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IOT Based Food Freshness Detection Using Deep Learning Techniques

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ABSTRACT

Nowadays we must be more concerned about the quality of the food items we consume and feed our loved ones. To get a full nutrition & mineral value in food items, it’s better to consume the fresh food items to avoid unnecessary health problems. We have various methods to determine or detect the freshness quality of our food items like the traditional method of lab testing the food sample, using images of the food sample with various machine learning and deep learning algorithms and even using the smell from the food sample. Many machine learning models have been developed to detect the freshness of food samples, but they lack fast and accurate detection. We have developed an IOT model that can predict the freshness of the food samples with image and its smell in a more accurate level with less time using deep learning algorithms. We have combined two deep learning algorithms for image detection to obtain more accurate results. We classify the images of food samples using the Convolutional Neural Network and detect the affected areas using the Object Detection Algorithm YOLO. We also take the level of gas emitted by rotten food samples using sensors and detect the spoilage level using the Artificial Neural Network model. We can determine the affected or rotten areas by combining the value from both image data and gas emitted by the given food sample. The result can be viewed in an application through a browser.

Keywords: deep learning algorithms, YOLO, CNN, ANN, IOT.

INTRODUCTION

Nowadays we must be concerned about the quality of the food items to get full nutritional values. It’s better to consume fresh food to lead a better life. To identify the freshness of the food items we go with the Image recognition technology and Artificial Neural Network. Most of the time we didn’t notice the freshness of the food item because of the busy life schedule and some people didn’t know how to find the freshness of the food item. To handle this situation, our project helps the user (people who handle the prototype of the project) to identify the freshness within a few seconds.

The existing system for the freshness detection in the earlier days is only based on the chemical-based detection later it developed to image-based classification and some existing system based on the sensor-based methods, but however it takes only a single parameter we can’t determine freshness based on the single parameter.

The proposed system will overcome the drawbacks of the existing system. In this system, it detects the freshness based on both the image and the sensor so the proposed system will give more accurate result than the existing system.

The proposed system is a combination of both smell and image data which leads to the absolute detection and accuracy of the food sample taken to determine its freshness level. It is a user-friendly environment, where food items taken to identify are easy to operate and use.

This system can be implemented in the food industries before the packaging stage to detect spoiled food items and automatically separate them from good ones before packing. This system ensures the reach of good quality food items to the customers.

LITERATURE SURVEY

[1] The final classification results are recorded for each type of fruit that show high accuracies (all above 80% in) for all six fruit species, where bananas are the most accurate in prediction. Accuracy for six species of fruit is above 80%.

[2] A performance analysis of different feature extraction techniques combined with SVMs classifiers has been performed for the addressed problem of classifying fresh and rotten fruit images. While comparing classification success rates of several features (such as Hist, GLCM, BoF, CNNsF) for different but very related tasks, CNNs appear to be the most successful feature extractors, as further have proven their efficiency in such applications. The concatenation of Hist and GLCM features leads to promising results for some classification tasks. Therefore, concatenation of different types of proper features might produce more successful and robust systems.

[3] Every 50 steps of training the dataset the accuracy calculated using cross-validation. This showed steady improvement in the network until reaching 100% accuracy on cross-validation. For the testing phase, we used the testing set and the calculated accuracy was 96.3%. Accuracy level is higher (80% to 96%). Datasets are taken from multiple viewing position. Takes more time for output execution.

[4] This system inspects fruit skin defects, which is more accurate, more robust to colour noise, and has reduced calculation cost. Packinghouses can adopt this system to distinguish damaged fruits from good ones before packing them into batches, therefore the quality of the products can be guaranteed at this stage. Developed a new method to inspect fruit skin defects, which was more accurate, more robust to colour noise, and reduced calculation cost Only detect the skin defect on the fruits.

[5] Low level processing is used to pre-process images. When imaging objects, different imaging and sensing devices can be simultaneously used to acquire images of samples and convert them into digital forms. High level processing includes image recognition and image interpretation. In this step, statistical methods or deep learning methods are commonly used to classify the target.

[6] CNN achieved 93.8% accuracy, which is significantly higher than that for the baseline method. CNN performed much better than traditional methods using handcrafted features. Accuracy level is

higher (80% to 94%). Developed only to classify the food items.

[7] The results presented indicate that most of the models are having a sensitivity of 100% for healthy class with the exception of MobileNetV2 and DenseNet121.The recognition rate during the real-time testing was found around 80% for most of the classifiers with highest value of 93.8% for EfficientNetB2. Accuracy level is higher (80% to 98%). Image was captured in a fixed view.

[8] Food is classified using the trained CNN model which makes the billing faster in the restaurants. The food detection system can classify 6 types of food using the Convolutional Neural Network (CNN) algorithm well on existing image data or stored in storage with 80% data partition for training data and 20% for test data and get an accuracy of 100% and can detect food with an average speed of fewer than 10 seconds. Have an epoch or step of 9383 steps with a loss of 0.05 and a learning rate of 0.0002.

[9] Using weights from apple models and training a few epochs further in very small amounts of pear images the accuracy reached 0.87. Some CNN layers are removed to decrease the output execution time. The model is able to detect from 85% of fruits to 95%. Hardware components with average performance are required for computation.

[10] Combination of sensors, IoT and machine learning gives the real time spoilage detection system which can be used in industries, houses (in refrigerators) to alert the user with a buzzer if spoilage is detected. Sounds a buzzer when it encounters a spoilt food item. This data is sent to a cloud platform.

[11] It can be concluded that consumers have a collective concept of freshness, but they use their different everyday experiences with fruits and vegetables to describe freshness. Overall, results indicate that fresh can be used in a variety of ways and contexts by consumers. However, it is mostly encountered in connection with food and most notably with vegetables followed by fruits. Freshness of food items are identified based on the information from the consumer who knows about the food item. Takes more time to get the output.

METHODOLOGY

The Proposed Module uses the technology of Internet of Things. First the food item was placed in a model and the model contains stepper motor connected rotatable arm with the camera. This arm rotates at an angle of 10 degree to capture the 360-degree view of the food sample. The images of the food item were captured by the Camera. To capture a High-Quality Image a strip of white light was focused on the food item. Simultaneously the gas emitted from the food item was detected by the MQ2 Gas Sensor and MQ135 Gas Sensor. MQ2 Gas Sensor detects the Methane gas emission and MQ135 Gas Sensor detects the Ethane Gas Sensor.

The input from the Camera and Gas Sensors are processed by the Raspberry Pi. The image input is processed by two trained models which are stored in the SD card. This SD card acts as a storage for the Raspberry Pi. The image first undergoes the trained model of CNN ImageNet Architecture Algorithm. The trained model of CNN ImageNet

Architecture Algorithm identifies the food item. Next the identified image again undergoes the trained model of YOLO Architecture Algorithm. The trained model of YOLO Architecture Algorithm detects the affected area on the surface of the food item.

The input from the Gas Sensor is sent to the trained model of Artificial Neural Network. Based on the reading from the Gas Sensor the trained model of Artificial Neural Network gives the output. The MQ2 and MQ135 sensors are read simultaneously which detecta high value of gas emission is taken as the output.

Both the output values are compared, and the final output is executed whether the food is fresh or rotten.

Convolutional Neural Network - ImageNet Architecture:

The input image was classified by the CNN ImageNet Architecture. The main goal is to accept the given input image and classify it according to the class definition. The computer sees an image as an array of pixels. For example, if the image size is 640 x 640. In this case, the size of the array will be 640x640x3. Where 640 is width, next 640 is height and 3 is RGB channel values. Each of these numbers is assigned a value from 0 to 255. This value describes the intensity of the pixel at each point of the image.The first layer is the Convolution layer. Before this layer the image is converted to a matrix form. The matrix value is fed into this convolution layer as input and its read from the top left corner.

The next process is to perform padding and filtering the matrix values. Padding is the total amount of extra pixels added to the image matrix during the pre-processing stage of the kernel of CNN. Filtering is a technique to multiple its value to a small matrix and sum up all the values to form a matrix from top left corner, it moves further by 1 unit performing the exact same process to the full matrix value of the image. The network consists of several convolutional networks mixed with non-linear and pooling layers. When the image passes through one convolution layer, the output of the first layer becomes the input for the second layer.The next layer is the Non-linear layer, which is added after every convolution process, it contains an activation function to bring the properties of Non-linear. The Non-linearproperties make the network sufficiently intense.

In the pooling layer, down sampling operation is performed in the image. By this process the volume of the image is reduced. As most details in the image are identified in the previous layer, the image is compressed to a less detailed image. After completion of a series of convolutional, non-linear and pooling layers, it is necessary to attach a fully connected layer.In the fully connected layer, the output information is taken from convolution networks and this layer is attached to the end of the network resulting in an N dimensional vector, where N is the number of classes from which the model selects the desired class.

Object Detection Algorithm - YOLO V_5 Architecture:

YOLO is an abbreviation for the term ‘You Only Look Once’. This is an algorithm that detects and recognizes various objects in a picture (in real-time). Object detection in YOLO is done as a regression problem and provides the class probabilities of the detected images.As the name suggests, the YOLO algorithm requires only a single forward propagation through a neural network to detect objects.This means that prediction occurs in the entire image in a single algorithm run. The CNN is used to predict various class probabilities and bounding boxes simultaneously.

First the input image is divided into a grid (S x S) to minimise the processing time. For each grid, the prediction process occurs to make a boundary box for the output. While detecting the object in an image, YOLO identifies the midpoint of the object to make the boundary box.Dense prediction is a basicproblem in computer vision to detect the object, which makes it easier to learn the mapping from input images to complex output structures. In dense prediction, it requires Pixel-level labelling.

Sparse prediction is used to detect the specified object from the various objects in the input image. It requires a quality image to detect the object. The accuracy values are displaced after conversion of Rectified Linear Units (ReLUs). The process of ReLUs is to convert the negative values to zero and for positive values it returns the same value.

The trained model using YOLO Architecture dividing the image into N grids, each having an equal dimensional region of (S x S). Each of these N grids is responsible for the detection and localization of the affected area it contains. Correspondingly, these grids predict B bounding box coordinates relative to their cell coordinates, along with the object label and probability of the object being present in the cell. They can be used for real-time object detection based on the data streams.

This process greatly lowers the computation as both detection and recognition are handled by cells from the image, but it brings forth a lot of duplicate predictions due to multiple cells predicting the same object with different bounding box predictions. YOLO makes use of Non-Maximal Suppression to deal with this issue.

Artificial Neural Network Algorithm:

ANN stands for Artificial Neural Networks; it is a computational model. That is based on structures and functions of biological neural networks. Although, the structure of the ANN is affected by a flow of information. Hence, neural network changes were based on input and output. The Artificial Neural Network is used for collecting and processing the data from the gas sensor. Using ANN to compare the gas emission from the rotten food sample by constructing a neural network which helps in detecting the gas level in the food sample. It is used for the fast evaluation of the learned target function, and it produces output even with incomplete information and has a high fault tolerance. The ANN has three layers, they areInput layer, Hidden layer, Output layer.

In the input layer, the data is accepted into the network and is sent to the rest of the network for processing. This layer has nodes which are passive means the data won't change. The received single input is multiplied and sent to all the hidden layer in the network.

The next layer is the hidden layer, it consists of one or more number of neural networks. This layer is the most important layer of ANN as it is responsible for better performance and less complexity of the neural network. The actual processing is done here via a system of weighted connections. The value entering the hidden layer is multiplied by the weights (weights is a set of predefined values stored in theprogram) and the weighted inputs are added to produce a single number.

The final layer is the output layer in which the result is displayed. Raw data is passed into the input layer and the output is received in the final output layer.

IMPLEMENTATION

Hardware Requirement:

I. **Raspberry Pi 4 Model B-**

Raspberry Pi 4 Model B is a minicomputer which can replace a desktop. It supports multiple IO devices with the help of 2 USB 3.0 ports and 2 USB 2.0 ports. It can be able to connect with both wired and wireless networks. Raspberry Pi 4 Model B requires power supply of 3v to 5v through the USB-C connector. It contains 2 mini-HDMI ports to connect an External display. It has 2GB LPDDR4-3200 SDRAM and for ROM it requires a Micro-SD card to set up the OS and for data storage. Raspberry Pi 4 Model B has 40 pins, and the Pin number 1 and 17 provides a power supply of 3.3V. Pin number 2 and 4 provides 5V power supply. Pin number 6, 9, 14, 20, 25, 30, 34 and 39 are used to give Ground connect to the devices or sensor used. Rest of the pins are used as the GPIO connection.

II. **Web Camera-**

The Web Camera is 2MP which captures the image at 720p resolution. It has a USB 2.0 connector to connect with any other devices.

III. **MQ2 Gas Sensor-**

MQ2 Gas Sensor is sensitive to flammability and smoke so it is mainly used for smoke detection. But the MQ2 Gas sensor is also able to detect Methane (CH_4), Carbon monoxide (CO), Liquid Petroleum Gas (LPG), Hydrogen (H_2) and Propane (C_3H_8). It requires a power supply of 5V.

IV. **MQ135 Gas Sensor-**

MQ135 Gas Sensor is an air quality gas sensor which is used to detect the air quality in public places. The MQ135 Gas Sensor is mainly used to detect Ammonia (NH_3), Sulphur (S), Alcohol (COOH), Benzene (C_6H_6), Carbon Dioxide (CO_2) and Nitric Oxide (NO_x). It requires an input voltage of 2.5V t0 5V.

V. **MG90S-**

MG90S is a Micro Servo Motor with metal gears. Its operating speed is 60 degree per millisecond with a torque of 1.8 kgf·cm. It is a lightweight motor of 9 grams and capable to rotate the object of weight up to 500 mg. To operate this motor, it requires an input voltage of 4.8V (approximately 5V).

VI. SD Card-

We used an 8GB SD card to install the raspberry pi operating system into it.

VII. ESP8266-

ESP8266 is a microcontroller with Wi-Fi capability. it requires external flash memory and some antennas to work.We use this ESP8266 microcontroller to determine the accurate gas level from both MQ-2and MQ-135gas sensor. This helps us to determine spoiled percentages in the given food sample.

Proposed System flow:

- In this project, camera and gas sensors are used to collect the data of the food items which helps in detection. First the food sample is placed on a platform with a clear white background.
- To collect data at full angle we must initialise the stepper motor and capture the complete views of the food sample taken. The Camera is mounted on the stepper motor with the help of a plastic frame. When the stepper motor starts to rotate the camera starts to capture the image rotating at an angle of 10 degree each time to cover a full possible view of the given food sample.
- The gas sensor is placed near the platform to detect the accurate gas level emitted by the food sample. The gas sensor usually sends analog data, but the Raspberry Pi cannot process the accurate value of analog data. Thus, we use the ESP8266 module to receive the analog data from the gas sensor and transmit it to Raspberry Pi. The gas level value given by ESP8266 is used to determine the spoilage level of the given food sample.
- The data collected from the camera and gas sensor modules are sent to the trained model that is stored in the Raspberry Pi for comparison & determination of freshness.
- We have used a large dataset to train an accurate model for classification and detection. The datasets collected from various sources are trained, validated, tested using ImageNet and YOLO V_5 architecture algorithms.
- The ImageNet algorithm's main purpose is to classify the food sample based on the trained dataset. Then the YOLO V_5 algorithm is used to detect the affected area in the food sample. Based on the trained dataset, this algorithm detects the affected area within a few seconds.
- The affected area (affected spot) is marked in a square shape with a red colour border.
- The data collected from the gas sensors is then analysed and

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processed with the help of ANN. ANN is used to predict the output based on the predefined value in each node. Based on this value, the data from the gas sensor is predicted whether it is fresh or rotten.

- The results from both the trained models are combined and then the output is shown in a web application.
- The application is developed with HTML and CSS for Frontend and Python for Backend.
- Python is also used in training and detection modules.
- The web application is used to display the freshness of the food items kept for detection in the sight of a camera.

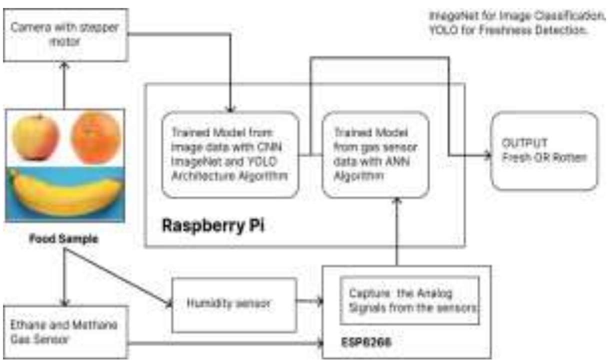

Figure 1 Architecture Diagram

Modules:

In the Freshness detection system contains several modules like,

- Image Capturing.
- Image Classification.
- Detection of Affected Area.
- Detection of gas emitted from the food.

Image Capturing-

- It is the first module in the detection system in which it is responsible for capturing a clear image of the food sample (i.e., Apple, Orange, Banana) taken.
- The food sample is kept in the platform to capture the 360-degree view of the food sample taken and the motor is rotated with different steps for image processing which rotate the Camera to capture the image.
- The camera is placed in a PVC pipe that is attached with the stepper motor to rotate the Camera. An LED light strip is attached with the Camera for the clear light source while capturing the images.

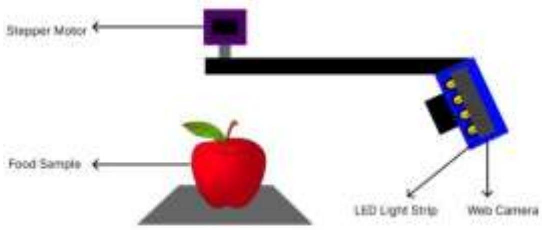

Figure 2 Image Capturing

Image Classification-

- After the image Capturing module, the captured image undergoes the image classification module, it is responsible for classifying the captured images whether it is an apple or orange or banana or any other food samples.
- This module contains the Raspberry pi which processes the input data sent by the external devices.
- The image gets classified based on many datasets given while

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training the classification model; the high-level accuracy trained model is stored in the Raspberry Pi.

- The captured image from the camera is transferred to the Raspberry Pi and it classifies the images of food samples based on the trained model and the output is given to the next module in the system.

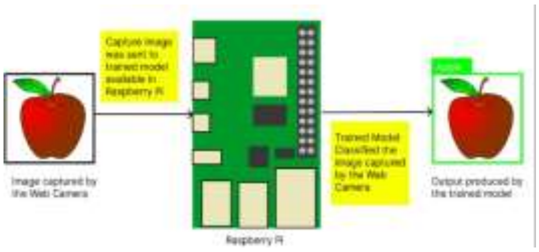

Figure 3 Image Classification

Detection of Affected Area-

- The classified food sample images are then transferred to the detection module which helps in detecting the affected area of the food sample taken.
- In this it contains the trained models for detection of affected and rotted areas of the food sample and the affected areas are detected by YOLO algorithm which is stored in Raspberry Pi.
- The expected output is produced for a particular food sample and the output absolutely clarifies the freshness.

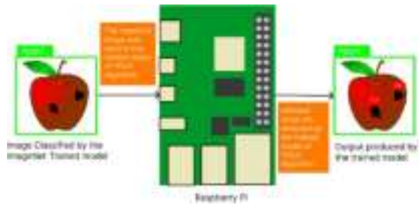

Figure 4 Detection of Affected Area

Detection of gas emitted -

- The food sample taken in the platform when the food sample starts to decompose, produces a gas.
- The emitted gases from the food samples also determine the freshness factors so we initialize the gas emission detection module responsible for detection of degraded items gases (i.e., methane gases for vegetations and ethane gas for the fruits).
- The gas emission reading value was analog data.
- The Raspberry Pi cannot detect the analog value accurately. So the ESP8266 was used to detect the analog signal from the gas sensor and send the accurate value to the Raspberry Pi.
- Finally based on the image detection and gas emission module it shows the accurate result.

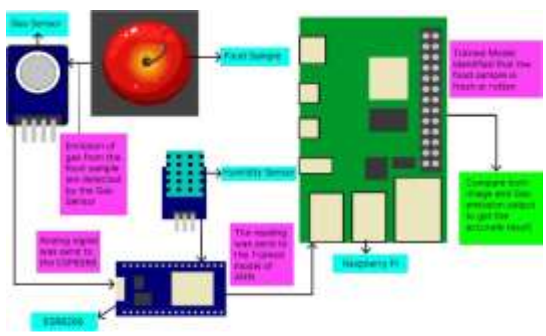

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Figure 5 Detection of gas emitted from the food

Result:

The figure-6,7,8 displays the training of our detection module using Object Detection Algorithm - YOLO v5 Architecture which detects the affected areas of the food sample given. We have trained for a minimum of 350 times to achieve this much accuracy level.

Figure 6 Training Images - Apple

Figure 7 Training Images - Banana

Figure 8 Training Images - Orange

Figure 9 Output image - Detection of Affected areas in apple.

Figure 10 Output image - Detection of Affected areas in banana.

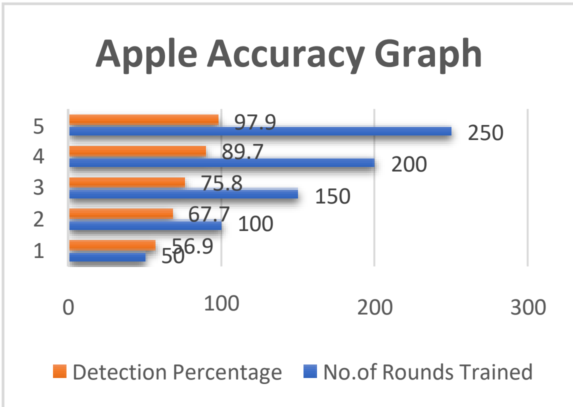

Figure 11 Apple detection percentage graph

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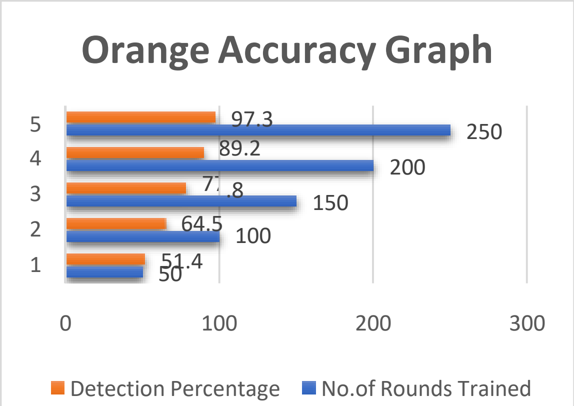

Figure 12 Orange detection percentage graph

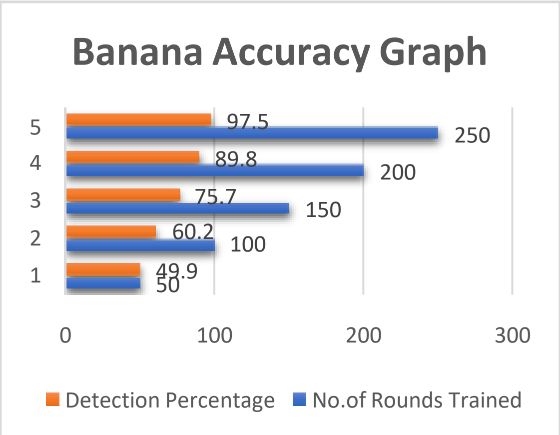

Figure 13 Banana detection percentage graph

CONCLUSION

The Proposed System provides a real time detection of food samples. It takes a 360-degree view of the food sample and detects the rotten spots using its image captured through camera and smell using a gas sensor (MQ-2, MQ-135). Our system provides 99.7% accuracy for apples, oranges and bananas as of now. This system helps food preparing centres, food packing industries and other food related companies to prove the quality of the food items they use. Being this much faster and accurate in detection of rotten or spoiled food items is the topmost advantage of our project.A large-scale implementation of our proposed system can help in delivering and consumption of fresh food items to stay healthy in this fast-moving world. A live example of our system is installing it near a conveyor belt (in which the washed food items move towards the preparation area) to detect and separate spoiled food items.

FUTURE WORKS

Our future implementation is to add more food items like vegetables and meat varieties. This system can be employed in the food packaging industries to check the quality of food items with high speed and accuracy. This method of detection can also be useful in food-based product-type Industries to check the manufacturing defects by changing the trained model. Based on the future requirement it can be easily updated and changes are made as per business requirement.

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