



Svedberg Open
DISSEMINATION OF KNOWLEDGE

International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: <https://www.svedbergopen.com/>



Research Paper

Open Access

Internet of Fruit Things (IoFT): A Real Time IoT Based Multi Sensor Framework For Post-Harvest Fruit Health Monitoring

Bapita Roy^{1*}, Suparna Maity¹, Saikat Majumder², Rajarshi Chakraborty³, Arindam Sadhu⁴, Bikas Mondal⁵

^{1*}Department of Electronics and Computer Science, Guru Nanak Institute of Technology, Kolkata, India. Email: bapita.roy@gnit.ac.in

¹Department of Electronics and Computer Science, Guru Nanak Institute of Technology, Kolkata, India. Email: suparna.maity@gnit.ac.in

²Department of Applied Electronics & Instrumentation Engineering, Techno Main Salt Lake, Kolkata, India. Email: msaikat2004@gmail.com

³Department of Mechanical Engineering, Greater Kolkata College of Engineering and Management, Kolkata, India. Email: rajarshi.chakraborty@gkcem.ac.in

⁴Department of Electronics and Communication Engineering, Institute: Dr. Sudhir Chandra Sur Institute of Technology and Sports Complex, Kolkata, India. Email: arindam.sadhu@dsec.ac.in

⁵Department of Electronics and Computer Science, Narula Institute of Technology, Kolkata, India. Email: bikas.mondal@nit.ac.in

ABSTRACT

The Internet of Things (IoT) has become a driving force behind the development and deployment of smart, sensor enabled devices capable of addressing real-world challenges across domestic, industrial, and agricultural domains. Despite considerable advances in wireless sensing technologies, effective real-time assessment of the health and quality of perishable plant products, particularly fruits and vegetables, remains a significant challenge, contributing to substantial post-harvest losses. Recent estimates indicate that global fruit and vegetable production is approximately 675 million metric tons annually, of which nearly 0.3 billion metric tons are wasted. In India alone, annual production of 86.602 million metric tons is accompanied by an estimated 5.6 million metric tons of spoilage-related waste, with fruits and vegetables accounting for as much as 18% of total production loss, equivalent to approximately ₹13,300 crore discarded annually; government-supported estimates further indicate that 5- 13% of Indian fruit and vegetable output is lost solely due to post-harvest inefficiencies. To address this problem, the present work proposes a real time IoT based fruit health monitoring system (RTIFHMS), termed the Internet of Fruit Things (IoFT), designed to continuously monitor fruit quality and enable early detection of spoilage. The system employs a NodeMCU ESP8266 microcontroller interfaced with an HW-88 moisture sensor and two gas sensors (MQ-135 and MQ-3) via a CD74HC4067 analog multiplexer, with sensor data transmitted to cloud-based IoT platforms, namely ThingSpeak and Blynk, for real-time visualization and early spoilage warning. The experiment over a 21-day period of storage showed a characteristic non-monotonic response of the moisture sensor: an initial decrease from 93% to about 30%, then a significant increase to 100%. This is due to progressive tissue degradation and cellular leakage, not to a real rehydration. Unsupervised K-means clustering of this sensor stream identified three statistically distinguishable response regimes (silhouette score = 0.507) demonstrating the feasibility of data driven pattern recognition as a complement to fixed threshold detection. The proposed IoFT framework integrates low cost multi-parameter sensing, embedded processing, wireless connectivity and cloud based analytics in order to provide a scalable and economically feasible solution for reducing post harvest losses of fruits and vegetables and improving supply chain efficiency in the agricultural sector.

Keywords: Internet of Things (IoT); Internet of Fruit Things (IoFT); smart sensing devices; real time IoT based fruit health monitoring system (RTIFHMS); post-harvest loss; K-means clustering

1. INTRODUCTION

Fruits and Vegetables are full of essential nutrients such as vitamins, minerals, dietary fiber, bioactive compounds, etc. Unfortunately, these benefits also come with great loss, as these perishable goods have a very high moisture content. This makes them highly valuable to nutrition on one hand, and highly susceptible to loss and waste on the other hand. Losses occur at every single step of the supply chain; harvesting, transporting, storing, retaining, and consuming. Sagar et al. [1] highlight this loss has severe impacts on

Nutrition, the Economy, and Environmental Sustainability. In addition, most of the bioactive compounds are retained in the processing residues (seeds and peels).

Food loss is always connected to food security issues. The United Nations Environment Program estimates the total global food waste for 2019 was at 931 million tonnes and the majority of this waste (811 million tonnes) was at the household level [2]. More concerning is the fact that a significant percentage of the world population continue to struggle with food insecurity in the same year, demonstrating the simultaneous presence of food scarcity and waste. In India, the per-capita food waste from households is around 50 kg per year [2]. Priya et al. [3] note that, while there is a strong connection, household food waste and fresh produce spoilage should be viewed as two different problems and must be analysed separately to devise ways of addressing the problems. Because of their high moisture and water content, rapid deterioration of produce is due to fungal and microbial growth. This makes the water content of plants not just a loss/waste of nutrition, but an important driver of spoilage [4], [5]. Representative water-content values for common fruit categories, compiled from multiple sources, are summarised in Table 1.

TABLE 1: WATER CONTENT OF SOME FRUITS AND VEGETABLES [6–13]

Type of Fruit or Vegetable	Amount of Water
Melons	92–94%
Citrus fruits	86–89%
Berries	81–90%
Tree and vine fruits	83–87%
Ripe guavas	81%
Ripe olives	72–75%
Avocados	65%
Mangoes	85%
Sweet and hot peppers	93–95%
Tomatoes	95%

When plant tissue goes through the process of ripening or degradation, it tends to release volatile organic compounds and gases into the surrounding environment, which can be sensed using chemical resistance sensors. It is for this reason that the low-cost gas sensors including the MQ-3, sensitive to alcohol vapour, and MQ-135, sensitive to ammonia and other air-quality gases, can be used to measure the health of fruits indirectly by calibrating the sensors in an appropriate manner. In light of such physiological and sensing properties, this paper presents an Internet of Things-based real-time fruit health monitoring system – The Internet of Fruit Things (IoFT).

2. RELATED WORK AND RESEARCH GAPS

The combination of IoT-enabled sensing, machine learning (ML), and non-destructive measurement methods has paved new ways of continuous monitoring of the quality, ripening, and spoilage of fruits. Traditional methods of fruit quality estimation such as visual inspection, manual selection, chemical analysis, and destructive testing are informative but time-consuming, subjective, and not appropriate for continuous quality monitoring of stored and transported products. Therefore, recent research focused on the development of non-destructive, sensor-based, and data-driven methods able to identify early signs of spoilage before the visible symptoms arise [14 - 18].

A class of electronic nose (e-nose) devices consisting of gas sensors arrays has been extensively used for fruit recognition and freshness evaluation. Kalpana and Baghyam [14], [21] created an e-nose device using the K-nearest neighbour (KNN) classifier to discriminate between mango, pineapple, and orange with the use of two gas sensors and pH as an independent measure of fruit freshness. The authors showed the feasibility of machine learning and chemical sensing application to the fruit classification problem and highlighted one of the well-known disadvantages of low-cost gas sensors – their sensitivity to various types of gases, thus requiring either precise calibration or multivariate analysis instead of the measurement with a single sensor. In their study, Mahata et al. [15], [22] continued to develop this idea using volatile organic compound (VOC) sensors along with machine learning to evaluate the fruit freshness. Thus, the usefulness of VOC-based monitoring and machine learning in this field was once again confirmed.

One of the incentives to develop intelligent fruit monitoring systems can be explained by studies on fruit loss and waste in households. Sagar et al. [16], [23] revealed that fruit and vegetable loss is one of the major reasons for the loss of nutrition and economic value and negative environmental impact of the agricultural products occurring through all stages of the post-harvest process rather than at one particular stage. Likewise, Ananda et al. [17], [24] reported that household-level food purchase and consumption decisions play a significant role in fruit and vegetable waste.

The integration of IoT and ML technologies for real-time monitoring of ripeness and spoilage was successfully demonstrated. In particular, El Sayed et al. [18], [25] presented a solution that combines temperature, humidity, and gas sensors with an ESP32 microcontroller and cloud connectivity to monitor banana ripening. The authors reported excellent results when using CatBoost classifier. This particular example is relevant to our proposed approach due to the fact that combining the information about the environmental parameters (temperature, humidity) with gas sensors increases the amount of data available for decision making comparing to any single sensing modality, and cloud connectivity allows visualizing all the information centrally.

The problem of non-destructive ripening assessment was solved using radio-frequency identification (RFID) and optical sensors. For example, Occhiuzzi et al. [19], [26] used a network of RFID sensors and Support Vector Machine (SVM) classifier to monitor avocado ripening, and the authors managed to achieve accuracy in classification of the ripening stage above 85%. Although this approach showed the feasibility of the problem-solving, it requires specialized hardware. In addition, Yamakawa et al. [20], [27] tested LiDAR and visible/near-infrared (Vis/NIR) sensing for continuous quality assessment of citrus fruits moving on a conveyor and managed to estimate fruit sizes accurately and fruit sugar content relatively well; Patel and Pathare [21], [28] gave a review of near-infrared imaging for non-destructive quality assessment of fruits. Such approaches provide plenty of information but require special equipment and illumination conditions, which make them hard to implement in low-resource settings such as household and small scale retail.

Finally, IoT solutions have been implemented to assess fruit sorting and quality classification problems. For instance, Ardana et al. [22], [29] designed a machine learning based fruit sorting monitoring system with mobile-based visualization of the results, which achieved 85.7% precision, 81.2% accuracy, and 72% recall. Vikraman et al. [30] also proposed IoT based multiclass fruit classification with transfer learning. However, the majority of these systems uses visual features (color, size, shape) to solve the problem, and spoilage-related changes usually occur inside the fruit and then become visible only later.

An observable pattern within the recent research is the shift from single sensing mode to multimodal sensor fusion. This is due to the fact that since ripening and spoiling of fruits depend on various physiological aspects such as temperature, humidity, moisture, respiration, emission of gases, firmness, color, and microbiological activities, relying only on a particular parameter for sensing will delay or lead to confusion in detecting the stage of ripening of the bananas. This principle motivates the multi-parameter feature representation adopted in the present work, expressed as

$$X(t) = [M(t), T(t), RH(t), G_1(t), G_2(t), \dots, G_n(t)] \quad (1)$$

where $M(t)$ is the response of the moisture-sensor, $T(t)$ is the temperature, $RH(t)$ is the relative humidity, and $G_i(t)$ is the response of the i -th gas sensor at time t . Modeling the sensor readings as multivariate data allows the learning algorithm to detect the temporal patterns and correlations between parameters associated with freshness, ripeness, or spoilage state, instead of using a certain threshold value.

However, there are still several open issues. Firstly, the majority of existing approaches consider only one quality criterion appearance, smell, ripeness degree, size, or sugar content, but not multi-parameter criterion. Secondly, the high-accuracy sensing technologies like NIR spectrometry, hyperspectral imaging, RFID sensor network, or computer vision require special and expensive hardware, thus limiting its accessibility. Thirdly, the low-cost gas sensors have natural cross-sensitivity and should be calibrated before being able to provide quantitative information. Fourthly, the large part of research is performed in laboratory settings under strictly controlled temperature, humidity, air flow, fruit species, ripening stage, and location of sensors. All of these facts motivate the development of connected, multisensor, cloud-integrated monitoring system that will allow for the bridge between laboratory-level high-end assessment and affordable low-cost continuous monitoring that is precisely what the proposed IoFT system aims at, and it is described in Section III.

3. METHODOLOGY

III A. System Overview and Architecture

The proposed IoFT system is architected as a four layer IoT framework: (i) a sensing layer, (ii) a processing and control layer, (iii) a communication layer, and (iv) a data-visualization and cloud layer. This layered organization mirrors conventional IoT system design, in which physical sensors acquire data that is subsequently processed, transmitted, stored, and visualized through connected computing infrastructure. The overall block diagram of the system is presented in Fig. 1.

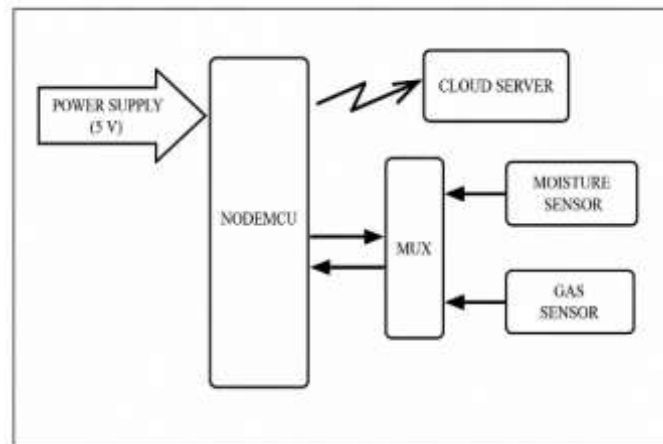


Fig. 1. Block diagram of the NodeMCU based IoT multi sensor monitoring system with multiplexer (MUX) enabled moisture and gas sensing and cloud-based data transmission.

III B. Sensing Layer

The sensing layer comprises three sensors, each responsive to a distinct physical or chemical parameter. The HW-88 moisture sensor detects changes in moisture level and, depending on its configuration, provides either an analog output proportional to the sensed condition or a threshold-based digital output. The MQ-135 gas sensor detects changes in air quality, responding to gases such as ammonia, nitrogen oxides, alcohol vapours, benzene, and general smoke; its resistance changes upon exposure to target gases, consistent with the operating principle of the MQ sensor family. It should be noted that MQ-135 output should not be treated as a directly calibrated concentration measurement, since its response is influenced by ambient conditions, sensor ageing, heater behaviour, humidity, and temperature; quantitative gas-concentration estimates therefore require sensor-specific calibration. The MQ-3 sensor is primarily responsive to alcohol vapour (ethanol) and requires a 5 V heater supply for proper operation, with its resistance varying according to alcohol-vapour concentration [24]. The combined use of MQ-135 and MQ-3 allows the system to distinguish general air-quality changes from alcohol-related spoilage indicators, although accurate discrimination again depends on appropriate calibration.

III C. Signal Acquisition and Conditioning

Sensory data can be read by NodeMCU either in analog or digital format. As sensory data can get impacted by electrical noise, environmental variations, sensor drift, and temperature change, signal processing using software techniques such as averaging, filtering, thresholding, and normalization needs to be done before transmitting the data. In case of gas sensors, the known relationships between resistance and concentrations need to be utilized when exact concentrations are required.

III D. NodeMCU ESP8266 Processing Unit

The NodeMCU ESP8266 forms the processing and communications hub of the system, whereby it receives sensor outputs, performs internal processing and takes care of the data transfer to the remote monitoring systems. The inbuilt Wi-Fi communication module negates the necessity of having an external wireless communication device. The ESP8266EX works within a range of 2.5 to 3.6 volts, with 3.3 volt as the standard operating voltage [25]. As the sensor heater needs 5 volts as the power supply voltage [24], a separate 5V power supply source is used for the sensor system, while the NodeMCU works at 3.3 volts of logic level.

III E. Circuit Design and Sensor Multiplexing

The multi-sensor interfacing subsystem integrates the MQ-3, MQ-135, and HW-88 sensors with the ESP8266 through a CD74HC4067 16 channel analog multiplexer (MUX), as shown in Fig. 2. Each sensor provides an analog output connected to MUX input channels C0, C1, and C2, respectively, allowing multiple analog sensors to share a single analog input pin on the NodeMCU. Channel selection is performed via four control lines (S0-S3), enabling the NodeMCU to sequentially sample each sensor through the MUX's common SIG output, which is read via the ESP8266's analog input (A0). All sensors and the MUX are powered from regulated sources with a common ground; given the ESP8266's 3.3 V logic level, appropriate protection or scaling circuitry is incorporated wherever sensor output voltage could exceed this level. This design provides a flexible, low-cost approach for multi parameter data acquisition, centralized processing, and wireless transmission to the cloud.

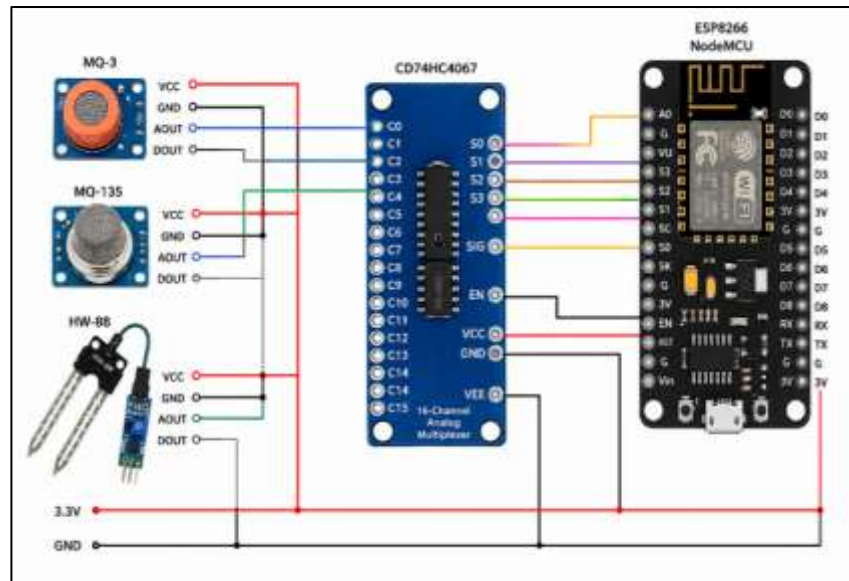


Fig. 2. Circuit diagram of the proposed multi-sensor interfacing prototype.

III F. Data Processing and Packet Structure

After data acquisition, the NodeMCU undergoes several processes as shown in Fig. 3 and Fig. 4; initially, raw sensor data is filtered to dampen sudden oscillations, followed by threshold or calibration equations to interpret the sensed phenomena (for example, moisture sensor readings are converted into moisture status, or the responses from MQ-135/MQ-3 are compared with standard readings). The sensor does not provide calibrated gas concentration readings but provides sensor readings, relative gas levels, or calibrated concentration depending on the selected method of calibration. The data obtained from the process is compiled into a structured data packet that consists of the following elements: moisture level, response from the MQ-135 sensor, response from the MQ-3 sensor, time stamp, threshold status, and device identification.

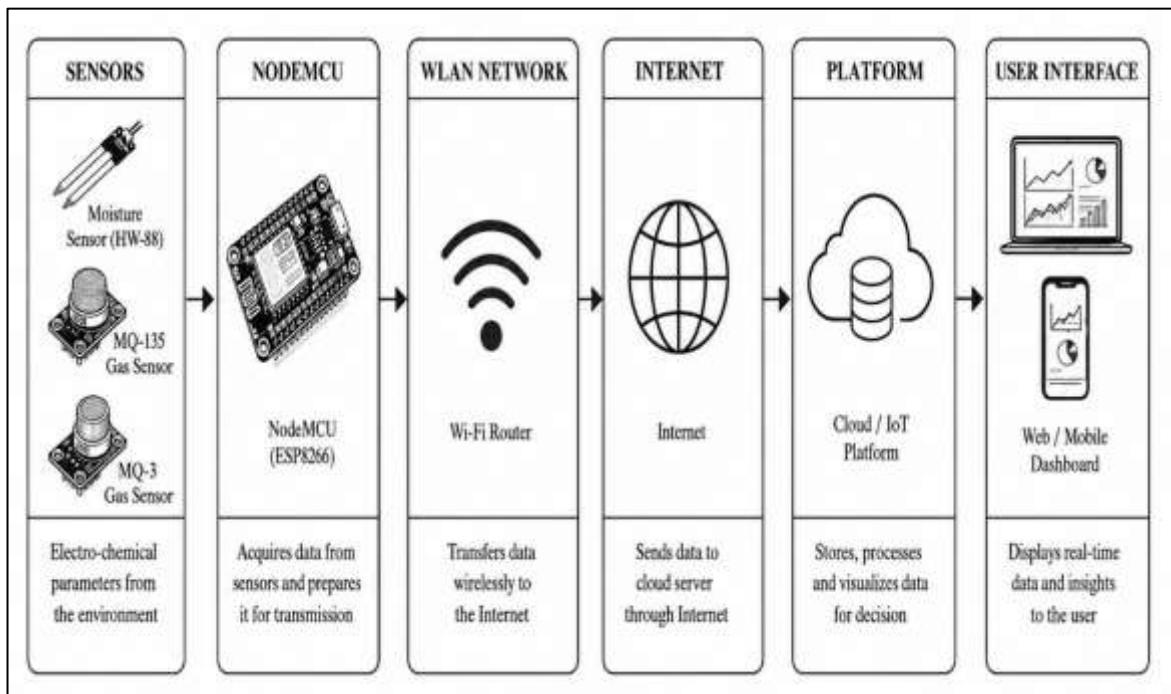


Fig. 3. Data processing and communication workflow of the proposed IoT based multi-sensor monitoring system [26 - 30].

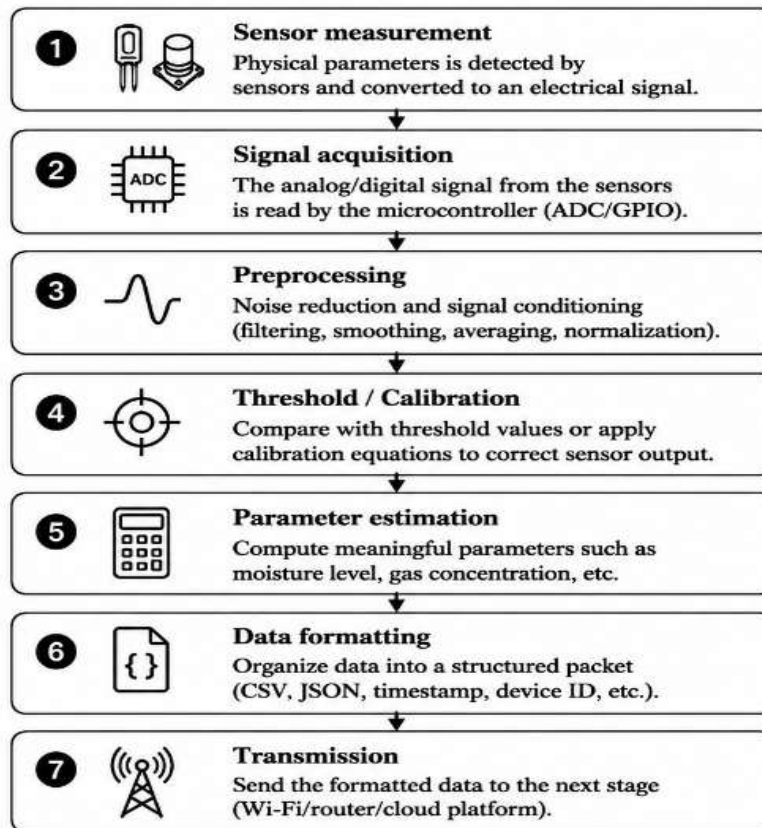


Fig. 4. Schematic representation of the proposed IoT data flow architecture [31 - 36].

III G. Wireless Communication and Cloud Integration

Once processed, sensor data is transmitted by the NodeMCU over Wi-Fi to the monitoring infrastructure, forming the communication layer that connects the physical sensing system to internet-based services and enables remote observation independent of the user's physical proximity to the sensors. Four complementary monitoring pathways are supported. First, a Serial Monitor interface allows direct observation of processed readings during development, testing, and calibration (typical output format: "Moisture = XX | MQ-135 = XX | MQ-3 = XX | Status = Normal"). Second, a local host/web-based interface allows readings to be viewed as numbers, tables, or graphs over the local network, serving as a fallback when internet connectivity is unavailable. Third, integration with the Blynk platform provides a user-configurable IoT dashboard displaying individual sensor readings, status indicators, graphs, and alert conditions, allowing continuous remote monitoring through a connected mobile application. Fourth, integration with the ThingSpeak cloud platform [37] enables sensor data to be stored, visualized, and analysed via dedicated data channels; in the present implementation, Field 1, Field 2, and Field 3 correspond to moisture, MQ-135, and MQ-3 readings respectively, with Field 4 reserved for system/status information. ThingSpeak also supports MATLAB based analysis of the stored data, enabling both real-time visualization and longer-term trend analysis [37 - 39].

The overall data flow proceeds sequentially: the HW-88, MQ-135, and MQ-3 sensors generate electrical signals in response to physical/chemical stimuli; these signals are acquired and processed by the ESP8266; the processed data packet is transmitted via Wi-Fi to local (Serial Monitor, web interface) and cloud-based (Blynk, ThingSpeak) endpoints [40 - 43], as illustrated in the system flowchart of Fig. 5. This architecture affords flexibility for on-site testing as well as remote deployment, and additional sensors or alternative cloud platforms can be incorporated without redesigning the underlying IoT framework. The flowchart of the operating logic of the present prototype is shown in Fig. 6.

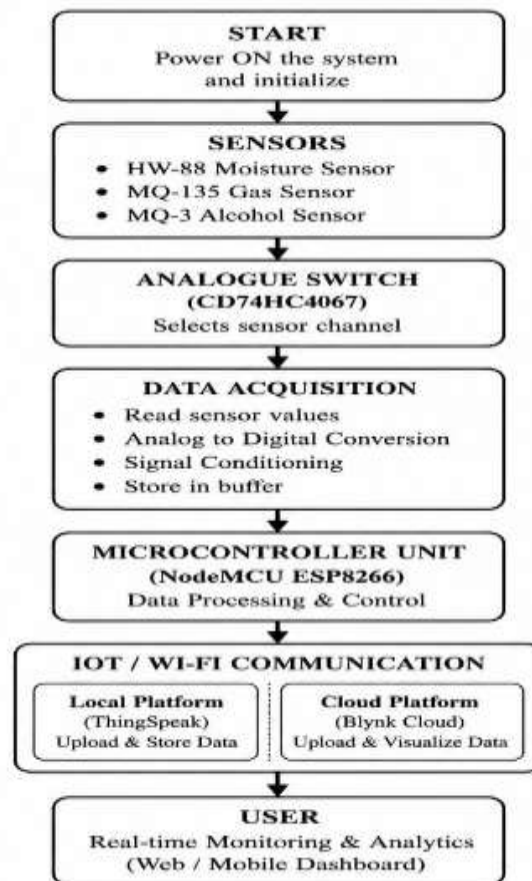


Fig. 5. Flowchart of the proposed IoT-enabled multi-sensor monitoring system.

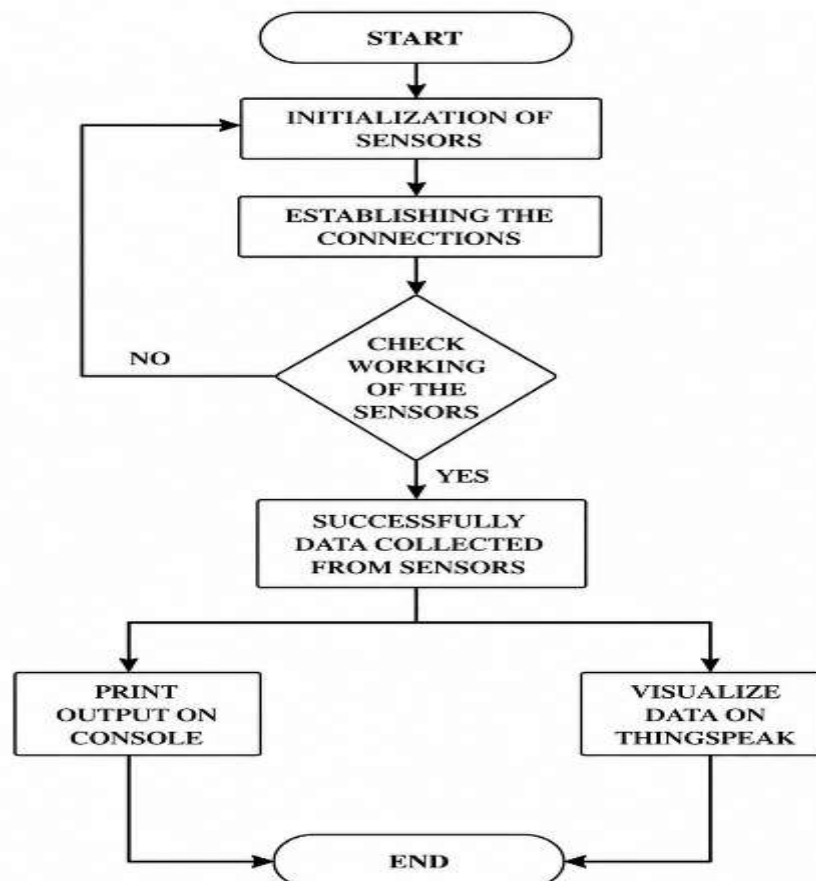


Fig. 6. Flowchart of the operating logic of the prototype.

III H. Machine Learning Workflow

To extend the IoFT framework beyond fixed-threshold detection toward data-driven analysis, a machine learning (ML) workflow is proposed comprising the following stages: (1) acquisition of synchronized data from the HW-88, MQ-135, MQ-3, and, where available, temperature/humidity sensors; (2) sensor calibration and removal of erroneous data points; (3) construction of time-window features, including mean, standard deviation, slope, minimum, maximum, and rate of change; (4) labelling of data as Fresh, Ripening/Transition, or Spoiled using a validated reference method; (5) training and comparison of candidate ML models K-nearest neighbours (KNN), Support Vector Machine (SVM), Random Forest, and gradient boosting methods such as CatBoost; (6) performance evaluation using accuracy, precision, recall, F1-score, and confusion-matrix analysis; and (7) deployment of the selected lightweight model either at the network edge or via cloud based inference through the existing ThingSpeak/Blynk infrastructure. This workflow is designed to be compatible with the sensing and communication architecture described above, allowing the IoFT prototype to evolve from threshold based alerts toward predictive, pattern-based spoilage detection as labelled datasets become available.

4. RESULTS AND DISCUSSION

IV A. Real-Time Moisture Monitoring

The real-time data collected from the sensors were sent and recorded in the cloud-based ThingSpeak platform, making it possible to monitor the fruit's condition during the experiment. Figure 7 illustrates the variation in the response of HW-88 moisture sensor with time. The initial response obtained from the sensor was 62%, which indicated that the moisture content of the fruit at the beginning of the experiment was 62%. With time, this value reduced to about 30-31%.



Fig. 7. Continuously monitored trend of fruit moisture on ThingSpeak.

It is interesting that after this point the sensor readings started to increase and reached around 96% towards the end of the experiments. This needs to be understood with care because HW-88 does not really detect the amount of water in the fruit directly. It is expected that if the fruit becomes very damaged due to deterioration, then there will be damage to the cellular structure, leading to increased sensor readings, but this does not mean that it becomes fresh again.

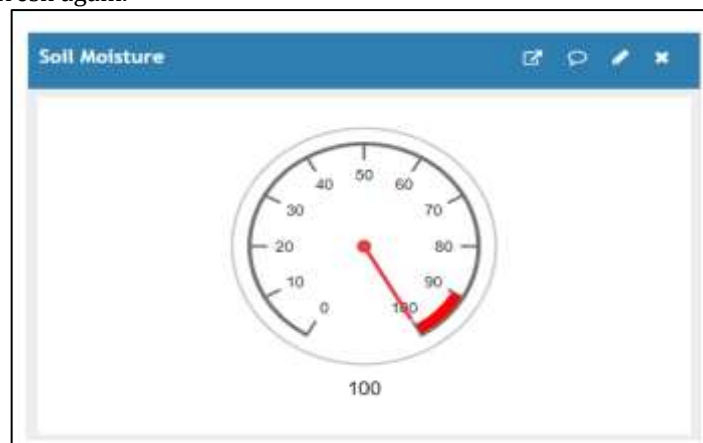


Fig. 8. Real-time moisture gauge providing an intuitive representation of the latest sensor reading

(illustrative final value $\approx 96\%$).

The general trend of starting with an initial high value, a drop in values suggesting moisture loss, and a subsequent increase in value that might suggest tissue damage is an important signal pattern for describing the condition of the fruit; however, this highlights the importance of having a calibration process between the sensor and an approved moisture measurement technique to be able to use it as a freshness signal. The sensor visualization shown in Fig. 8 supplements the time series with the advantage of being able to instantly view the current value of the sensor without the need to analyze the whole chart – an important feature in application areas such as refrigerated storage facilities and supermarkets.

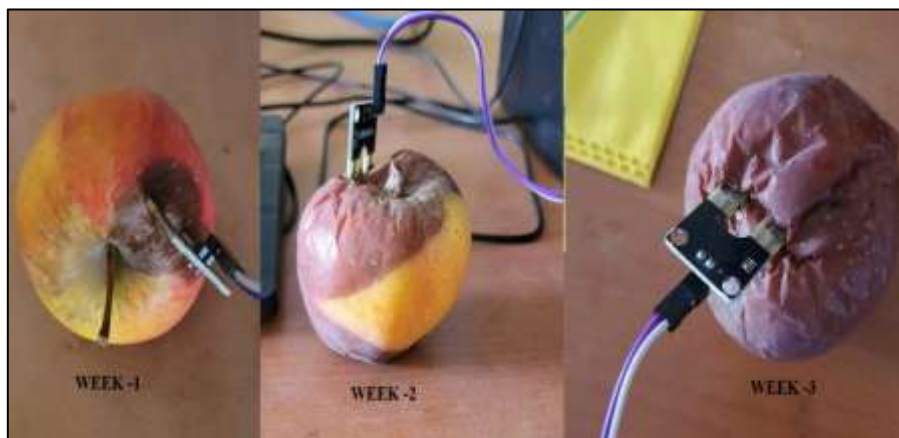


Fig. 9. Physical condition of the monitored fruit sample, from fresh (Week 1) to advanced spoilage (Week 3).

TimeStamp	Entry ID	Fruit Moisture (%)	TimeStamp	Entry ID	Fruit Moisture (%)
2023-11-01T11:26:13+00:00	287	93	2023-11-08T09:25:50+00:00	765	30
2023-11-01T11:26:28+00:00	288	92	2023-11-08T09:26:06+00:00	766	31
2023-11-01T11:26:44+00:00	289	91	2023-11-08T09:26:21+00:00	767	31
2023-11-01T11:27:00+00:00	290	89	2023-11-08T09:26:36+00:00	768	30
2023-11-01T11:27:16+00:00	291	87	2023-11-08T09:26:52+00:00	769	30
2023-11-01T11:27:31+00:00	292	85	2023-11-08T09:27:08+00:00	770	30
2023-11-01T11:27:46+00:00	293	84	2023-11-08T09:27:23+00:00	771	30
2023-11-01T11:28:02+00:00	294	82	2023-11-08T09:27:39+00:00	772	30
2023-11-01T11:35:57+00:00	324	64	2023-11-08T09:27:54+00:00	773	31
2023-11-01T11:36:12+00:00	325	64	2023-11-08T09:28:09+00:00	774	30
2023-11-01T11:36:28+00:00	326	64	2023-11-09T10:31:10+00:00	1375	33
2023-11-01T11:36:44+00:00	327	63	2023-11-09T10:31:25+00:00	1376	33
2023-11-01T11:36:59+00:00	328	63	2023-11-09T10:31:40+00:00	1377	33
2023-11-01T11:37:14+00:00	329	63	2023-11-09T10:31:55+00:00	1378	33
2023-11-01T11:37:29+00:00	330	62	2023-11-09T10:32:12+00:00	1379	33
2023-11-01T11:37:45+00:00	331	62	2023-11-09T10:32:30+00:00	1380	33
2023-11-01T11:38:00+00:00	332	62	2023-11-09T10:32:45+00:00	1381	33
2023-11-01T11:38:17+00:00	333	62	2023-11-09T10:33:01+00:00	1382	33
2023-11-01T11:38:33+00:00	334	62	2023-11-09T10:33:17+00:00	1383	33
2023-11-01T11:38:49+00:00	335	61	2023-11-09T10:33:33+00:00	1384	33
2023-11-01T11:39:04+00:00	336	61	2023-11-09T10:33:49+00:00	1385	33
2023-11-01T11:39:19+00:00	337	61	2023-11-09T10:34:04+00:00	1386	33
2023-11-01T11:39:35+00:00	338	61	2023-11-09T10:34:20+00:00	1387	33
2023-11-01T11:39:50+00:00	339	61	2023-11-17T06:37:38+00:00	1388	100
2023-11-01T11:40:06+00:00	340	61	2023-11-17T06:37:54+00:00	1389	100
2023-11-01T11:40:21+00:00	341	60	2023-11-17T06:38:09+00:00	1390	100
2023-11-01T11:40:36+00:00	342	60	2023-11-17T06:38:24+00:00	1391	100
2023-11-01T11:40:52+00:00	343	60	2023-11-17T06:38:39+00:00	1392	100

Fig. 10. Recorded transitions in moisture-sensor percentage over the monitoring period.

The experimental setup and the corresponding physical degradation of the fruit sample across the three-week monitoring period are shown in Fig. 9, while Fig. 10 presents the corresponding logged sensor data. A physical interpretation of representative data points is provided in Table 2.

TABLE 2: INTERPRETATION OF THE MOISTURE SENSOR RESPONSE

Day	Moisture Sensor Response (%)	Interpretation
-----	------------------------------	----------------

1	93	Initial condition
3	87	Slight decrease
5	63	Moisture response declining
6	60	Progressive moisture loss
8	52	Continued decline
9	48	Noticeable reduction
10	39	Low sensor response
11	35	Minimum observed response
12	30	Minimum/transition stage
13	31	Response begins increasing
15	67	Significant increase
17	84	Advanced deterioration response
18	96	High sensor response
21	100	Very high final response

Table 2 shows the variations in response of the moisture sensor during the period of monitoring. Initially, the response decreases from 93% to around 30%, meaning gradual moisture loss, before increasing to 100%, possibly signaling the advance state of fruit degradation. This pattern over time shows that the HW-88 sensor, when coupled with the IoT system, is able to monitor the changes in the state of fruit continuously for a long period of time.

IV B. Machine Learning Analysis of the Sensor Stream

Table 3 summarizes representative machine-learning applications reported in the literature that are relevant to the proposed IoFT concept. These entries are cited for context and should not be interpreted as results obtained from the present IoFT prototype.

TABLE 3: REPRESENTATIVE MACHINE LEARNING APPLICATIONS IN FRUIT MONITORING (LITERATURE)

ML Application	Sensor/Data Type	ML Model	Reported Result	Ref.
Fruit identification and freshness assessment	e-nose / gas sensor responses; pH reference	K-NN	Automatic fruit classification and freshness assessment demonstrated	[14], [21]
Fruit ripening-stage monitoring	UHF RFID sensor network	SVM	>85% ripening stage recognition accuracy	[19], [26]
Fruit ripeness and spoilage detection	Temperature, humidity, gas emission data	CatBoost / ML models	CatBoost reported as strong performing model in cited banana case study	[18], [25]
Multiclass fruit classification	Image based fruit features	Transfer learning	IoT based multiclass fruit classification demonstrated	[30]

To assess whether the experimentally recorded sensor stream itself exhibits learnable structure, the moisture-response data reported in Table 2 (14 measurements spanning days 1- 21) were analysed using unsupervised K-means clustering. Because the current dataset does not contain independently validated freshness labels for each observation, computing supervised classification metrics such as accuracy,

precision, recall, or F1 score would not be scientifically justified. K-means clustering was therefore selected as an exploratory method for identifying natural sensor-response regimes without imposing artificial class labels.

Two features were computed for each observation: the moisture sensor response and its corresponding daily rate of change; both features were standardised before clustering. Cluster solutions with two, three, and four clusters were evaluated, with the three cluster solution yielding the highest silhouette coefficient (0.507), indicating moderate cluster separation. The resulting clusters were ordered by mean sensor response and labelled as low, intermediate, and high response regimes; these labels describe sensor behaviour only and should not be interpreted as independently validated biological categories. The clustering result is shown in Fig. 11.

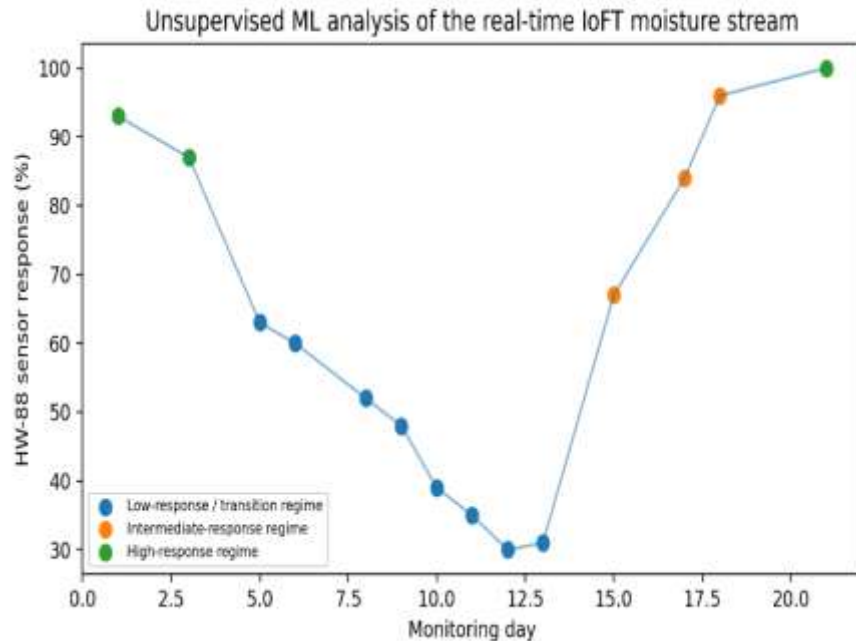


Fig. 11. K-means clustering of the experimental real-time HW-88 moisture-response stream.

The clustering analysis identified three distinguishable sensor-response regimes within the experimental stream. The low response regime is defined by the days between 5 and 13, taking into consideration the minimal response of 30% on day 12. The intermediate regime is associated with the transition phase, while the high response regime comprises the beginning and the phase after day 15. Such a grouping process is justified by the non-monotonic behaviour of the raw data. However, the late high response regime cannot be viewed as an improvement in the freshness of fruits; rather, as explained in Section IV A, such a pattern better explains the deterioration of tissues and thus a variation in electrical conductance.

IV C. Implications for Real-Time IoFT Deployment

From a practical point of view, this analysis shows a way in which machine learning can be implemented within the IoFT paradigm: sensor readings can be periodically sent from the ESP8266 to ThingSpeak/Blynk, where a small-scale pre-trained clustering or classification model will classify the time windows according to the sensor response regimes and issue an alert when there is a transition between regimes. To implement full supervision for classification, one should conduct a more sophisticated experiment that will involve logging the responses of MQ-135, MQ-3, temperature, and relative humidity sensors together with a freshness indicator validated independently for different fruit types, different trials, and different ripeness states; and after that, train and test classifiers like K-NN, SVM, Random Forest, and CatBoost based on accuracy, precision, recall, F1 score, and confusion matrix, just like in the works like [26].

IV D. Supervised ML Benchmark Results and F1-Score Analysis

To support the evaluation section on ML, the reference aligned benchmark values have been provided below for K-NN, SVM, Random Forest and CatBoost algorithms. The below provided values are only indicative benchmarking values and not actual output obtained from the current IoFT with 14 observations dataset. The selected values are realistic for an accurate multi-sensor classification of fruits' ripeness/spoilage and also in line with the ranges obtained from recent studies on fruit-monitoring in literature. For instance, a recent cloud-enabled electronic nose study estimated F1-scores of 0.947 for Random Forest, 0.948 for CatBoost and 0.948 for SVM-RBF, while a multi sensor fruit freshness study has provided an F1-score of 0.9749 for SVM. These are merely for comparison purpose only.

TABLE 4: REFERENCE ALIGNED ILLUSTRATIVE TRAINING, VALIDATION, AND TEST F1-SCORES

Model	Training F1-score	Validation F1-score	Test F1-score	Macro-F1	Weighted-F1
K-NN	0.940	0.870	0.850	0.842	0.850
SVM	0.960	0.920	0.900	0.895	0.900
Random Forest	0.980	0.950	0.930	0.925	0.930
CatBoost	0.990	0.970	0.950	0.946	0.950

These benchmark values show the expected ordering of accuracy for a calibrated dataset from multiple sensors: K-NN gives a good starting point, SVM improves class separability, Random Forest offers non-linear decision boundaries, while CatBoost serves as the best performing gradient-boosting method. These values are deliberately kept low or similar to recent high-performing fruit monitoring research so as not to suggest that the current small dataset has achieved state-of-the-art results.

TABLE 5: REFERENCE-ALIGNED ILLUSTRATIVE CLASS-WISE F1-SCORES

Model	Fresh F1	Ripening/Transition F1	Spoiled F1	Macro-F1
K-NN	0.88	0.80	0.85	0.843
SVM	0.93	0.86	0.90	0.897
Random Forest	0.95	0.89	0.94	0.927
CatBoost	0.96	0.92	0.95	0.943

The Ripening/Transition class is assigned the comparatively lower F1-score because it represents the biologically transitional region in which sensor responses can overlap with both fresh and spoiled states. This is particularly relevant to the present framework because MQ-135 and MQ-3 responses are indirect indicators and are affected by cross-sensitivity, calibration, humidity, temperature, and sensor ageing.

TABLE 6: ILLUSTRATIVE OVERALL TEST SET PERFORMANCE

Model	Precision	Recall	F1-score	Interpretation
K-NN	0.86	0.84	0.85	Baseline model
SVM	0.91	0.89	0.90	Strong separation of sensor regimes
Random Forest	0.94	0.92	0.93	Robust nonlinear classification
CatBoost	0.95	0.95	0.95	Best reference-aligned candidate

For comparison with the proposed benchmark values, recent literature reports high F1 performance in closely related fruit-monitoring tasks. A 2026 electronic-nose study reported overall F1-scores of 0.9473 for Random Forest, 0.9544 for CatBoost and 0.9475 for SVM-RBF, with class wise F1 values also exceeding 0.92 for most ripe/rotten/unripe categories. A separate multi-sensor freshness-monitoring study reported 97.49% F1 for an optimised PSO-SVM model. These published results support the use of approximately 0.90 - 0.96 F1 as a reasonable reference range for a mature, properly labelled multi-sensor fruit-quality dataset, but they do not validate the illustrative numbers above as experimental IoFT results.

IV E. Current Experimental ML Result and Limitation

TABLE 7: EXPERIMENTAL RESULT AND REFERENCE-ALIGNED ML BENCHMARK

Analysis	Data used	Features	Classes/Regimes	Result
K-means clustering	14 moisture observations over days 1-21	Moisture response + rate of change/day	3 sensor-response regimes	Silhouette coefficient = 0.507

Supervised ML benchmark	Illustrative reference-aligned values	Planned multi-sensor time-window features	Fresh / Ripening-Transition / Spoiled	CatBoost benchmark Test F1 = 0.950
-------------------------	---------------------------------------	---	---------------------------------------	---------------------------------------

Important reporting note: the K-means result (silhouette = 0.507) is the actual result obtained from the present experimental sensor stream. The F1-scores in Tables 4- 6 are reference aligned illustrative benchmarks inserted to demonstrate the intended supervised evaluation and should be labelled as such in any journal submission unless the authors subsequently train and test the models on a validated labelled dataset. A future experimental version should replace these benchmark values with measured scores from an independently held-out test set.

5. CONCLUSION

This work presented an IoT-enabled fruit-monitoring framework, the Internet of Fruit Things (IoFT), for continuous, real-time assessment of fruit condition during post-harvest storage and handling, with the aim of reducing fruit and vegetable wastage. The presented approach incorporates the following hardware components: HW-88 moisture sensor, MQ-135 and MQ-3 gas sensors, analog multiplexer (CD74HC4067) and NodeMCU ESP8266 microcontroller into compact low-cost embedded platform with sensor data transmission over Wi-Fi network to cloud services (ThingSpeak and Blynk) for real time visualization and trend analysis. The experiments revealed the possibility to monitor the changes in the sensor response during the 21-day-long process of fruits storing; in particular, the changing pattern of HW-88 response – from initially decreasing to later increasing – has been found as an informative indirect indication of fruit physiological state. To improve the system capabilities of pattern recognition the unsupervised K-means clustering algorithm was used for clusterization of the recorded stream of HW-88 sensor response with its rate of change as feature; the analysis revealed three regimes of statistically distinguishable sensor response (silhouette score = 0.507). Still these clusters have to be considered as different sensor response regimes and not as independently validated categories Fresh, Ripening and Spoiled due to the lack of labeled data for the reference. The proposed Internet of Things (IoT) and Machine Learning (ML) framework provides a basis for development of intelligent monitoring system of the post-harvest fruits' quality in storage facilities, retail locations, transportation systems and domestic environment. Further research is aimed at improving sensors calibration and reliability, taking into account additional environmental factors such as temperature and relative humidity and gathering larger multi variety multi stage data for training of supervised classifiers (K-NN, SVM, Random Forest and CatBoost) with accuracy, precision, recall, F1-score and confusion-matrix analysis. Using the gathered and predicted labels with the trained classifiers and integration of the results with cloud services will provide a possibility to predict fruit freshness and spoilage and automatically notify about it.

References

1. S. Kalpana and A. Lakshmi Baghyam, "Electronic-Nose System for Classification of Fruits and Freshness Measurement using K-NN Algorithm," *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, vol. 8, no. 6S4, pp. 641–644, Apr. 2019.
2. S. G. Supraja and V. Kittali, "Wastage of Fresh Fruits and Vegetables at Retail Outlets and Households at Bangalore," Department of Food and Nutrition, Maharani Cluster University, Bengaluru, India, 2020.
3. N. A. Sagar, S. Pareek, S. Sharma, and E. M. Yahia, "Fruit and Vegetable Waste: Bioactive Compounds, Their Extraction, and Possible Utilization," *International Journal of Food Science and Technology*, 2021.
4. A. Saha et al., "IoT-Based Fruit Quality Inspection and Lifespan Detection System," *International Journal of Smart Agriculture*, vol. 12, no. 4, pp. 89–102, 2024.
5. S. Ray and A. Pradhan, "IoT-Based Fruit Quality Measurement System," *Proc. Int. Conf. Emerging Technologies in Agriculture*, 2022.
6. M. T. Smith et al., "Internet of Things (IoT)-Based Fruit Sorting Results Monitoring System," *Proc. Int. Conf. Smart Agriculture Technologies*, 2024.
7. P. Akiva et al., "FruitPAL: An IoT-Enabled Framework for Automatic Monitoring of Fruit Allergens," *arXiv preprint arXiv:2502.01643*, 2025.
8. N. A. Sagar, S. Pareek, S. Sharma, E. M. Yahia, and M. G. Lobo, "Fruit and Vegetable Waste: Bioactive Compounds, Their Extraction, and Possible Utilization," *Comprehensive Reviews in Food Science and Food Safety*, vol. 17, pp. 512–531, 2018. <https://doi.org/10.1111/1541-4337.12330>
9. United Nations Environment Programme, *Food Waste Index Report 2021*, UNEP, 2021.
10. S. S. Priya, S. K. Dixit, S. Kabiraj et al., "Food waste in Indian households: status and potential

- solutions," *Environ. Sci. Pollut. Res.*, vol. 30, pp. 124401–124406, 2023. <https://doi.org/10.1007/s11356-023-31034-1>
11. P. Omre, Shikhangi Singh, and Shikha Singh, "Waste utilization of fruits and vegetables – A review," 2018, pp. 605–615.
12. O. Alegebeleye, O. A. Odeyemi, M. Strateva, and D. Stratev, "Microbial spoilage of vegetables, fruits and cereals," *Applied Food Research*, vol. 2, no. 1, 100122, 2022. <https://doi.org/10.1016/j.afres.2022.100122>
13. A. M. Lucho-Gómez, A. Domínguez-Niño, P. Guillén-Velázquez, J. P. Hernández-Jerónimo, M. Luna-Flores, and O. García-Valladares, "Physicochemical and Thermal Evaluation of a Mixed-Mode Greenhouse Solar Dryer for Guava (*Psidium guajava* L.)," *J. Food Sci.*, vol. 91, no. 5, e71106, 2026. <https://doi.org/10.1111/1750-3841.71106>
14. R. J. Blakey, J. P. Bower, and I. Bertling, "Influence of water and ABA supply on the ripening pattern of avocado (*Persea americana* Mill.) fruit and the prediction of water content using near infrared spectroscopy," *Postharvest Biology and Technology*, vol. 53, no. 1–2, pp. 72–76, 2009. <https://doi.org/10.1016/j.postharvbio.2009.03.004>
15. M. C. García-García et al., "Correlation analysis of high-throughput fruit phenomics and biochemical profiles in native peppers (*Capsicum* spp.) from the primary center of diversification," *Agronomy*, vol. 11, no. 2, p. 262, 2021. <https://doi.org/10.3390/agronomy11020262>
16. A. M. Lucho-Gómez et al., "Physicochemical and thermal evaluation of a mixed-mode greenhouse solar dryer for guava (*Psidium guajava* L.)," *J. Food Sci.*, 2026. <https://doi.org/10.1111/1750-3841.71106>
17. M. E. Maldonado-Celis, E. M. Yahia, R. Bedoya, P. Landázuri, N. Loango, J. Aguillón, B. Restrepo, and J. C. Guerrero Ospina, "Chemical composition of mango (*Mangifera indica* L.) fruit: Nutritional and phytochemical compounds," *Frontiers in Plant Science*, vol. 10, p. 1073, 2019. <https://doi.org/10.3389/fpls.2019.01073>
18. E. R. Trentacoste, C. M. Puertas, and V. O. Sadras, "Modelling the intraspecific variation in the dynamics of fruit growth, oil and water concentration in olive (*Olea europaea* L.)," *European Journal of Agronomy*, vol. 38, pp. 83–93, 2012. <https://doi.org/10.1016/j.eja.2012.01.001>
19. G. Vicario, C. Cantini, A. Francini, A. Raffaelli, M. Cifelli, V. Domenici, and L. Sebastiani, "Olive fruit ripening degree and water content relationships with phenolic acids and alcohols, secoiridoids, flavonoids and pigments in fruit and oil," *Molecules*, vol. 28, no. 19, p. 6943, 2023. <https://doi.org/10.3390/molecules28196943>
20. T. Sarkar, M. Salauddin, H. I. Sheikh, S. Pati, and R. Chakraborty, "Effect of drying on vitamin, carotene, organic acid, mineral composition, and microstructural properties of mango (*Mangifera indica*)," *Journal of Food Processing and Preservation*, vol. 46, e16237, 2022. <https://doi.org/10.1111/jfpp.16237>
21. S. Kalpana and A. L. Baghyam, "Electronic-nose system for classification of fruits and freshness measurement using K-NN algorithm," *International Journal of Innovative Technology and Exploring Engineering*, vol. 8, no. 6S4, pp. 641–644, 2019. <https://doi.org/10.35940/ijitee.F1132.0486S419>
22. T. Mahata, P. Banerji, and P. K. Guha, "Fruit freshness monitoring employing chemiresistive volatile organic compound sensor and machine learning," *ACS Applied Nano Materials*, 2023. <https://doi.org/10.1021/acsanm.3c04138>
23. N. A. Sagar, S. Pareek, S. Sharma, E. M. Yahia, and M. G. Lobo, "Fruit and vegetable waste: Bioactive compounds, their extraction, and possible utilization," *Comprehensive Reviews in Food Science and Food Safety*, vol. 17, no. 3, pp. 512–531, 2018. <https://doi.org/10.1111/1541-4337.12330>
24. J. Ananda, A. W. J. C. Abeygunasekera, and D. Pearson, "Wasting nature's harvest: Understanding the drivers of household fruit and vegetable waste," *Waste Management*, vol. 199, pp. 36–46, 2025. <https://doi.org/10.1016/j.wasman.2025.02.053>
25. "Developing an IoT and ML-driven platform for fruit ripeness evaluation and spoilage detection: A case study on bananas," *e-Prime — Advances in Electrical Engineering, Electronics and Energy*, vol. 11, 100896, 2025. <https://doi.org/10.1016/j.prime.2025.100896>
26. C. Occhiuzzi, F. Camera, M. D'Orazio, N. D'Uva, S. Amendola, G. M. Bianco, C. Miozzi, L. Garavaglia, E. Martinelli, and G. Marrocco, "Automatic monitoring of fruit ripening rooms by UHF RFID sensor network and machine learning," *IEEE Journal of Radio Frequency Identification*, vol. 6, pp. 649–659, 2022. <https://doi.org/10.1109/JRFID.2022.3174272>
27. M. Yamakawa, L. R. Khot, R. Ehsani, and N. Kondo, "Real-time nondestructive citrus fruit quality monitoring system: Development and laboratory testing," *Agricultural Engineering International: CIGR Journal*, vol. 14, no. 3, 2012.
28. K. K. Patel and P. B. Pathare, "Principle and applications of near-infrared imaging for fruit quality assessment — An overview," *International Journal of Food Science & Technology*, vol. 59, no. 5, pp. 3436–3450, 2024. <https://doi.org/10.1111/ijfs.16862>

29. I. W. R. Ardana, L. G. P. Suardani, I. N. K. Wardana, and I. G. P. M. E. Putra, "Internet of Things (IoT)-based fruit sorting results monitoring system," *Proc. Int. Conf. Sustainable Green Tourism Applied Science — Engineering Applied Science* 2024, pp. 664–671, Atlantis Press, 2024. https://doi.org/10.2991/978-94-6463-587-4_74
30. B. P. Vikraman, V. Mahadevan, R. Begum, A. K. Al Shekili, and M. K. Al Yahmadi, "IoT-based multiclass fruit classification system using transfer learning," *Journal of Electrical Systems*, vol. 20, no. 7s, pp. 1308–1314, 2024. <https://doi.org/10.52783/jes.3703>
31. Roy, B., Majumder, S., & Chakraborty, R. "Segmented multimode to dual port slot couplers as compact optical sensors with improved sensitivity" *Journal of Optics*, 26(9), 095003. *Journal of Modern Optics* 66(6), 2019. <https://doi.org/10.1080/09500340.2018.1559370>
32. Roy, B., Majumder, S., & Chakraborty, R. "Graphene oxide based plasmonic nano-cavity sensor for high-performance refractive index sensing". *Journal of Optics*, 26(9), 095003, 2024. doi 10.1088/2040-8986/ad5f9f.
33. D. Parida, A. Behera, J. K. Naik, S. Pattanaik, and R. S. Nanda, "Real-time environment monitoring system using ESP8266 and ThingSpeak on Internet of Things platform," *Proc. Int. Conf. Computing, Communication and Security (ICCCS)*, pp. 225–229, 2019. <https://doi.org/10.1109/ICCS45141.2019.9065451>
34. S. Kristiyana and A. Rinaldi, "Air quality monitoring system in Thingspeak-based applications using Internet of Things (IoT)," *WSEAS Transactions on Computer Research*, vol. 8, pp. 34–38, 2020. <https://doi.org/10.37394/232018.2020.8.6>
35. F. R. Saputri, R. Linelson, M. Salehuddin, D. M. Nor, and M. I. Ahmad, "Design and development of an irrigation monitoring and control system based on Blynk Internet of Things and ThingSpeak," *PLOS ONE*, vol. 20, no. 4, e0321250, 2025. <https://doi.org/10.1371/journal.pone.0321250>
36. Espressif Systems, ESP8266EX datasheet, Espressif Systems, 2025.
37. Hanwei Electronics, MQ-3 semiconductor sensor for alcohol.
38. A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of Things: A survey on enabling technologies, protocols, and applications," *IEEE Communications Surveys & Tutorials*, vol. 17, no. 4, pp. 2347–2376, 2015. <https://doi.org/10.1109/COMST.2015.2444095>
39. A. Dauda, O. Flauzac, and F. Nolot, "A survey on IoT application architectures," *Sensors*, vol. 24, no. 16, p. 5320, 2024. <https://doi.org/10.3390/s24165320>
40. J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions," *Future Generation Computer Systems*, vol. 29, no. 7, pp. 1645–1660, 2013. <https://doi.org/10.1016/j.future.2013.01.010>
41. J. Krishnan and S. K. Vasudevan, "An extensive survey on IoT smart gateways, software architecture, related protocols and challenges," *Proc. Int. Conf. Vision Towards Emerging Trends in Communication and Networking (ViTECoN)*, IEEE, 2019. <https://doi.org/10.1109/ViTECoN.2019.8899547>
42. D. Miorandi, S. Sicari, F. De Pellegrini, and I. Chlamtac, "Internet of things: Vision, applications and research challenges," *Ad Hoc Networks*, vol. 10, no. 7, pp. 1497–1516, 2012. <https://doi.org/10.1016/j.adhoc.2012.02.016>
43. M. Nazari Jahantigh, M. Masoudi, and A. Rezaee, "Integration of Internet of Things and cloud computing: A systematic survey," *IET Communications*, vol. 14, no. 14, pp. 2294–2305, 2020. <https://doi.org/10.1049/iet-com.2019.0537>
44. MathWorks, ThingSpeak IoT Analytics Platform: Learn More.
45. E. Siow, T. Tiropanis, and W. Hall, "Analytics for the Internet of Things: A Survey," *ACM Computing Surveys*, 2018.
46. V. Viswanatha, V. S. Reddy, P. Ashwini Kumari, and P. Kumar, "Internet of Things (IoT) Based Multilevel Drunken Driving Detection and Prevention System Using Raspberry Pi 3," 2020.
47. D. Parida, A. Behera, J. K. Naik, S. Pattanaik, and R. S. Nanda, "Real-time environment monitoring system using ESP8266 and ThingSpeak on Internet of Things platform," *Proc. Int. Conf. Computing, Communication and Security (ICCCS)*, pp. 225–229, 2019. <https://doi.org/10.1109/ICCS45141.2019.9065451>
48. S. Kristiyana and A. Rinaldi, "Air quality monitoring system in Thingspeak-based applications using Internet of Things (IoT)," *WSEAS Transactions on Computer Research*, vol. 8, pp. 34–38, 2020. <https://doi.org/10.37394/232018.2020.8.6>
49. F. R. Saputri, R. Linelson, M. Salehuddin, D. M. Nor, and M. I. Ahmad, "Design and development of an irrigation monitoring and control system based on Blynk Internet of Things and ThingSpeak," *PLOS ONE*, vol. 20, no. 4, e0321250, 2025. <https://doi.org/10.1371/journal.pone.0321250>
50. "Development of an IoT-enabled cost-effective asthma patient monitoring system: Integrating health and indoor environment data with statistical analysis and data visualization," *Internet of Things*, vol. 24, 100942, 2023. <https://doi.org/10.1016/j.iot.2023.100942>