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Circular Supply Chains: An Internet of Things Application for Rotten Product Detection in Aggregate Food Industry

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Abstract: Today, the majority of food created is wasted rather than consumed, which has a negative impact on worldwide hunger and the economy. Improvements to aggregate supply chains are at the forefront of the actions needed to meet the nutritional requirements of an expanding population. One of such improvements noted in this research was aggregate food storage. The ESP8266-Microcontroller, along with the DHT11 temperature and humidity sensor and the MQ3 alcohol sensor, is put in the storage area to measure the storage conditions of fruit products on a regular basis. The data gathered is sent to the Internet of Things Application in AWS cloud computing service via the microcontroller and MQTT communication protocol and is stored in both the S3 Bucket and Firehose Kinesis databases using the rules defined in this console. As result, the sensor data stored in the database is examined using AWS-Internet of Things -Analysis and SageMaker. Fruits should be kept at temperatures ranging from 4 to 7 degrees Celsius. When the temperature outside of this range rises, the crops begin to decompose. Accordingly, a rule in the AWS Internet of Things Application is defined to fire with out-of-range measurements, and the AWS Simple Notification Service is triggered to send ambient temperature, humidity, and methanol values to user via SMS and e-mail. A Convolutional Neural Network model was also developed to classify fruits based on their variety and whether they are fresh or rotten. The model was first taught using images of 1693 fresh apples, 1581 fresh bananas, 1466 fresh oranges, 2342 rotten apples, 2224 rotten bananas, and 1595 rotten oranges over 50 epochs. Then, images of 395 fresh apples, 381 fresh bananas, 381 fresh oranges, and 388 rotten apples, 601 rotten bananas, and 530 rotten oranges were evaluated. This CNN Model had a training accuracy of 98.6% and an assessment accuracy of 96.4%.

Keywords: Circular economy, Sustainability, Industry 4.0, Agrifood supply chain, Internet of things

Introduction

Elimination of food waste is a major worldwide challenge and a vital prerequisite for economic development. Poor food management has a substantial impact on waste generation. Therefore, to reach the goal of zero food waste, sustainable practices should be monitored from farm to fork from an economic, social, and environmental standpoint. In the 2030 Agenda for Sustainable Development, it is stated that urgent measures should be taken on sustainable consumption and production, sustainable management of natural resources and climate change for the continuity of life on Earth. The circular economy(CE) model is a model of production and consumption, which involves sharing, leasing, reusing, repairing, refurbishing, and recycling existing materials and products as long as possible and is the most favored strategy (92%) for managing food waste. In terms of the supply chain, the focus of the circular economy is to ensure the optimal environmental results by enhancing the efficient use of resources. The optimized material flows in circular supply chains, leads to higher economic rewards compared to the traditional take-make-dispose aspect of linear ones. As a result, applying the circular economy in agri-food supply chains has the potential to alleviate the negative operational, economic, and environmental effects of food waste. These mostly include energy and resource waste, idle time wasted on food production, raised emissions of greenhouse gases, and increased food expenses due to decreased food supply.

Food service organizations must improve efficiency at each phase of the supply chain, through procurement to logistics, production to marketing, and sales to after-sales support. Specifically, the agri-food sector additionally is volatile and complicated, necessitating the use of advanced techniques to maximize efficiency by optimizing resources, and reducing costs. (Duncan et al., 2019.; Angkiriwang et al., 2014.). At this stage, industry 4.0 is playing an essential role in the circularization of agri-food supply chains by transforming supply networks into intelligent systems capable of attaining full traceability of goods. (Zhang, 2020). Internet of Things and big data are major aspects in the industry 4.0 framework, proposing a linear-to-circular model transition to assist sustainability issues. Internet of Things(IoT) has an impact on agri-food supply chain through improved connectivity, reduced interference from humans, and energy conservation. (Vaibhav et al., 2022) The use of IoT in food chains has grown, with numerous linked devices that span portable agricultural equipment, tools, and hardware to residential devices and temperature-sensing devices. (Rao & Clarke, 2019). Moreover, the utilization of big data has advanced IoT networks by precisely documenting supply chain variables based on sensor network data; improved information visualization across the food network; promoted higher transparency, efficiency, and data-driven decision-making. (Ji et al., 2017; Li & Wang, 2017). As a result, more intelligent decisions are made, allowing food chains to run more efficiently, minimize expenditures, expedite the decision-making procedure, and reduce risks. This paper is structured as follows; Methodology section briefly describes how the study is conducted: CNN structure for image classification and WSN model. Results and Discussions section presents outputs of the implementation that are classification accuracy, sensor outputs and user information measures. Conclusions and Perspectives section restates the findings in terms of sustainability and under the improvement purpose of circular supply chains, and also presents relevant research for future investigations.

Industry 4.0 Applications for the Detection of Food Freshness

Food Image Classification

Creating methods to automate the fruit grading process is of great interest. Support vector machines, decision trees, and K-Nearest Neighbor algorithms are examples of machine learning techniques that have been effectively used to solve classification issues in the literature, notably for fruit categorization. Recently, artificial neural networks(ANNs) and CNNs, have also been used to the fruit categorization class, with extremely encouraging results. (Rizzo et al., 2023.). In computer vision applications including image classification, object identification, and visual question answering, convolutional neural networks are often utilized compared to others due its various advantages as: focusing on the different parts rather than the complete picture (Chakraborty et al., 2021.), and attaining higher accuracy (Das et al, 2020.).

Table 1. CNN models for fruit/vegetable classification

References	Dataset	Model	Accuracy
Lu, Y. (2019)	ImageNet	5-layer CNN	With augmentation 90.00%
Zhang et. al. (2019)	VegFru	13-layer CNN	94.94%
Wang et. al. (2018)	VegFru	8-layer CNN	95.67%
Sakib et. al. (2019)	Fruits-360	Own CNN model	99.79%
Mureşan et. al. (2018)	)Fruits-360	AlexNet, GoogLeNet, Own	~99.00%
Zhang et. al. (2015)	UEC-FOOD100	5-layer CNN	80.80%

As indicated in Table1, numerous studies have been conducted that aims to monitor the freshness of the food via in terms of the image classification. However, there was a gap in combining image classification with sensor data and the storage and processing of the outputs in a cloud-based system. Regarding this issue, our study combines provides a profound system that integrates the image classification and sensor gathered data in one and uses cloud platform as a baseline. In addition, most studies regarding the agri-food supply chain improvement are concerned with the production-to-retailer phase; whereas our study provides a different aspect for the waste management since, it targets the retailer-to-consumer phase.

Necessity of Cloud Architecture

IoT applications rely on sensor data to function, but processing and storing it may be quite difficult. Data aggregation from many and remote sources of information causes several privacy issues regarding information leaking. (Guo & Wang, 2019). In addition, using many IoT devices to monitor and assess various parameters, adds to the intricacy due to the variety of sensors and data formats in usage. Therefore, a sound monitoring system is needed for the data security of the aggregate food storage. One of the key applications for companies is maintaining the volume, speed, variety, and quality of data gathered by sensors in a cloud-based or hybrid IoT infrastructures. Considering this issue, our study provides a cloud-based data acquisition system that ensures security of the data gathered via key and certificate assurance and root user/user roles. The focus of this study is to contribute to the CE by improving the storage conditions in the retailer stage of the supply chain with the industry 4.0 approach, where considerable amount of food is wasted, e.g., 31% of the 195 million tons food is wasted in U.S. retail stores in 2010 (U.S. Dept. of. Agriculture, 2010). In this perspective, the literature on the classification of perishable products, and IoT applications for the freshness detection were reviewed. Based on our findings, a cloud embedded wireless sensor network (WSN) model is proposed and implemented to measure freshness of perishable products. The proposed model is composed of a CNN model using a dataset with images to classify fruits based on their freshness and ESP8266 microcontroller integrated with DHT11 and MQ3 sensors to measure variables affecting crop storage conditions and transmits gained results to AWS cloud system via Message Queue Telemetry Transport (MQTT) protocol.

Method

The proposed model, illustrated in Figure 1, initiates by taking input data from the shelf of retail stores or from their warehouses. It includes temperature, humidity and gas sensors, and also a camera for real-time detection of objects. The camera is used to take images of the products in retail stores. The sensors' humidity, excess gas, humidity reading outputs, and image info are fed to the Amazon Web Services (AWS) Cloud Platform. In AWS Cloud Service, taken images are processed using image processing feature extraction via CNN. Images are then grouped based on their types and freshness property using classification method. By doing so, our project will contribute to the retailer-to-consumer phase of the agri-food supply chain.

Fruit Image Classification

Image Classification Dataset

In this study, a dataset from Kaggle website named as "fruits: fresh and rotten for classification" was utilized. This dataset contains the following categories: fresh apples, fresh bananas, fresh oranges, rotten apples, rotten bananas, and rotten oranges. We used images of 1693 fresh apples, 1581 fresh bananas, 1466 fresh oranges, 2342 rotten apples, 2224 rotten bananas, and 1595 rotten oranges for training, and images of 395 fresh apples, 381 fresh bananas, 381 fresh oranges, and 388 rotten apples, 601 rotten bananas, and 530 rotten oranges for testing.

Convolutional Neural Network

A particular kind of artificial neural network called CNN is widely used for analyzing images, natural language, and other cognitive tasks.

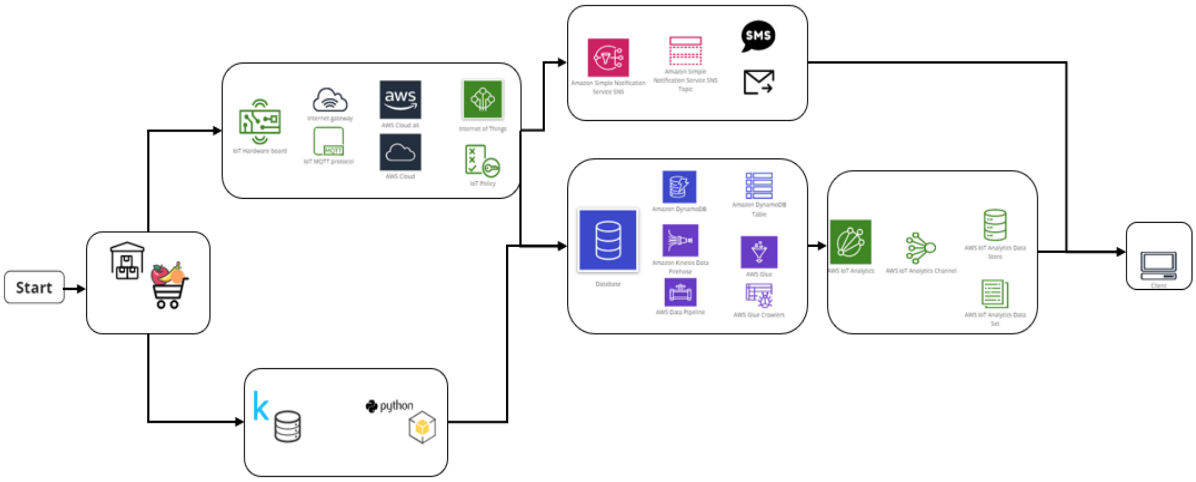

Figure 1. Proposed model diagram

The methodology used in this study is as following: The fruit images are selected and resized to (100×100×3) format. Then, RGB images are converted into gray scale and the dataset is transformed from having shape (n, width, height) to (n, depth, width, height). The dataset is partitioned into train and test sets and values were normalized from 0-255 to the range [0, 1]. Class labels are pre-processed, and the model architecture is designed. The model is compiled with Adam optimizer and categorical-cross entropy with learning rate=0.001. As the final step, model is taught with training set over 50 epochs and tested with 50 epochs using testing set.

Cloud Architecture

The implemented cloud architecture is based on the AWS Cloud. Via the ESP8266 Node MCU microcontroller, the data obtained from the DHT11 temperature and humidity sensor and the MQ3 alcohol sensor is sent to the AWS IoT Core Application, the first step of the AWS Cloud Architecture with the MQTT communication protocol. The microcontroller is coded with Arduino IDE 2023. A virtual microcontroller equivalent to the original microcontroller is defined on the cloud to display the data instantly with the IoT Core Application. For data security, determination of the parties that can access the data and have the authority to modify it, a policy that provides subscription, receive, and publish authorizations to the cloud platform by creating a device certificate is prepared and placed in the certificate. In our model, sensors' data is stored in S3 storage buckets via Kinesis Firehose Streamline for the SQL users and in the DynamoDB Database for the NoSQL users for the ease of analysis and since both has different advantages. The data accumulated in databases are then further analyzed in IoT Analytics platform for the purpose of enhanced monitoring and the visualization of the conditions in the retail store. In addition, to improve the user interaction with the system and to inform the users in case of rottenness, sensors' data are sent to SNS Push Notification Channel from IoT Core Application via the defined rules for message routing. By this way, system users are notified with an SMS and an e-mail including the values of the temperature, humidity, and gas level variables when the storage conditions, are out of the defined ranges. Furthermore, the CNN model created was transferred to AWS which works with the same Anaconda 3 Jupyter Lab interface, again for the purpose of enhanced data storage, accessibility of further analysis and for accumulation of the entire monitoring system within the same platform.

Results and Discussion

Classification Accuracy

The trials were run on Anaconda Software Jupyter Lab Notebook via a computer with an Intel® 11th Gen i7-11800H CPU processor running at 2.30GHz, a 1 TB SSD, and 8 GB of RAM to enable parallel processing and boost the classification task's computing capacity. This CNN Model had a training accuracy of 98.6% and an assessment accuracy of 96.4% over 50 epochs both.

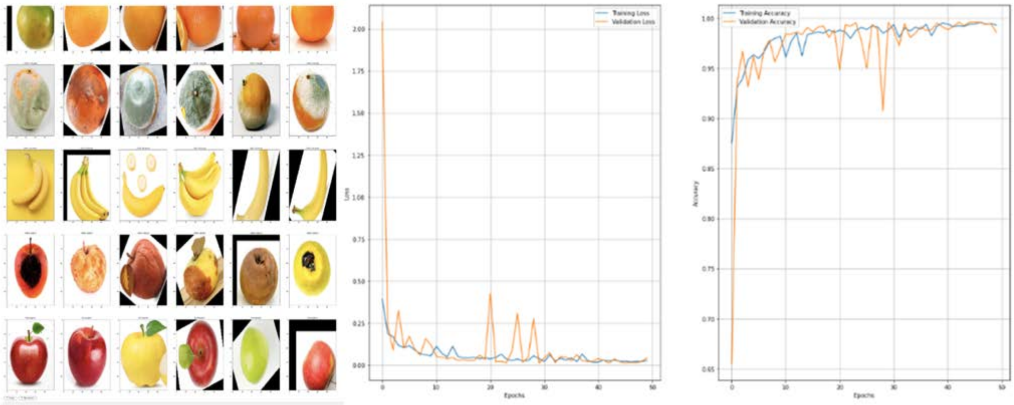

Figure 2. Training and validation accuracy

MQTT Communication & Cloud Architecture

As the outtakes are shown in Figure 3, DHT11 temperature, humidity, and MQ3 alcohol sensor data are transferred to the AWS IoT Core Application, the initial stage of the AWS Cloud Architecture, using the ESP8266 Node MCU microcontroller and the MQTT communication protocol.

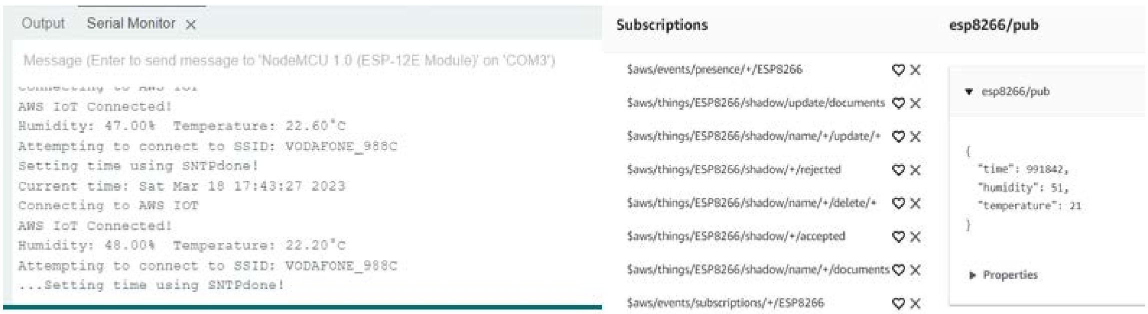

Figure 3. Sensor data readings (Arduino IDE Serial Monitor and the AWS Cloud)

Measurements from the sensors are delivered via the set rules for message routing to SNS Push Notification Channel to further enhance user involvement with the system and to alert users in the case of ripeness. In this approach, when the storage conditions are beyond the set limits shown in Figure 4, users of the system are alerted by SMS and email with the values of the temperature, humidity, and gas level parameters.

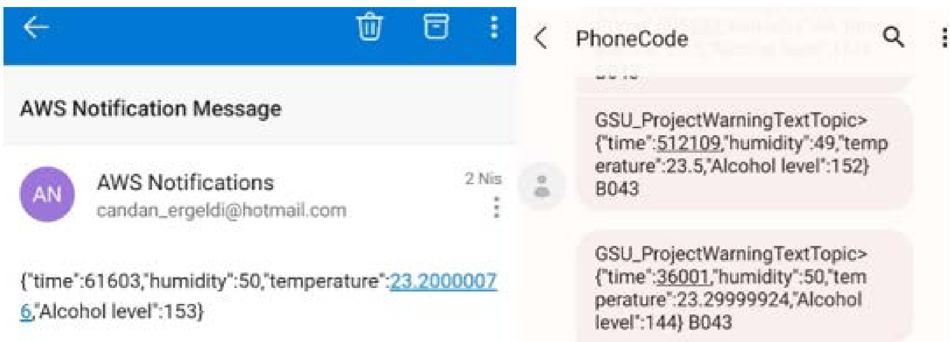

Figure 4. SNS push notifications (E-mail and the SMS)

Conclusion

The CE has the potential to increase food security and attain price stability. Regarding this issue, there have been I4.0 practices in agri-food supply chains, such as to improve sustainability for automating the fruit grading process. However, there is a gap in the making of a profound model that combines the sensor data and CNN model together onto a cloud platform. To cope with this issue, we provided in this study a wireless sensor network model that was coupled with a CNN to determine the freshness of the food. The suggested application recognize the crops and categorizes them according to their freshness using a trained CNN model. Additionally, to improve the accuracy of the ripeness level, our ensemble model interfaces with the ESP8266 Node MCU microcontroller to relay the temperature, humidity, and alcohol level to the cloud system. As result, our CNN Model showed training accuracy of 98.6% and a testing accuracy of 96.4% over 50 epochs for each.

The approach used in this paper can precisely identify images of the inputted fruit types and classify them based on their ripeness. In addition, our model rapidly transmits data to the AWS Cloud; hence, the model is secure for industrial purposes the data accumulated in cloud can be further analyzed. For the future work, maturity levels of the fruits can be classified and categorized based on their relevant further use such as donating them to a food bank or for composting.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

Acknowledgements or Notes

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