PAPER 24 - Development of an Intelligent Evaporative Cooling System for Post-harvest Storage of Tomato

O. R. Isah[1]*, S. E. Adebayo[2], B. K. Nuhu[3], B. U. Umar[4], D. Maliki[5], I. M. Abdullahi[6], E. M. Dogo[7], O. M. Olaniyi[8], J. Agajo[9]
[1,2,3,4,5,6,7,8,9]Department of Computer Engineering, Federal University of Technology, Minna
*Email: isah.rabiu@futminna.edu.ng

ABSTRACT

This research developed an intelligent evaporative cooling system for post-harvest tomato preservation that adapts to its suitable temperature, humidity, and CO_2 states to store, preserve quality, and increase the shelf life of the fruits. This was accomplished through the use of transfer learning for fruit classification, the Internet of Things (IoT) for remote monitoring and shelf life tracking, and the integration of the evaporative cooling system with a CO_2 sensor, a temperature sensor, a humidity sensor, an Arduino Uno, and a Raspberry Pi 4b. The system can classify tomato fruit status as ripe or overripe with a prediction accuracy of 87.5% and a receiver operating characteristic (ROC) value of 88.89%. The developed evaporative cooling system extended the shelf life of ripe tomatoes from 5 to 14-17 days at 20℃ and 90% relative humidity and overripe tomatoes from 3 to 9-11 days at 18℃ and 95% relative humidity. These results emphasize the crucial function of evaporative cooling in fruit and vegetable storage, as it extends the shelf life of tomatoes by 180–200%, hence minimizing post-harvest loss as it also increases the farmers' income, thereby contributing positively to the economy.

KEYWORDS: Intelligent, Evaporative, Cooling system, Tomato, post-harvest, Transfer Learning

1. INTRODUCTION

The word "tomato" is derived from the Nahuatl word tomato, which means "swelling fruit" (Online Etymology Dictionary). After potato (*Solanum tuberosum L.*), tomato (*Solanum lycopersicum L.*) is the second most important fruit or vegetable crop, with around 182.3 million tons of tomato fruits grown on 4.85 million ha each year [1]. Asia produces 61.1 percent of the world's tomatoes, while Europe, America, and Africa each contributed 13.5 percent, 13.4 percent, and 11.8 percent of the total tomato harvest [1]. Deterioration of food products after harvest is a severe issue in underdeveloped countries, such as Nigeria. It results in considerable reductions in socioeconomic well-being, including decreased household income and the likelihood of hunger [2]. Tomatoes are essential vegetable crop but are naturally perishable, resulting in post-harvest losses before the produce is consumed [3]. In Nigeria, approximately 1.8 million tonnes of fresh tomatoes are produced annually, but over half of these are lost due to insufficient storage, transportation, and processing facilities [4]. Due to its great importance as a source of livelihood for farmers and food for consumers, these losses are detrimental and must be reduced to the barest minimum.

Evaporative cooling is a heat and mass transfer method that uses water evaporation to cool the air, transferring a considerable quantity of heat from the air to the water and lowering the air temperature [5]. Evaporative cooling has many advantages, including significant energy and cost savings, the absence of CFCs, lower CO_2, enhanced indoor air quality, and increased life-cycle cost-effectiveness [6].

One in every nine persons lacks enough food to live a healthy life. However, one-third of all food produced globally is lost or squandered. Food loss occurs owing to factors beyond the farmers' control, such as weather, market volatility, storage facilities, and post-harvest technology [8]. Numerous approaches have been applied to reduce post-harvest loss, including cold storage systems, which have been shown to maintain fruit quality and characteristics better than chemical and biological methods. Additionally, the evaporative cooling approach has been shown to extend shelf life and preserve average fruit quality over time when combined with high relative humidity, low temperature, and enough cooling [3, 7]. Some post-harvest storage systems use fuzzy logic [9, 10], while other evaporative cooling systems require manual operation [11, 12]. However, none of these systems coupled transfer fruit classification using transfer learning, remote monitoring, and shelf life tracking using IOT into an evaporative cooling system [17, 18 and 19]. These characteristics improve the efficacy of the evaporative cooling system used for tomato post-harvest storage, necessitating the design and development of an intelligent evaporative cooling system.

1.1 REVIEW OF RELATED WORKS

The purpose of this project is to develop an intelligent evaporative cooling system. There have been several developments in the evaporative cooling system. Still, none have included tomato fruit image classification, adaptive evaporative cooling, remote monitoring, automated control of temperature and humidity, and fruit shelf-life tracking. To this effect, the reviews of related works are presented thus:

A cost-effective tomato maturity grading system for farmers was developed [13]. This system used an inexpensive material and image processing algorithms to identify the six essential stages of tomato ripening. The algorithms were designed using Simulink, a part of MATLAB 2011b, on a 2.5GHz GPU. This system had an overall 98% accuracy concerning maturity grade detection. The execution speed of the system was 7.6 times greater than other popular methodologies. The limitation of this system was that it did not have a storage facility for the tomato.

A system that measures the ripeness and grading of tomatoes using an image analysis on a Raspberry Pi was developed [14]. This system used the tomato's size, shape, and degree of ripeness to determine its quality. An edge detection algorithm was used to estimate the size and shape. In contrast, a colour-detecting algorithm was used to determine its degree of ripeness, and all these were implemented on a Rasberry Pi development board. This system, however, did not provide storage for classified tomatoes.

Researchers [15] worked on a computer vision system for defect discrimination and grading in tomatoes using Machine Learning and image processing. This research presented a Red, Green, and Blue (RGB) image-based tomato grading machine. A Radial Basis Function-Support Vector Machine (RBF-SVM) classifier was used to detect infected regions using LAB colour-space pixel values. This system had an overall accuracy of 98.9%. This system did not handle the storage of the tomato after successful sorting.

Machine learning techniques were used [16] for evaluating tomato ripeness. This article described an automatic multi-class classification method for measuring and assessing tomato ripeness by examining and classifying the various maturity/ripeness levels. For feature extraction and classification, the method presented in this article employed Principal Components Analysis (PCA), as well as Support Vector Machines (SVMs) and Linear Discriminant Analysis (LDA) algorithms. The suggested classification solution achieved a ripeness classification accuracy of 90.80% using a one-against-one (OAO) multi-class SVMs algorithm with linear kernel function, a ripeness classification accuracy of 84.80% using a one-against-all (OAA) multi-class SVM algorithm with linear kernel function, and ripeness classification accuracy of 84 percent using one-against-all (OAA) multi-class SVMs algorithm with a linear kernel function. This system, however, did not provide storage for classified tomatoes.

Other researchers [20] worked on Tomato volume and mass estimation using computer vision and machine learning algorithms: Cherry Tomato model. A prediction method of mass and volume of cherry tomatoes based on a computer vision system and machine learning algorithms was introduced in this study. The relation between tomato mass and volume was established as M=1.312, V=0.9551, and was used to estimate mass on a test dataset at an R2 of 0.9824 and RMSE of 15.84g. The RBF-SVM outperformed all explored models with an accuracy of 0.9706 (only 2D features) and 0.9694 (all features) in mass and volume estimation, respectively. This system did not classify good or bad tomatoes.

The study [12] developed an effective evaporative charcoal cooler for the post-harvest preservation of tomatoes and kale. The air temperature and relative humidity were measured to examine the cooler microclimate and outdoor temperatures. The mean temperature differential between the cooler and the outside was 9.2 °C during the study period, while the maximum relative humidity difference was 36.8%. Temperature and relative humidity variations were significantly decreased due to the effects of light rain and low solar radiation. Despite the light rain, the cooler still had a maximum relative humidity of 83.5 percent and a maximum cooling performance of 91.5 percent. The limitation of this system was that it did not sort the tomatoes before they were stored in the cooler.

The quality of tomatoes stored in the Zero Energy Cool Chamber (ZECC) was studied [11]. The ZECC is an environmentally friendly and low-cost post-harvest technology for storing fruits and vegetables. Vitamin C content 39.95 mg / 100g, pH 4.15, total acid 0.40, total soluble solids 5.40Brix, and weight loss 4.66 grams were the chemical analysis results of tomato deposited in ZECC. Tomatoes can be stored for 20 days in ZECC, 15 days at cool temperatures, and ten days at room temperature. Although this system increases the shelf life of the tomato, it does not classify the tomato-based on its ripeness.

Another research work [21] proposed some tomato post-harvest handling practices and treatment methods for tomato handlers in developing countries revealed that the tomatoes' post-harvest quality and shelf life would depend on the practices and treatments carried out after harvest, like precooling, grading, packaging, storing, and transportation. A conclusion was made that by using specific post-harvest techniques, there could be an extension in the shelf life of the tomatoes, and failure to adopt such practices would result in a high level of wastage of tomatoes.

The incidence of post-harvest diseases can affect the quality and restrict the shelf life of horticultural fresh produce [22]. Since some countries have limited the amount of pesticide residue left on imported farm produce, some fungal pathogens have been reported to have developed resistance to synthetic fungicides. Therefore, this review summarises the use of essential oils to control post-harvest diseases of horticultural commodities, their mode of action, their effects on the defense mechanism, and the quality of fresh fruit.

A technique using a Metal Oxide Semiconductor (MOS) electronic nose and Extreme Learning Machine (ELM) to predict the post-harvest quality of cherry tomato fruit treated with high-pressure argon was developed [23]. The purpose was to investigate the reliability and validity of using electronic nose (e-nose) technology to evaluate the quality and freshness of cherry tomatoes after high-pressure argon treatments. The results showed that the freshness of the tomatoes based on flavour over the time of storage was categorized into four groups (fresh, acceptable, stale, and very stale, respectively). Pressure argon at 0.8 MPa maintained the freshness and quality of cherry tomatoes during cold storage.

Recent advances in modeling and predicting quality parameters of fruits and vegetables during post-harvest storage was studied [24]. The study stated that ANN, genetic algorithm, fuzzy logic, and an adaptive nervously inference system (ANFIS) have been applied in every aspect of food science in recent years. These models are valuable tools for fruit and vegetable monitoring, grading and classification, sorting, predicting the food and modeling properties, modeling microbial growth, and forecasting chemical, physical, and sensory characteristics during post-harvest storage processing. Also, these models were used for different fruit and vegetable storage process modeling, detecting chilling injury, detecting defects, controlling various drying processes, and improving climate control.

2. THEORETICAL ANALYSIS

2.1 Control Unit Design Calculation.

Equations (1 and 2) compute the power rating, ampere-hour rating, and how long the control unit can continuously run before recharging.

$$P_T = I_{op} \times V_{op} \quad (1)$$

$$Ampere\ hour = \frac{power \times time}{voltage} \quad (2)$$

Where,

P_T represents the total power of the control unit

V_{op} represents the operating voltage of the control unit

I_{op} represents the operating current of the control unit

T_c represents the total lasting time of the control unit

$I_{op} = 3.0A$, $V_{op} = 5V$, $P_T = 3.0 \times 5$, $P_T = 15.0W$. Calculating the control unit ampere-hour rating $Amphr = \frac{15.0 \times T_c}{5}$, $Amphr = 3.0T_c\,Ahr$. A 10000mAh 5V battery will power the ECS for T_c hours, $10000Ahr = 3.0T_cAhr$, $T_c = 3.33hrs$, $T_c = 3hr\ 20mins$

2.2 Evaporative Cooling System Calculations

Volume of the Storage System: The capacity of the storage system was determined using Equation (3);

$$V_s = L_S \times B_S \times H_S \quad (3)$$

$V_s = 0.4 \times 0.5 \times 0.8 = 0.16m^3$

Where; V_s = volume of the storage system, L_s = Length of the storage system, B_s = Breadth of the storage system, H_s = height of the storage system

The volume of Reservoir:

The volume of the reservoir was determined using Equation (4);

$$V_c = \pi r^2 h \quad (4)$$

$V_c = 3.14 \times 0.16^2 \times 0.3 = 0.024m^2 = 24litres$

Where; V_c = volume of reservoir, $\pi = 3.142$ r= radius of reservoir, H_c = height of the reservoir

2.3 Heat Transfer Analysis of the System

The heat gain by the aluminum material used for the cabinet construction was estimated using Fourier's law of heat conduction.

$$Q_h = \frac{-cA\Delta T}{l} \quad (5)$$

$Q_h = \frac{-204 \times 1.418 \times 10}{0.001} = 2892720w$

Where; Q_h = Quantity of heat gained by the material (W), A = Area of the material (m), c = Thermal conductivity of the material $(W/m\ K)$, ΔT = Temperature difference of thermal $(°C)$, l = Thickness of the material (m).

3. MATERIALS AND METHODS/METHODOLOGY/EXPERIMENTAL PROCEDURE

The system is made up of two modules, namely hardware and software. The hardware module is made up of various units that are used to build the evaporative cooling system. In contrast, the software module contains the deep learning model for sorting the tomato and the mobile app for feedback.

3.1 System Hardware

The evaporative cooling system, a Raspberry Pi 4, an Arduino Uno, sensors, a servo motor, and a pump comprise the system hardware components. Figure 1 shows the 3-D model of the developed system.

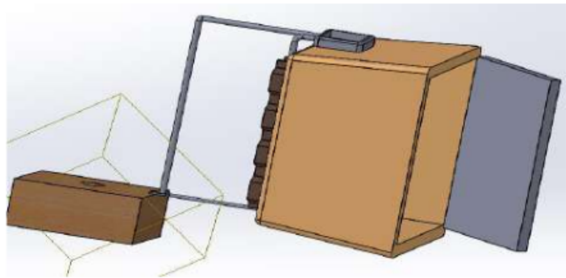

Figure 1: 3-D model of the system

3.2 System Block Diagram

The sensing unit monitors the state of critical components that contribute to the tomato's health; the Arduino, a control unit member, then retrieves these values. This unit is in charge of the overall system's operation. The Arduino shows the parameters on the LCD and sends them to the Raspberry Pi, which uploads them to the database and finally sends them to the mobile application. The automation unit comprises two DC fans and a DC pump connected to a robotic switch that operates via signals from the Arduino. Additionally, the Raspberry Pi is responsible for photographing and submitting photos to the web server for fruit classification, as shown in Figure 2.

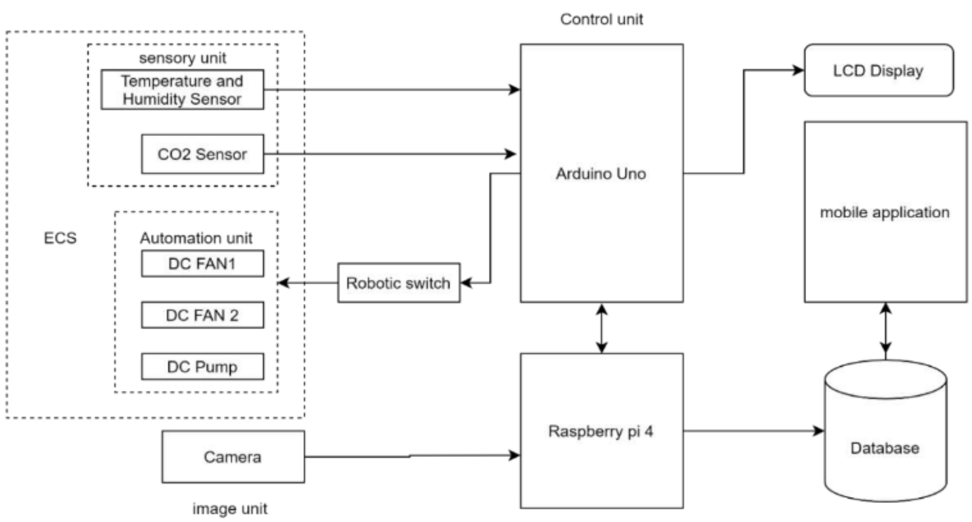

Figure 2: System Block Diagram.

When the system is turned on for the first time, it initializes the parameter monitoring unit consisting of temperature, humidity, and CO_2 sensors. It then captures the camera's image for classification. After classifying the image as ripe or unripe, the evaporative cooling system's parameters are adjusted according to the classification result. The parameters are then monitored continuously to verify that the system is acceptable for the stored tomato by maintaining the conditions and, if not, by lowering or increasing the temperature and relative humidity. The shelf life is calculated and communicated to the mobile application for user feedback.

3.3 The System Flowchart

The system shows the operational flow of the Evaporative cooling system sequence in steps. The flow sequences are explained and shown in Figure 3.

Figure 3 shows the flowchart of the system. Once switched on, the parameter monitoring unit, which consists of temperature, humidity, and CO_2 sensors, is initialized. It then captures the camera's image for classification. After classifying the image as ripe or unripe, the evaporative cooling system's parameters are adjusted according to the classification result. The parameters are then monitored continuously to verify that the system is acceptable for the stored tomato by maintaining the conditions and, if not, by lowering or increasing the temperature and relative humidity. The shelf life is calculated and communicated to the mobile application for user feedback.

3.4 Software Design Consideration

The design of the software is concerned with the development of an online server and a mobile application. The classification model was programmed using Python on the Tensor Flow machine learning platform with Keras Library. These are flexible, efficient, easily understandable machine learning tools. The Firebase cloud server holds feedback information from the Raspberry Pi 4, where a get request from the mobile application could fetch it. Firebase provides fast and flexible real-time data.

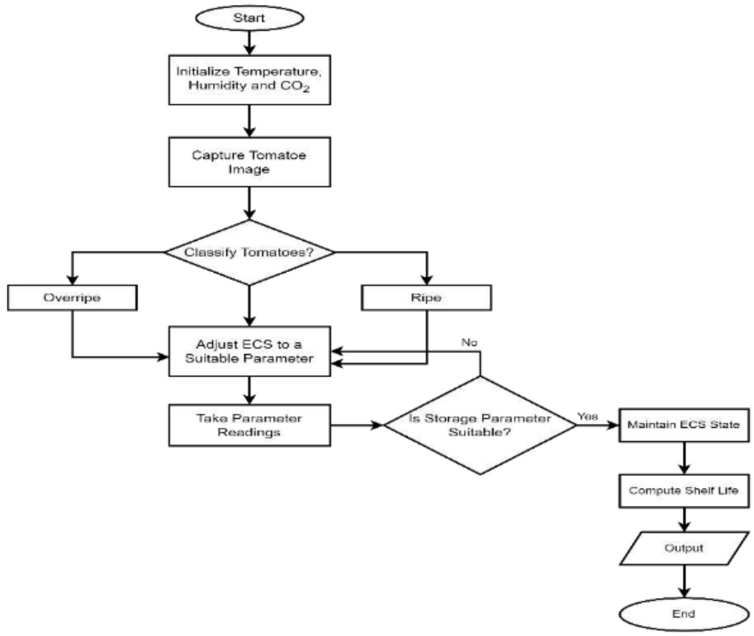

Figure 3: Flowchart of the system

The communication protocol between the cloud server and the Raspberry Pi is an HTTP POST request. In contrast, communication between mobile applications is done through HTTP GET requests to fetch real-time data. Figure 4 shows the user interface of the mobile application.

Figure 4: Mobile App for monitoring parameters

4. RESULTS AND DISCUSSION

This section discusses the results obtained after designing, developing, and testing the intelligent evaporative cooling system. It will include hardware development, software development, and system performance evaluation.

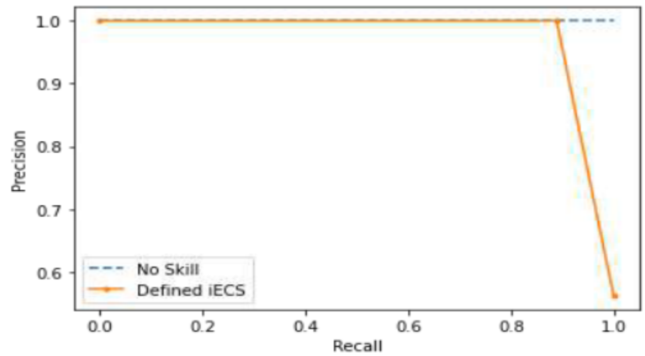

Figure 6: Precision-Recall curve

Furthermore, the software model (deep learning) had a precision value of 1, as shown in Figure 6, with a recall value of 0.888889. The F1 Score calculates the harmonic mean of the precision and the recall rates. It also signifies a summary of the model skill for a specific probability threshold. This model has an F1-Score of 0.941176. These results depict the efficacy of the deep learning model in its prediction.

4.1 Average Shelf Life

One of the performance metrics of the evaporative cooling system is the increased shelf life of the stored fruits. Table 2 shows the average shelf life at room temperature and after storage of tomatoes using an evaporative cooling system. At 25 degrees Celsius, which is the room temperature of the system, ripe tomatoes could stay for a shelf-life of 5 days, after which they start to deteriorate, while overripe tomatoes have about three days of shelf-life, however, after being subjected to the evaporative cooling system at 20 degrees Celsius, the ripe tomatoes have an increased shelf-life within the range of 14-17 days and the overripe within 9-11 days.

Shelf-life performance was calculated using equation 6:

$$S_I = \frac{y_2 - y_1}{y_1} \times 100\% \tag{6}$$

where,

y_2 denote shelf-life after storage in iIECS,

y_1 denotes shelf life at room temperature.

Table 2: The Shelf Life Performance Result of the Evaporative Cooling System

	Ripe (days)	Overripe (days)
Temperature (Ambient condition)	5	3
Temperature (20°C) and 90% RH in iECS	14-17	__
Temperature (18°C) and 95% RH iECS	__	9-11
Percentage increase in shelf-life	180%	200%

4.2 Percentage Weight Loss of Tomato

Fresh fruits and vegetables contain high levels of water (80-90 percent), making them highly perishable. Accordingly, to find the system's efficiency, we must measure the percentage weight loss of the tomato. Table 3 shows the weight loss recorded in the tomato stored in the evaporative cooling system and at ambient temperature.

Table 3: Weight Loss Relationship between Tomatoes in ECS and Ambient Temperature Measured In Grams

	Weight in iECS (g)	Weight in Ambient Temperature (g)
Day 1	1.7	9.7
Day 2	3.2	14.2

Day 3	4.7	18.8
Day 4	5.2	14.1
Day 5	5.8	11.9
Day 6	5.9	10
Day 7	6.2	8.3
Average Weight Loss	4.67	12.43

Over seven days (1 week), tomato fruits were stored in two conditions: inside the intelligent evaporative cooling system and in a container with ambient conditions. The loss of weight measured daily is as follows;
The tomatoes stored in IECS exhibit an average weight loss of 4.67, while the traditional cooling system depicts an average weight loss of 12.43. These results were due to the ability of the IECS to optimally adjust its temperature and humidity suitable for the stored fruits.
It is a fact that there were weight losses in both conditions; however, as illustrated, there is a slow and steady increase in the weight loss in tomatoes that were stored in the Intelligent Evaporative Cooling System, while for those stored in ambient temperature, there was a high and Rapid loss in the weight in the first three days, followed by a gradual decrease in the weight loss. These results denote that the Intelligent Evaporative Cooling system helps reduce the loss in weight while preserving the fruit quality over time compared to when stored at ambient temperature.

5. CONCLUSION

This research developed an intelligent evaporative cooling system that reduces the post-harvest wastage of tomatoes while increasing the food security potential. The designed system classifies stored fruits and adapts to temperature and humidity states suitable for storing, preserving quality, and improving the shelf life of the fruits, thus providing enough market time for the farmer to get his fruits to the customers. Intelligent storage, automatic control, and remote monitoring were achieved after the implementation of this research.

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