Food Freshness Detection Using AI

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Abstract. Maintaining food freshness levels ensures quality, health, and taste while reducing the amount of wastage generated. Relying on human senses to assess food freshness or qualitative chemical tests can be time-consuming and impractical. In the past few years, deep learning has vastly expanded various fields with its ability to recognize patterns and perform qualitative data analysis. Our project, Food Freshness Detection using AI, is an attempt to produce a self-evaluating solution for the appraisal of the quality of food products with Deep Learning approaches. This project hopefully will use CNN along with other modern approaches of deep learning on images and/or sensor data so that an accurate classification of foods based on their freshness can be done and categorized into their respective classes.

Keywords: Food freshness · CNN · Feature extraction

1 Introduction

There are many reasons why maintenance of freshness is important: quality, health, taste, and environmental impact. Freshness directly influences nutritional value and flavor, thus directly influencing the satisfaction and well-being of consumers. Overconsumption of food once it loses its freshness causes health hazards due to bacteria or bad compounds present, and lower freshness typically involves a reduced taste and general quality of food. Moreover, incorrect freshness evaluation leads to waste of enormous amount of food supply. Millions of tons of food are wasted each year, mostly unnecessarily, in all parts of the globe, due to inadequate measures taken to detect freshness. It contributes to emissions as organic matter decomposes in a landfill and is also one huge loss in terms of the use of water, energy, and labor channeled into producing this food.

Traditional determination methods for food freshness rely heavily on human senses or qualitative chemical tests that consume considerable amounts of time. People typically inspect the food by eye, nose, or touch, which can be subjective

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and in no way reliable since various people may have different perceptions of what freshness is. Manual inspection is further difficult and, in most cases, cannot be practically applied on a large scale, particularly in food distribution networks where time is always limited. Qualitative tests, however, are inapplicable for quick or instant evaluation since they need certain chemical reagents or lab equipment. Traditional methods can be invasive as well, and the food under inspection can be destroyed and contribute to waste.

Recent developments in AI and deep learning have expanded possibilities across a variety of domains to a great extent, and powerful tools for data analysis and pattern recognition have emerged. In particular, tasks of finding complex patterns or planning based on data were greatly excelled by the deep learning algorithm, making it invaluable for many applications in healthcare, logistics, or agriculture. Therefore, development in the sphere of assessing food quality comes from this ability of deep learning algorithms. High precision in visual data processing allowed deep learning to provide a non-invasive and highly automated way toward better precision and accuracy in freshness evaluation.

Our project is an effort to beat the drawbacks of traditional freshness-detecting methods. It should develop a completely automated assessment of food quality using deep learning approaches. This will classify food items based on freshness with a high level of accuracy by using CNNs and other modern techniques in deep learning through images or sensor data. CNNs are particularly well-suited to this task, as they are good at extracting features from images that include color and texture and could possibly indicate decay. Building a complex view of visual patterns relating to freshness, CNNs especially outperform in the differentiation of fresh from non-fresh food items.

The proposed solution that will encapsulate images and maybe even sensor data of the food items to provide a full and real-time assessment. Sensor data will include, for example, gas composition data coming from ethylene or any other volatile organic compounds VOCs produced when produce decomposes; supplementing this will be a visual analysis through CNNs on the overall internal and external state of the food product. It is from this dual approach that combines image analysis and sensor readings that makes for a system likely to produce accurate classifications of freshness on the produce items with a minimal probability of false positives or negatives.

The aims behind developing this system of automatic freshness detection go towards a greater objective: reducing food waste. The system will save enormous quantities of food from avoidable disposal that is safe and consumable, thereby saving resources and reducing the effects of food waste on the environment by providing accurate and objective freshness assessments. This will allow real-time freshness detection that will help smooth supply chains, reduce reliance on human inspections, and make it possible for food distributors and retailers to react rapidly to changes in food quality. This capability is highly valued in fast-paced environments that process large volumes of food every day, thus avoiding any delay and ensuring fresh high-quality products to the consumer.

It will be the creation of a reliable, non-invasive, and efficient deep learning-based solution for the real-time assessment of food freshness. Such is the promise of this food quality control project to further enhance food quality but help meet sustainability goals, while at the same time trying to reduce food waste as much as possible, therefore contributing to healthy consumer groups. The integration of CNNs and sensor data will lead to a food supply chain that is smart, resistant, and prioritizes the fresh and efficient approach towards it.

2 Literature study

García, et al., [1] created a low-cost colorimetric sensor based on RGB sensing and Cu-based nanoMOFs for on-site detection of food freshness, especially for biogenic amines as markers for spoilage. The device is non-invasive as it detects color changes from amine reactions by using immobilized nanoMOFs on cellulose disks. It was capable of distinguishing various concentrations of spoilage gases with high sensitivity and selectivity. Their Internet of Analytical Things (IoAT) platform enabled remote sensing via an ESP32 controller. The sensor also had high accuracy in detecting shrimp sample freshness loss, with good performance at low amine concentrations and different temperature settings. However, its sensitivity will be based on amine types and environmental factors on reaction time and color sensor stability.

Bhuiyan et al., [2] proposed an IoT-based system with gas sensors and a custom Convolutional Neural Network (CNN) to identify meat freshness and type. Their system combines high-resolution image processing from an ESP32-CAM module and gas concentration from MQ135, MQ136, and MQ4 sensors, targeting emissions like ammonia, methane, and hydrogen sulfide. CNN was trained on a 9,928-image dataset and performed more accurately than ResNet-50, SVM, and k-NN, at 99% accuracy. The feedback was given in real time using LEDs for freshness levels and results on an LED display. Although good performance was shown, the system's reliability could be affected by environmental conditions such as humidity and temperature, which could affect gas sensor accuracy.

Kurian et al., [3] applied a dual-mode battery less ammonia sensor using polyvinyl alcohol-reinforced Clitoria ternatea anthocyanin with graphene nanoplatelets to monitor the quality of food. The system was prepared via a dip-coating process with anthocyanin, followed by ethyl cellulose and a gold nanoparticle brush coating. A UV-Vis spectrometer and FTIR were applied for analysis, and RGB color values were captured by digital cameras. The sensor was evaluated at different temperatures, and gas sensing measurements of ammonia exposure were taken. However, temperature and humidity affected the reliability of the sensor, and differences in preparation processes added challenges for consistent operation.

Ren et al., [4] relied on the CNN-based e-nose, using the time series features, to classify food freshness. It used the gas sampling module along with the gas sensor array in order to gather the odor sample data. The system processed the gathered data with the" loss" method in order to filter noise and analyze transient features. Then a Convolutional Neural Network was used for classification purposes based on a time series features of sensor responses. Still, the system was sensitive to temperature fluctuations, humidity, and air pressure, while the amount of error incurred would depend on the type of data collected and processed, which is bound to be adversely affected by such environmental factors.

Saha et al., [5] developed a compact highly sensitive pH sensor based on a polymer waveguide Bragg grating. This device used FEM and CMT simulations for the study of the evanescent field interaction with the pH-responsive PAA/PAH layer. In sensor fabrication, the silver layer was deposited and after that PMMA core was spun-coated, and then its grating was developed via UV exposure. Although the sensitivity of the system improved, accuracy in layer thickness was critical, particularly for the high-index layer. Efficiency of the sensor might be reduced due to higher propagation loss because of greater modal power in the metal layer, and its tolerance in performance was found at $\pm 10\%$ for PMMA core dimension deviations.

Chiang [6] proposed a fish meat freshness detector for IoT-based seafood market applications. The system measures and averages fish resistance, which translates to voltage, making it possible to assess freshness through a Fish Meat Resistance Sensor. Analog circuits coupled with a sigma-delta modulator process and transmit signals minus low-frequency noise, but the market devices' low-frequency noise still appears to influence the accuracy of the system. Calibration for swordfish and others has to be done, thus measurement times have to be considerable to obtain precise readings of freshness. This real-time detection system sends freshness data to IoT devices.

Sakai, et al., [7] used low-frequency A-mode ultrasound for the inspection of the freshness of frozen tuna. The system inspected 43 frozen tuna samples and converted signals to frequency domains using a Fast Fourier Transform (FFT). Eight classification machine learning algorithms, including SVM and Random Forest, were used with averaging freshness scores to diminish noise. The system was very effective but relied on supplier tail-cutting for labeling without any scientific validation. Further, probe positioning and pressure had some variability, which may require mechanized equipment for more consistent data acquisition. Using amplitude spectrum features only limits the system.

Kojić, et al., [8] prepared a biodegradable pea protein isolate (PI) film to maintain the freshness of fruits and vegetables. Electrochemical Impedance Spectroscopy (EIS) was used for the assessment of fruit quality variation over time and against wrapped and unwrapped samples. The system presented promising performance in short-term freshness preservation but was only able to capture information at intervals of three hours and failed to capture long-term trends. Measurements were taken between 2 kHz and 200 kHz; therefore, any critical data may have been missed at very low or high frequencies. The results were deemed specific to pears and zucchini, with the system not being applicable to other fruits and vegetables.

3 Methodology

This" Food Freshness Detection using AI" is based on deep learning by applying the method of Convolutional Neural Networks (CNNs) for the non-invasive assessment of fresh fruits and vegetables. Along these lines, the approach takes up image processing-based studies for the quality of foods that will be aimed toward automation and better accuracy in detecting freshness in supply chains for food products.

The first step in this methodology is data collection. For this purpose, photographs are taken of many food items, including apples, oranges, and bananas, for the construction of the dataset. This dataset is loaded with images of both fresh and non-fresh samples. Data preprocessing further adds to the quality as well as diversity of the dataset through processes of normalization, resizing, and augmentation. This further enhances the model's ability to perform well by generalizing over a variety of lighting conditions and quality images.

The CNN model is the core of this system. For this system, the CNN model included feature extraction and classification operations. Several layers include convolutions, pooling, and fully connected layers on images to detect freshness. Then the network is trained with labeled images as either fresh or not fresh to classify images. That falls under the training process techniques including early stopping and adjustment of learning rates among others, all aimed at maximizing model performance while containing overfitting.

The model performance is checked during the testing phase by determining how well it works on an unseen validation dataset. Real-time testing is performed to ensure that the model functions as effectively in practice as is theoretically expected, which allows freshness to be detected immediately. The final model is integrated, allowing it to be part of a real-time system that provides non-invasive freshness assessments.

3.1 System Architecture

The System Architecture represents a sequence of different sequential processes that will end in categorizing whether the food is fresh or not fresh. It is therefore from the input level as it captures an image from the camera and it views this captured image as its raw form of input, after which the system proceeds and processes accordingly according to its acquisition of data in any particular kind of food. This is the most critical step in determining the level of food freshness as the primary input is image data.

The captured images are further fed into a Convolutional Neural Network (CNN) algorithm, which runs the analysis of the image. CNNs are indeed the strongest networks for recognizing images because they can extract important features automatically from the images, including texture, color, and patterns. Such features determine whether the food is fresh or not. For example, any alteration in texture or color might indicate spoilage, while patterns that remain unaltered signify freshness.

There are two main phases in the architecture: the training phase and the testing phase.

Training Phase In this phase, the system will be fed training food data in the form of labeled dataset images of food with some labels that indicate freshness or spoilage associated with images of the food, assisting the system in learning what is ground truth.

Feature Extraction: The extracted features from the training images are descriptions of important attributes about food products, surface patterns or texture and color, for instance, changes related to freshness.

Selection for Training: For the extracted features, this method selects the most suitable features. The process hence enhances the accuracy of this system by only letting useful data points influence the course of training.

Freshness Classifier: It uses these features for a freshness classifier. The classifier is trained on the extracted features with their labels/annotations that indicate whether food in the image is fresh or spoiled. It learns to associate particular feature patterns with food being fresh or spoiled.

Training Off-Line Parameters: The parameters include the weights and biases of learned parameters which are the same things that the CNN employs while testing. These are conserved and optimized such that during the test phase, new images are well-classified that the system would be encountering for the very first time.

Test Phase **Testing Food Data:** Once the model has been trained, it should be tested with pictures that weren't in the initial training set. This procedure is used to test the system's ability to generalize to previously unseen input. Feature Extraction and Selection: As it is in the training stage, the CNN extracts the features from test images whereas the classifier only permits the passing of those features which have maximum relevance.

Freshness Classification: This means that the system will classify the test image by the type and parameters that the classifier would have acquired in the training stage. It uses the classifier to check whether the value of the features that it extracts is fresh or a not fresh food item in that particular image.

The overall system will be robust in detecting food freshness. Applying its knowledge on the feature extraction and classification process by a CNN on various images, it classifies the new, unseen foods very accurately. All steps starting from training to testing have been optimized.

4 Implementation

This food freshness detection system called for the development and integration of various deep learning and image processing techniques. This system was able to classify images of food items as either fresh or not fresh, relying on analysis. The aim of the project was to enable real-time food freshness evaluation in an efficient manner and with accuracy.

Fig. 1. System Architecture.

Module Descriptions The system consists of the following basic modules, which fragment the pipeline of food freshness detection into a series of tasks: 1) Image Capture Module: This module captures images of food items using a camera. 2) Preprocessing Module: The module pre-processes the captured images by the techniques of resizing, normalizing, and noise removal before feeding them to CNN. 3) Feature Extraction Module: The module takes these precise images and captures necessary details regarding color, textures and other relevant patterns describing food in order to ascertain their fresh status. 4) Classification Module: This module feeds the collected characteristics into a trained classifier and the classifier is created from labeled images related to food. The produced is the predicted status concerning their freshness as" Fresh or not". 5) Testing

Module: A module that runs a test to check whether this model outputs results that agree with the actual freshness statuses of products.

Libraries and Algorithms Used During the implementation of the food freshness detection mechanism, the following libraries and algorithms were used:

1. Tensorflow: This one was used during deep learning-building CNN models and training on them by using the higher APIs of Tensorflow; this time, it is that module, which is tf.keras-application of optimum and control training model with intuitively understandable code for setting all layers.
2. OpenCV: applied during the whole image-processing procedures with various operations with images for reduction of image resolution size and smoothing the noise level.
3. NumPy and Pandas: Both those libraries helped to do array operations on the arrays within the computational library. This made it fairly easy to use and manipulate collections of images.
4. Convolutional Neural Network (CNN): Learns the features of the images and classifies them.
5. Matplotlib: Plotting the outcome after training and testing the model. This can be confusion matrices and accuracy graphs.

Deployment Procedure This is the step-by-step process in which this system was implemented:

1. Data Collection: Collected images of food items, ranging from fresh to spoiled categories. The dataset was divided into training and testing sets.
2. Preprocessing of Data: All images were resized to a uniform size using OpenCV and a normalization technique was applied to pixel values.
3. Training: A CNN model was developed and trained over the food images. Convolutional and pooling layers with fully connected layers are used to construct the proper features.
4. Classification: The model was tested on new images of unknown food to predict their freshness.
5. Hyperparameter Tuning and Optimization: The learning rate, batch size, and epoch have been adjusted to find the optimal fit for the accuracy of the model.
6. Deployment: The model was thus deployed in an application whereby users can upload images at real-time for freshness predictions.

Testing and Validation Process Some tests and validation procedures performed on the system to check their reliability and accuracy are stated below:

1. Model Validation: Here, while training the model, performance, accuracy, precision, recall, and F1 scores are tracked over a range of performances using a validation set.

2. Cross-validation verifies the robustness of the model by checking if it endures the test of time. It also checks if it operates equally on different splits of the data.
3. Accuracy Check: The model operated to an accuracy of almost 90%. This gives it a stronger basis for use in the real world with a realistic classification of freshness among foods.
4. Real-life testing: Simulated real-life scenarios with live feeds from the camera and photographed food items to estimate how fresh they would be on time based on food conditions.

5 Results and discussion

The proposed food freshness detection system was tested on some samples of fruits, namely bananas, apples, and oranges, on trained CNN. The results here demonstrate the system accurately detects the freshness status by being different from non-fresh ones, as provided by the following sample prediction examples.

5.1 Result Overview

The model predicts the test data would classify them into fresh and non-fresh categories just fine. A few visual outputs follow below.

- Predicted: Not Fresh banana – Spotted and browned banana as not fresh.
- Predicted: Not Fresh apple – Two rotten apples with discolored, moldy surfaces correctly classified as not fresh.
- Predicted: Fresh apple – A healthy red clean was correctly classified as a fresh apple.
- Predicted: Not Fresh orange – The orange with black spots that have decayed was classified as not fresh.
- Predicted: Fresh banana – Both clean bananas without blemishes were correctly labeled fresh.

5.2 Quantitative Analysis

From the below plot, we can observe the trends in the accuracy of the model over the epochs. The training accuracy consistently rose to around 90%, whereas the validation accuracy was approximately 85%. The model seems to learn pretty well and generalizes reasonably on new data, although a little minor overfitting may exist.

5.3 Performance Metrics

- Training Accuracy: 90%
- Validity Accuracy: 85%
- Precision and Recall: The measures were always quite high in all classes. This indicates that the model can discriminate between fresh and non-fresh fruits.

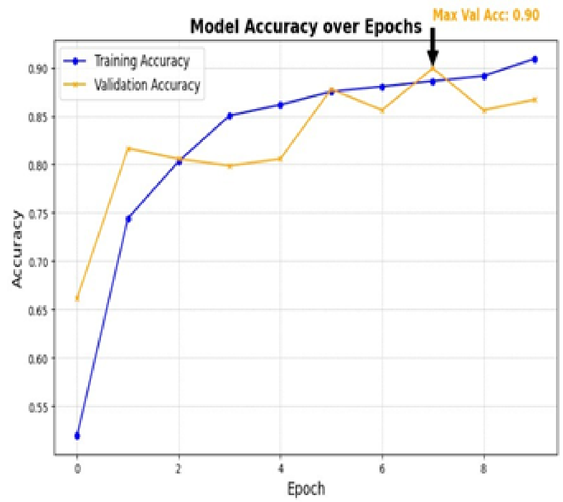

Fig. 2. Model Accuracy.

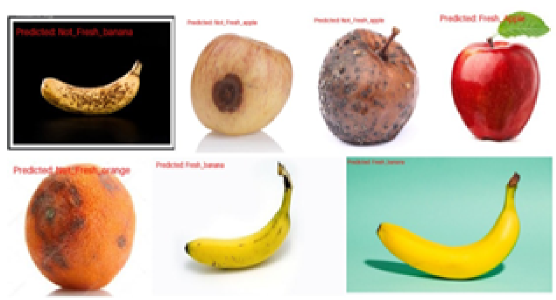

Fig. 3. Prediction results.

5.4 Discussion

The model performs well on simple and more complex spoilage scenarios. However, minor improvements can be seen in the following examples:

1. Borderline ripeness problems – A scenario in which a banana with an almost acceptable degree of ripeness is difficult to classify as fresh or not fresh due to subjective thresholds.
2. Variability of light in image- Lighting conditions have some correlation with the predictions of the model. Histogram equalization could be applicable to eliminate variability in the results.

Figure 3 depicts some examples of the model outputs.

6 Conclusion

The deep learning model considered for food freshness detection in this work infused an accuracy rate of 90%. The result shows that our model is functioning well with image dataset processing and CNN techniques for differentiating between fresh and non-fresh. The model can precisely predict the freshness of fruits, which are treated as fresh (egocentric baseline), and spoiled as 'not fresh' respectively for assessing food product's health in a fast and non-invasive real-time way. This tool is said to significantly help improve food quality control as well as reduction in wastage and supply chain management.

6.1 Implementation and Contribution

Scale detection of food freshness is a valuable systems model, as it can automate the evaluation process to reduce dependence on manual inspections, thereby accelerating and improving the reliability of freshness assessments. Significant reductions in food waste, supply chain efficiency gains, and cost savings for both producers ultimately benefit consumers.

In conclusion, using a CNN-based image processing model in food safety is an important application where AI can contribute to this kind of use case under real-world conditions and it presents quite significant research.

In addition, this strategy is consistent with sustainability objectives by reducing food waste and promoting resource utilization. These are the two key conditions, assuming it lives up to its hype as a scalable and real-time tool for industry-wide use.

6.2 Future Works

Moving ahead, we are working on creating a state-of-the-art vacuum system with various sensors installed throughout the machine (for gas, humidity, and temperature possibly even microbial) that will lead to near-perfect real-time freshness detection. This new system will also work to address several of the key limitations that were identified in additional research, most notably those associated with visual-only assessments, as it uses more extensive indicator sets by which to detect food freshness.

Instead, the sensor-based method will identify a range of freshness markers such as small changes in chemical compounds or humidity and temperature fluctuations (not detected quite that easily by image analysis). This training will allow the system to predict food items' internal and external state leading to a more complete evaluation of freshness.

Using this cutting-edge vacuum sensor data and our deep learning model, we intend to build a reliable freshness detection solution in three-dimensional space for additional foods that are unlikely to go bad without obvious signs. By using AI to choose foods, this technology will improve food product cleanliness, reduce waste, and ensure that only the best items are delivered to the point of consumption.

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