 2023. This makes a total of 223380 seconds. This means we will have a total of 14892 entries.

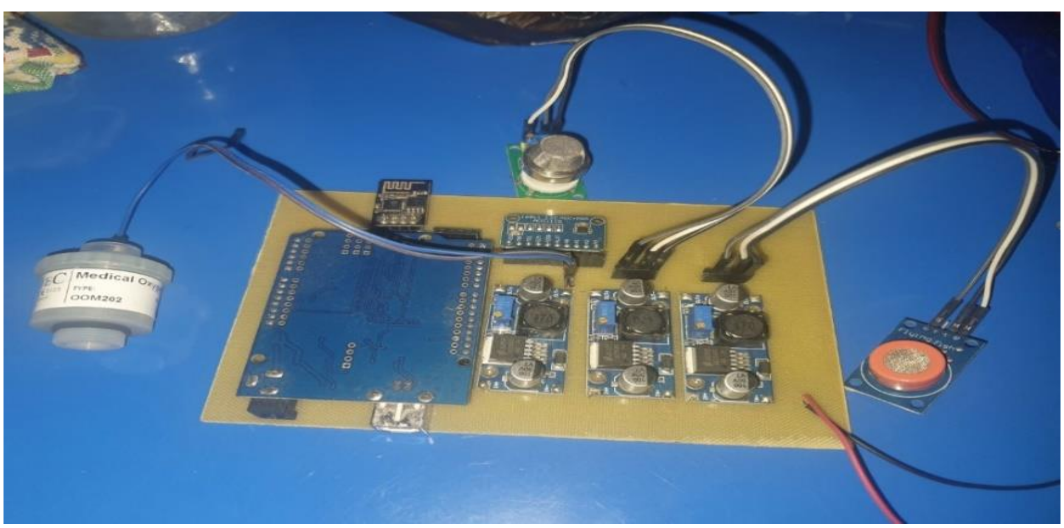


Figure 4.1 Circuit developed for the detection of volatile gases from tomatoes

$$data_{loss} = Data\ expected - Data\ uploaded$$

$$data_{loss} = 14892 - 14892 = 0$$


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$$\boldsymbol{Upload\ efficiency} = \frac{Data\ uploaded}{Data\ expected} \times \mathbf{100}$$

$$\boldsymbol{Upload\ efficiency} = \frac{14892}{14892} \times \mathbf{100} = \mathbf{100\%}$$

Additionally, to evaluate the accuracy of the sensors, the experiment was performed for different condition of tomatoes and the result is compared with the work of Felix, 1936. The graph in Figure 4.2 and 4.3 shows the data generated from alcohol and ammonia sensor when green tomatoes was placed in the apparatus. It was observed that the concentration of the alcohol is at range of 140 – 160 and the fluctuations is as a result of the effect of anaerobiosis (Felix,1936). Additionally, when orange-red tomato was used, the value for alcohol concentration is also within the range of 230 – 250ppm as shown in Figure 4.4 and 4.5. This validated

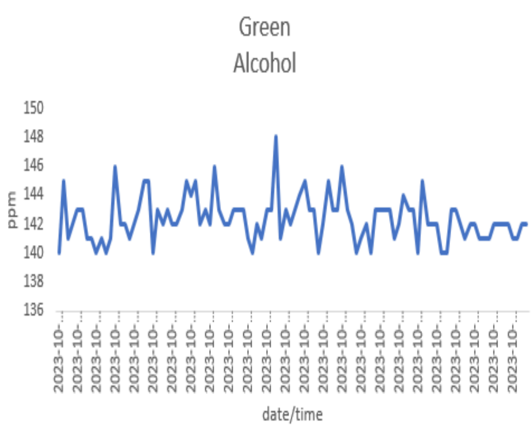

Figure 4.2. graphical representation of alcohol concentration of green tomatoes

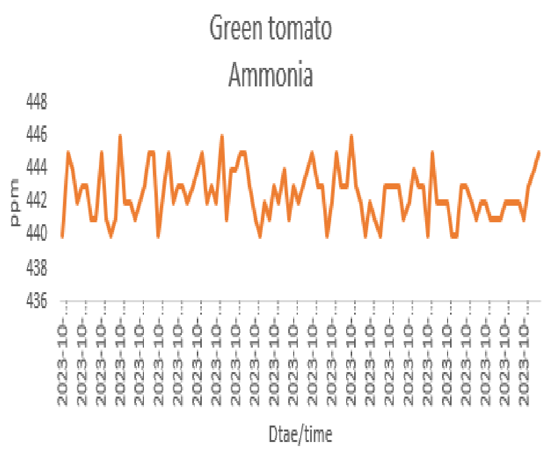

Figure 4.2. graphical representation of ammonia concentration Of green tomatoes

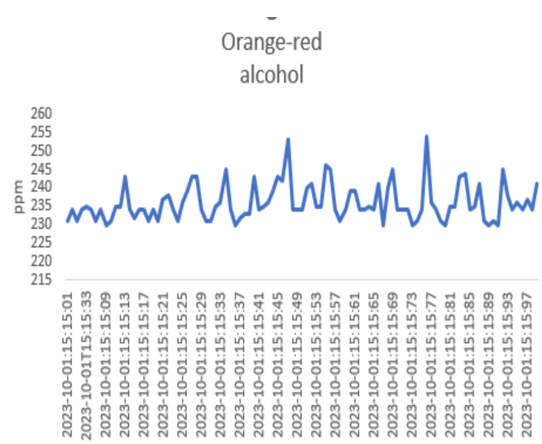

Figure 4.4. representation of alcohol concentration of orange-red tomato

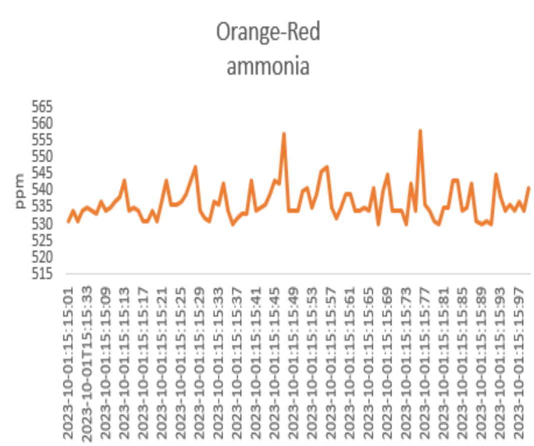

figure 4.5 representation of ammonia concentration of orange-red Tomato

## Hardware testing

The hardware was powered with a battery that was always charged via the use of solar panels to avoid power interruption. The sensors were placed in the plate where the tomatoes were kept. This test started on the 30th second at 1:12 pm on the 29th of June 2023 and terminated on the 24th seconds of 11:55 am on the 2nd of July 2023 after mold started developing on the tomato's fruit. The plots as shown in Figure 4.6 , illustrate a steady rising trend in the generation of alcohol and ammonia. The sudden spiking up and coming down of the quantities within the trend is as a result of varying concentrations of gas per time. However, it is observed in Figure 4.6 that alcohol generation has a steeper up trend compared to ammonia. This implies that during the process of spoilage, more alcohol was generated with time but the amount of the ammonia generated at the beginning was small. This was the reason why the foul smell was not noticed at the beginning of the experiment.

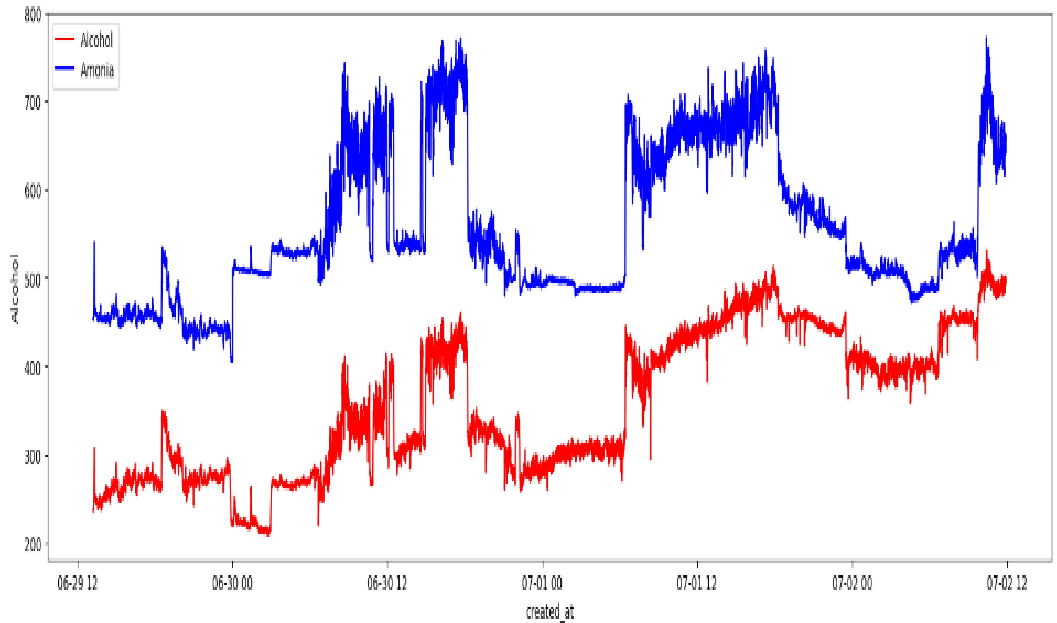


Figure 4.6 Graphical representation of the experimental result.

## Data processing

To be able to employ the LSTM module, the data was preprocessed. Figure 4.8 and Figure 4.9 shows when the data was split into individual component. The vertical axis is the concentration of gases generated measured in ppm and horizontal axis is the time.

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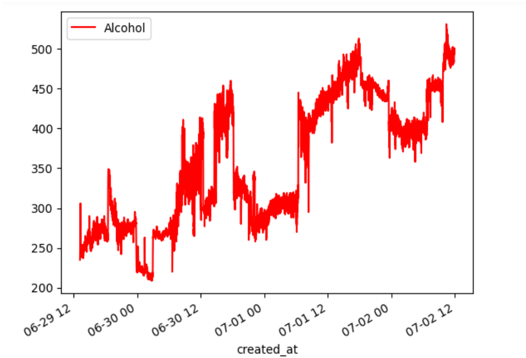


Figure 4.8 Graphical illustration of alcohol generated alone.

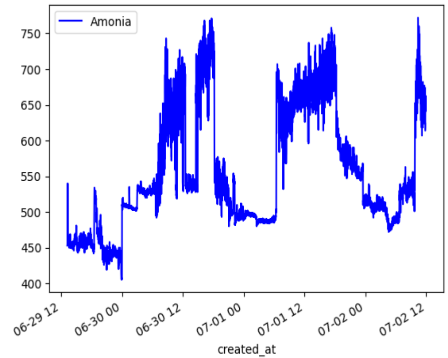


Figure 4.9 Graphical illustration of ammonia generated alone.

After the splitting, as shown in Figures 4.10 and 4.11, these measured quantities were then observed using the seasonal decompose library of Python to ascertain their trends. From both graphs, it is observed that both quantities are characterized by an uptrend. Furthermore, when the noise or residue is filtered off, the season signal is seen to be linear for both cases. Afterwards, both data are arranged to have x and y components such that one has one input, three features, and one output. This is why the shape as shown in plate 1 is [1, 3, 1]

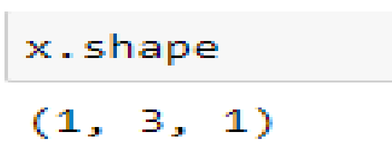


Plate 1 is the shape of the neural network.

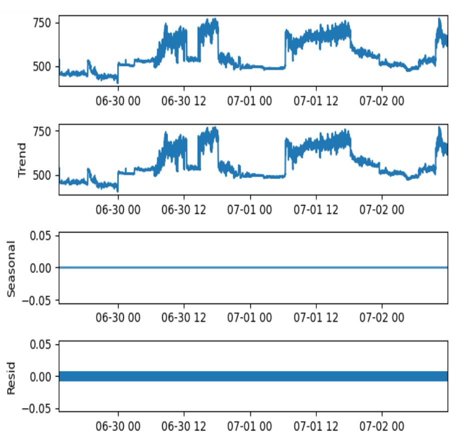


Figure 4.10 graphical representation of the seasonal decompose of alcohol data

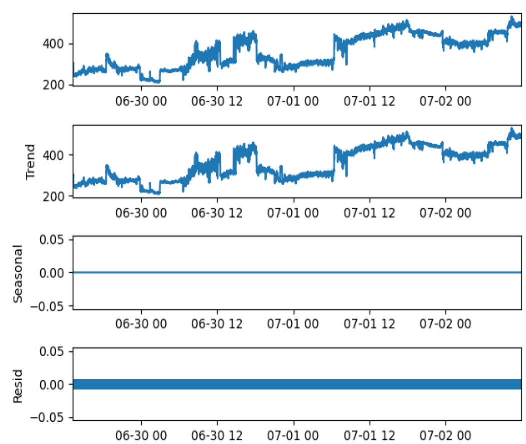


Figure 4.11 graphical representations of the seasonal decompose of ammonia data.

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## LSTM training

Figure 4.13 and Figure 4.14 shows the loss per epoch after the data of alcohol and ammonia has been trained using the LSTM model. As shown in figure 4.8, the data was trained for 30 epochs which is represented in the horizontal data. Furthermore, the loss is observed to reduce and no further reduction was observed after 0.0003. Similarly, figure 4.9 shows that the loss per epoch did not change after a value of 0.0006 while training the ammonia dataset. This implies that around 15 epochs there was no need for further training.

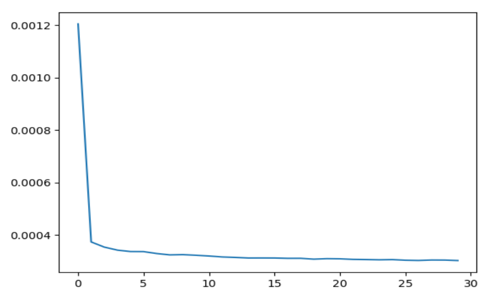


Figure 4.13 loss per epochs while training alcohol dataset.

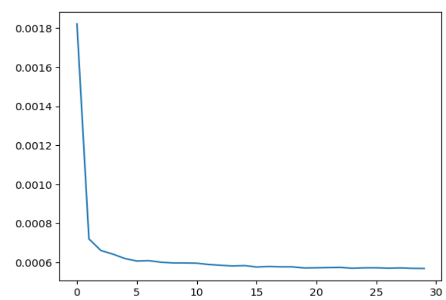


Figure 4.14 losses per epoch during ammonia dataset

## LSTM forecasting

During forecasting, the portion of the data used as test data was used to compare the predicted data for both alcohol and ammonia. Figure 4.15 and Figure 4.16 show that the predictions followed the same trend as the test data. However, it is observed that the predictions for alcohol were the same as the test data at about 11:53, and 11:43. Additionally, that of ammonia was the same as the test data at about 11:53 and 11:54. The performance of this model was evaluated using root mean square error. The root mean square error for the forecasting of alcohol was 5.09 while that of ammonia was 8.68.

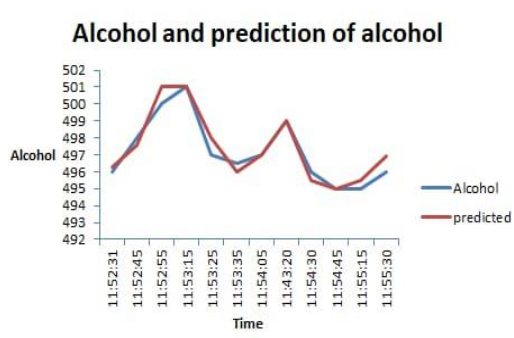


Figure 4.15 predictions of the value of alcohol generated from tomatoes

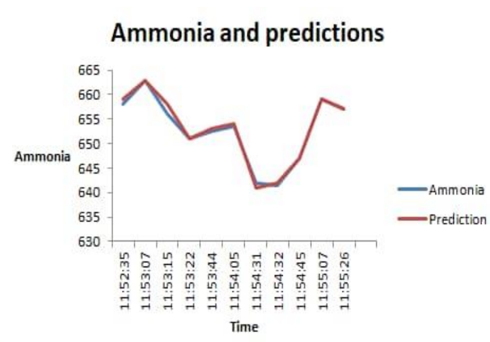


Figure 4.16 prediction of the value of ammonia generated from tomatoes

## Conclusion and recommendation

The developed IoT-enabled hardware is capable of monitoring alcohol, and ammonia levels in the vicinity of tomato fruits. Advanced machine learning algorithms like Long Short-Term Memory (LSTM) is utilized to predict the point at which tomato will become unfit for consumption at 500ppm. We also conduct rigorous performance evaluations to assess the accuracy and effectiveness of the forecasting algorithm employed using root mean square error for the forecasting of alcohol and ammonia which are 5.09 and 8.69 respectively.

## Recommendation for future works

The following are recommended areas for extension and improvement of this research work:

1. Radio-frequency identification (RFID) tag can be introduced for easy traceability of different fruits in food chain
2. Temperature and relative humidity sensors can also be introduced to maximize the accuracy of the detection and prediction.

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