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AI BASED SYSTEM FOR ROTTEN FRUIT CLASSIFICATION AND SEGREGATION

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Abstract: This paper aims to develop a system for automated classification of rotten fruits using artificial intelligence (AI) and integrate it with a mechanical arm to segregate. The system will use Deep Learning techniques to analyze the images of fruits and identify the ones that are rotten based on their color, texture, and other visual cues. The data set of images of fruits, both fresh and rotten will be used for training. Once the system is trained, tested and validated it can be used in identifying the freshness of any new fruit given as input to the system. The fruits will be placed before the camera one after the other. The Trained AI Model will classify the images captured by the camera and identify the ones that are rotten. Once the rotten fruit is identified the robotic arm will be activated to separate the rotten fruit from the others.

Index Terms* - *AI, CNN, Image Acquisition, Deep learning, Arduino.

I. INTRODUCTION

This paper presents a novel system for the automated classification and sorting of rotten fruits, leveraging the power of artificial intelligence (AI) and robotic integration. The system analyses fruit photos and detects the bad ones based on their colour, texture, and other visual cues using deep learning techniques, notably Convolutional neural networks (CNNS). The Al model is trained and validated using a large data set made up of both fresh and rotten fruit photos. After training, the system can determine a fruit's freshness with accuracy.

In the suggested process, fruits are progressively placed in front of a camera, and the trained AI model instantly classifies them as fresh or rotten by analyzing the acquired photos in real-time. A specialized mechanical arm is actuated when a bad fruit is detected, effectively segregating it from the remaining fruits. With the use of automation, food waste should be drastically decreased, and the quality of fruits that are sold should also improve.

Specific software elements, such as the Image Processing Toolbox, Deep Learning Toolbox, and the Image Acquisition Toolbox of MATLAB are used.

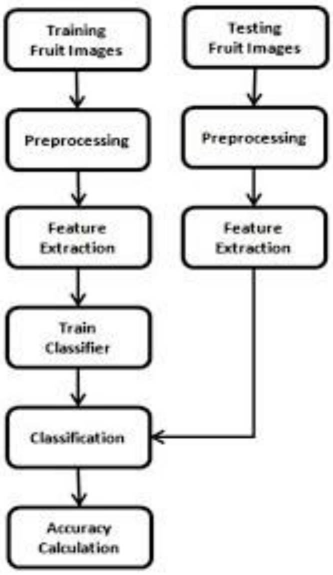
II. PROPOSED SYSTEM

The main goal of this work is to develop a prototype needed to construct this system. The widely used programming language and
development environment MATLAB offers a full set of tools for developing algorithms, visualizing data, and analyzing data. The Deep Learning Toolbox is particularly suited for fruit picture analysis and categorization since it provides specialized functions and methods for constructing, training, and deploying deep neural networks. The Image Acquisition Toolbox enables real-time image acquisition and processing by facilitating easy connection with cameras.

Numerous prior research efforts have been made in this direction, let us examine few of them. In [1], the authors main emphasis of
their study was on the categorization of fruit ripeness using Convolutional neural networks (CNNS) is the.[2] Talks about the categorization of bad fruit and how image processing and artificial neural networks are used for fruit grading. Utilization of CNNs to recognize rotting fruit from photos was exhibited in [3]. In [4] the authors have come up with an efficient deep learning model for evaluating the quality of fruit that includes the ability to identify rotting fruit. Usage of real-time fruit identification and the integration of a robotic arm for fruit harvesting was introduced in [5]. Later a further improvement was done by providing a soft touch gripper in fruit harvesting system by authors in their work [6]

Some studies [7]- [10] have concentrated on the use of loT sensors to track the quality and maturity of fruit, which can be combined
with AI for categorization. IoT-based fruit quality assessment systems are one example of pertinent investigations. Deep learning and transfer learning. For fruit categorization, several recent research use transfer learning methods using deep neural networks. For this, pretrained models like ResNet and Inception are frequently adjusted.

The difficulties of varying illumination and background clutter in fruit categorization and robotic arm integration are addressed in
some study. Adapting AI models for actual surroundings may be a solution. Accuracy in fruit categorization may be increased by combining data from several sensors (such as cameras and spectroscopy) with AI. for segregating the fruits into rotten and fresh and separate them using the mechanical arm. This work mainly uses the CNN, Robotic Arm, Arduino, Servo Motor. The work aims to make the industrial labour suffer less from mechanical work and focus on more efficient task so as to improve their knowledge. The block diagram of the proposed system is shown in the following fig-1.



Block diagram of proposed system

III. HARDWARE REQUIREMENTS

Arduino nano

It is a type of microcontroller board that is built using an ATMEGA328P microcontroller. We used this microcontroller because it is small, flexible, and capable of providing the same specifications as other microcontrollers. It is capable of interfacing software and hardware efficiently.

This microcontroller uses a USB cable for the power supply and can provide an operating voltage of 5 volts. The flexibility and eco-friendly nature of Nano make it a unique choice to create electronic devices and works with compact size Here, this microcontroller is programmed using Arduino software (IDE) and operates both offline and online. It is small in size compared to the UNO board. The Arduino Nano is organized using the Arduino (IDE), which can run on various platforms. Here, IDE stands for Integrated Development Environment.

Using the constant voltage, the Arduino Nano is used to produce a clock of a precise frequency. The Arduino Nano is used in various applications such las
Robotics, Control System, Instrumentation, Automations, and Embedded Systems. The pin diagram of Arduino nano is shown in following fig-2.

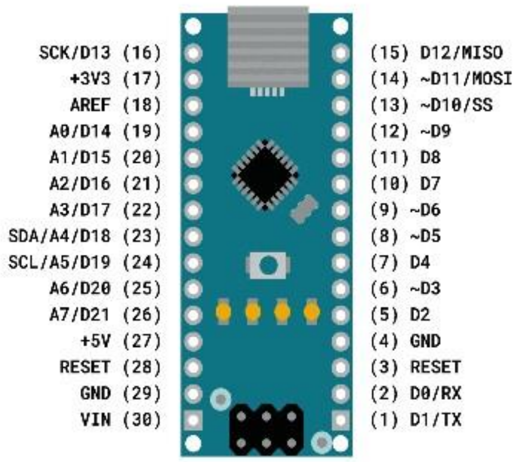


Fig-2: Pin description of Arduino nano

The other hardware components utilized in the system are as follows:

Servo Motor

Servo motors are a type of electromechanical device that are widely used in various applications to control the position, speed. and
acceleration of mechanical components. They are particularly popular in robotics, automation, and other precision control systems due to their accuracy and ability to maintain a desired position.

Arm Links

Arm Links refers to the individual rigid segments or components that make up a robotic arm. Each link has its specific length, shape,
and structural properties. and they are typically classified based on their rale in the robotic arm's movement.

IV.SOFTWARE EQUIREMENTS

To perform the work of segregation. we used MATLAB. especially the Image Processing Toolbox, the deep learning Toolbox
and the Image Acquisition Toolbox. MATLAB offers a powerful and flexible environment for implementing the different stages of Rotten Fruit Classification. MATLAB is used to read and pre-process the images of the fruits. This includes operations like reading images from the dataset, resizing or cropping them to a consistent size, and converting them to grayscale or other color spaces if needed. It is also used to split the dataset into training and testing sets. You can randomly divide the dataset into these two subsets using MATLAB's built-in functions.
However, it provides rich visualization capabilities that are used to plot and visualize the results, such as displaying the original and
pre-processed images. showing the feature distribution and plotting the evaluation matrices.

Deep learning toolbox

In rotten fruit classification using the Deep learning Toolbox in MATLAB, the focus shifts from hand crafted feature extraction to
automatic feature models, particularly learning. Deep learning models, particularly Convolutional Neural Networks (CNNs) are capable of automatically learning relevant features from raw image data, which can lead to better classification performance compared to traditional feature extraction methods. It streamlines the process of designing. training and evaluating deep learning models for image classification tasks like rotten fruit classification. We used MATLAB Deep learning Toolbox to load pre-trained CNN models which is called Transfer learning like VGG. ResNet, or Inception. These models are trained on massive image datasets and have learned generic features useful for various image classification tasks. Transfer learning allows you to utilize these pre-trained models and adapt them to your specific rotten fruit classification task. We fine-tuned the pre-trained CNN by modifying the last few layers to match the number of classes in the rotten fruit dataset. This process helps the network specialize in the specific task of rotten fruit classification. Trained the customized CNN using the training data. We have MATLAB's functions like train Network for training the model.

Image Acquisition Toolbox

The Image Acquisition Toolbox in MATLAB is used for acquiring images from various imaging devices, such as cameras. In the
context of rotten fruit classification, we used this toolbox to capture images of fruits directly from a connected camera and then perform the classification using the acquired images. The Image Acquisition Toolbox supports a wide range of camera models, and uses MATLAB functions to check the list of available devices and select the appropriate one. Position the fruits in front of the camera and trigger images using MATLAB functions. After pre-processing. we used the classification model trained using the deep learning toolbox to classify the acquired fruit images as rotten or fresh. The image acquisition Toolbox can be used to display the acquired images along with the classification results, indicating whether each fruit is classified as rotten or fresh.

V. WORKING

The block diagram of the system model was given in Section-III in fig-1. A detailed description of each step is provided in this section.

Data collection: A comprehensive dataset of fruit images is collected, comprising both fresh and rotten fruits. These images are captured using a high-resolution camera under varying lighting conditions.
The dataset has included a variety of fruits to ensure robust training of the Al model.

Data Pre-processing: The collected fruit images undergo pre-processing steps to enhance their quality and standardize their format. This includes resizing the images to a consistent resolution, normalizing the color channels, and removing any noise or artifacts that might interfere with the analysis. For pre-processing, simple rescaling of the images was performed to 277*277*3.

Model Architecture Design: A deep learning model architecture is designed for the classification of fresh and rotten fruits. Convolutional neural networks (CNNs) are commonly used for image analysis task due to their ability to extract relevant features. The model architecture consists of multiple convolutional and pooling layers. Followed by fully connected layers for classification.

Image input layer: The model starts with an image input layer with an input shape of (277, 277, 3). It specifies the dimensions of the input images.

Convolutional laver: This layer performs a convolution operation with 32 filters of size 3*3.
The padding is set to 'same' to preserve the spatial dimensions of the inpút.
Batch normalization layer: Batch normalization is applied to normalize the activations of the previous convolutional layer, helping with the training process and improving model performance.
ReLU laver: the ReLU (Rectified Linear Unit) activation function is applied element-wise to introduce non-linearity and increase the model's representational power.
Fully connected layer: This layer consists of two units, which serves as a dense layer where each neuron is connected to every neuron in the previous layer. It helps capture higher-level features from the flattened feature maps.
Softmax layer: The Softmax activation function is applied to convert the output of the previous layer into a probability distribution across the classes.
Classification layer: This layer is the final output layer of the model. It consists of the desired number of units, typically representing the number of classes in the classification task.

The model is compiled with the Adam optimizer, categorical cross-entropy loss (assuming a multi-class classification problem), and accuracy as the evaluation metric.
Training the Al Model: The designed model is trained using the pre-processed fruit image dataset.
The dataset is split into training and validation sets, with a portion of the data reserved for testing the model's performance. During training, the model learns to identify distinguishing features of fresh and rotten fruits by optimizing its weights through backpropagation and gradient descent.
Model Evaluation: The trained model is evaluated using the test set to assess its accuracy, precision, recall, and FI score. Various performance metrics are calculated to determine how well the model can classify fresh and rotten fruits based on color, texture, and other visual cues. Any necessary fine tuning or adjustments to the model are made based on these evaluations.
Integration with Robotic Arm: Once the Al model is trained, tested, and validated, it is integrated with a customized mechanical arm. The camera is positioned to capture images of the fruits placed before it one by one. The AI model analyzes each image, determines if it is fresh or rotten, and sends the classification result to the robotic arm.

Robotic Arm Activation and Fruit Segregation:
Upon receiving the classification result, the robotic arm is activated to separate the identified rotten fruits from the others. The arm's movement is coordinated to remove the rotten fruits, reducing food waste and ensuring that only fresh fruits proceed further precisely and efficiently in the sorting process.
System Performance Evaluation: The integrated system is evaluated to assess its overall performance, including classification accuracy. speed of fruit analysis, and efficiency of fruit segregation. Experiments are conducted with different fruit types and quantities to validate the system's effectiveness in reducing food waste and improving fruit quality.

IV . RESULTS Output1: FRESH FRUIT AS INPUT

JPG format is selected from the dataset. Initially, the image undergoes resizing for standardized processing. Subsequently, the image is fed into the classification process, where the AI model analyzes it. If the outcome of this analysis is that my Prediction equals
"Fresh," the system displays "my Prediction = Fresh." Simultaneously, the fresh fruit image is presented as shown. This seamless process ensures that when the AI model confidently identifies a fruit as "Fresh", the corresponding image is promptly showcased, demonstrating the system's accurate classification capabilities and delivering the desired outcome to users. If the value of my_Prediction is equal to fresh then the output is displayed as my_Pridiction =Fresh. And the fresh fruit is displayed as shown in fig-3 and fig-4 respectively.

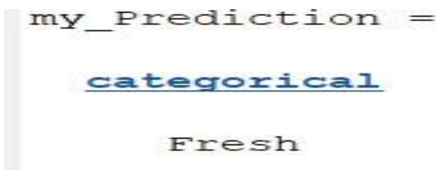


Fig-3: Output displayed when a fresh fruit is given as input

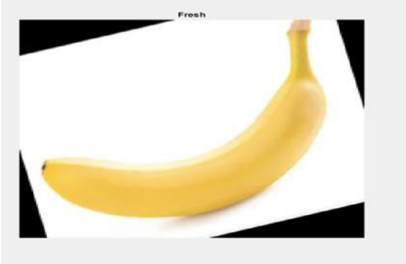


Fig-4 : fresh fruit image provided as input

Output2: ROTTEN FRUIT AS INPUT

In the system, a JPG-format image of selected from the dataset. The image is first resized to ensure uniform processing. Subsequently, the AI model classifies the loaded image. If my_Prediction equals “Fresh” during this classification, the system displays
“my_Prediction=Rotten.” Simultaneously, the image of the identified rotten fruit is showcased as shown. This process effectively identifies and promptly presents rotten fruits when the AI model mistakenly categorizes them as fresh, ensuring accurate fruit classification and displaying the appropriate output for users. If the value of my_Prediction is equal to Fresh then the output is displayed as my_prediction=Rotten. And the rotten fruit is displayed. When my_Prediction=Rotten then Arm rotates in 180 degrees as shown in fig-7.

```
my_Prediction =
  categorical
     Rotten
```

Fig-5 output displayed when a rotten fruit is given as input

Fig-6 rotten fruit image provided as input

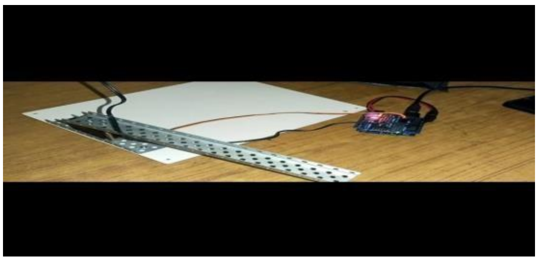


Fig-7: Mechanical movement of arm by 180 degrees when rotten fruit is detected

VII. CONCLUSION

The "Automated Rotten Fruit Classification and Segregation System using AI and Robotic Integration" is revealed as a key development in the fields of agriculture and technology. By combining AI and robots, this solution improves efficiency, sustainability, and quality while addressing pressing problems in the food supply chain.

The system's automation of fruit categorization and segregation produces notable efficiency advantages in the first place. It speeds up operations, eliminates manual labor, and works around the clock by utilizing AI algorithms and robotic mechanisms. Businesses benefit from increased productivity and resource optimization as a consequence.

Additionally, the system's ability to detect and eliminate rotting fruit directly contributes to the reduction of food waste. Only fresh product gets to customers thanks to the accuracy of AI-driven identification, which also reduces disposal costs and environmental effect. This supports financial savings and is in line with eco-friendly behaviors.

Finally, the approach improves market competitiveness by improving fruit quality and coordinating with shifting customer desires for ethical sourcing. Because of its modular architecture, it may be integrated into a variety of situations, including big agricultural operations and local marketplaces, promoting scalability and industry-wide effect.

The "Automated Rotten Fruit Classification and Segregation System using AI and Robotic Integration" illustrates the possibilities of technological cooperation in an environment where efficiency and sustainability are crucial. With its many benefits, the food sector is moving towards becoming more resource-efficient, waste-free, and consumer-focused, demonstrating the revolutionary power of cuttingedge technology.

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