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# SEPARATION OF SOLID WASTE USING CNN TECHNIQUE

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***Abstract:*** Solid waste management is a critical issue in urban areas as it has an impact on public health, environmental sustainability, and economic growth. The segregation of waste is an essential step in the waste management process, as it enables the identification and separation of different types of waste, which can be further recycled or disposed of in an appropriate manner. However, manual segregation of waste is a time-consuming and error-prone task, and can result in inefficient waste management practices. To overcome this challenge, we use computer vision techniques, such as Convolutional Neural Networks (CNN), has emerged as a promising solution. CNNs are a type of deep learning algorithm that can automatically identify and classify objects in images, making them suitable for the classification of waste. This process of segregating waste using CNNs is performed by capturing images of waste using a camera. These images are then preprocessed to enhance their quality and normalize their size and orientation. The preprocessed images are then fed into a CNN model that has been trained on a dataset of waste images. This model identifies the different types of waste in the image and assigns them to specific categories, such as biodegradable and non-biodegradable waste.

***Index Terms*** – Waste Separation, Arduino, Convolutional Neural Networks (CNN)

# I. INTRODUCTION

The segregation of solid waste is a crucial step in waste management, as it allows for the proper disposal and recycling of different types of waste. One way to automate this process is through the use of computer vision techniques, such as Convolutional Neural Networks (CNNs).

CNNs are a type of deep learning algorithm that can recognize patterns in images or other types of data. They have been used extensively in computer vision applications, such as object recognition and classification.

In the context of waste management, a CNN can be trained to classify solid waste into two categories: biodegradable and non-biodegradable. Biodegradable waste includes organic matter that can be broken down by bacteria and other microorganisms, while non-biodegradable waste includes materials that cannot be easily decomposed, such as plastic, glass, and metal.

To train a CNN for waste classification, a large dataset of labeled images is required. These images could be taken from various sources, such as waste management facilities, recycling centers, or even public places where waste is disposed of.

The images should be preprocessed to remove any unwanted noise or artifacts and to enhance the features of the waste items. This could involve techniques such as cropping, resizing, and normalization.

The CNN architecture can be designed using various frameworks such as TensorFlow, Keras, or PyTorch. The architecture typically consists of a series of convolutional layers that extract features from the input images, followed by pooling layers that downsample the feature maps, and finally, fully connected layers that classify the images into the two categories of biodegradable and nonbiodegradable waste.

During training, the CNN learns to adjust the weights of its neurons to minimize the error between the predicted outputs and the true labels of the training images. This is done using a technique called backpropagation, which updates the weights based on the gradient of the loss function with respect to the weights.

Once the CNN has been trained, it can be used to classify new images of waste items into the two categories. This could be done using a mobile or web-based application that allows users to take a picture of the waste item and receive an instant classification result.

# II. LITERATURE SURVEY

[1] Smart garbage classification and management system using Internet of Things (IoT) & Machine Learning (ML) an article by Shamin.N, P.Mohamed Fathimal, Raghavendran.R, Kamalesh Prakash. In this article, an intelligent garbage sorting and management device placed on the Internet of Things is presented to detect garbage in the trash by sensor devices. Once detected, the waste in the bin is separated by sensors and the information is immediately transferred via the Internet of Things to a cloud database. Plastics and compostable items are distributed by an image processing algorithm and placed in separate sections. From this article, the points we have made are degradable and non-degradable elements that can be identified by image processing algorithms. Metal sensors are used to separate metal elements, which are then grouped into different sections.

[2] The article titled "Waste segregation using programmable logic controller", published by S.M. Dhumal, B.S. Jonwal and Professor H.P. Chaudhari, describes that it is possible to develop a prototype to divided metals from waste using a programmable logic controller. The feeding system consists of hoppers and other mechanisms that bring waste to the conveyor. Sensors will identify waste on the conveyor belt and start rotating the conveyor belt. We took the following points from the article: An electromagnet attached to the robot arm removes metal from the waste. He will put it in a metal box. The controller is used to control the start, stop, forward and reverse of the conveyor belt.

[3] In their paper titled "Convolutional Neural Networks Application in Plastic Waste Recognition and Sorting," Andrey N. Kaolin, Aleksandr I. Tur and Aleksandr A. Yuzhakov describe the IoT application and their convolutional neural network in a reversal vending device project. A reversal vending machine is a device that accepts pre-owned (empty) beverage containers and reward cash to the user. Shows CNN's IoT implementation for reverse vending machines. We take the following points from the paper: We can analyse, remove and group these items on a moving conveyor applying computer vision and artificial intelligence (AI). CNN (convolutional neural network).

[4] A paper titled "VGG16 Convolutional Neural Network-Based Garbage Classification and Recognition System" was published by Wang Hao, which describes that this project finally classified the bio-waste activities, risky waste, kitchenette waste and other wastes using the VGG16 network. After actual testing, the division efficiency of the garbage sorting system using the VGG16 network is 75.6%, so the

system meets the needs of everyday households. In this paper, we study image recognition and classification.

[5] An article titled "Waste Classification at the Edge for Smart Bins.". Already published by Gary White, Christian Cabrera, Andrei Palade, Fan Li, Siobhan Clarke, who describe that in this paper the authors introduce WasteNet, a waste grouping model based on an integrated neural network. short. Waste is classified within six class: plastic, glass, metal, cardboard, paper and others. This model has an accuracy of 97 based on the test data set. We draw: High predictive accuracy of the data set of this article.

[6] **"**Intelligent Waste Classification System Using Deep Learning Convolutional Neural Network," paper by Olugboja Adedeji, Zenghui Wang. This paper proposes an smart garbage distribution system, developed by using a 50-layer convolutional neural network model (ResNet-50) as a machine learning tool and acting as a extraction, and Support Vector Machines (SVM) are used to sort waste into various groups/types like glass, metal, paper and plastic etc. From this article, we learned that the more images in the dataset, the higher the accuracy.

[7] "A Smart Waste Management and Segregation System that Uses the Internet of Things, Machine Learning and Android App" is an article contributed by Shaunak Varudandi, Harshwardhan Parmar, Raj Mehta, Krishna Samdani, Jahnavi Mahetalia . Management and separation system using Internet of Things, machine learning and Android. Bins are linked to the cloud to help with efficient waste acquiring by hunting and uploading different data points for a specific bin. An Android application is also part of this classification that will help the concerning authorities manage the trash in real time.The ultrasonic sensor and the humidity sensor are the two essential components that help in sorting waste.

[8] In the paper "Valuable Waste Classification Modelling Based on SSD-MobileNet," submitted by Sorawit Thokrairak, Kittiya Thibuy and Prajaks Jitngernmadan describe how SSD-MobileNet, a convolutional neural network, is used to optimize waste segregation. This waste includes glass bottles, plastic bottles and metal cans. They used 952 image datasets in their work. Here are the points we took from the article: The prototypical is tested on a Raspberry Pi 4 along the maximum possible division accuracy. Using a mobilenet SSD allows for rapid object detection.

[9] The article "Towards artificially intelligent recycling: Improving image processing for waste classification", by Youpeng Yu, Ryan Grammenos describes how to use transfer learning and data augmentation techniques to advance the efficiency of waste distribution. Starting with a convolutional neural network (CNN), a efficient approach is applied to choose the right split ratio and tune several training parameters, along with the learning rate scheduler, freeze layer, batch size and loss function, in the connection of the given scenario. requires sorting waste into different types of recycling. We have taken the following points from the paper: Use of data split technique, data augmentation techniques.

[10] According to the article "Municipal Solid Waste Segregation with CNN C" by Srinitha, Chutimet; Kanharattanachai, Sivakorn, home waste can be classified within four categories: common waste, compostable waste, recyclable waste and unsafe waste. The derived classifiers outperformed their respective direct classifiers in the test. Here's what we took from the article: The teaching data set is limited; derived classifier might be a viable option.

[11] "Towards intelligent waste management in depth S", is an article published by Jadli, Aissam; Hain, Mustapa. This paper proposes a redesigned architecture for an intelligent waste management system based on artificial intelligence approach and target on the combined help of the Internet of Things

(Internet of Things). Iodine). From this article, we learned that by integrating deep learning approach into this industry, it is possible to significantly reduce costs while enduring top performance.

[12] The article by Mohammad Tariqul Islam, "CNN-based smart Waste Management System using TensorFlow Lite and LoRa-GPS Shield in an Internet of Things Environment", describes how the system is integrated with sensors. IoT-based variable and LoRa-GPS module to identify bins position and transfer bin information over long distances. From this article, we learned that building object detection model with higher accuracy and pace on microcontrollers with higher processing capability can improve detection and analysis performance garbage type.

# III. METHODOLOGY

The main aim of the proposed project is to classify different types of wastes like biodegradable and nonbiodegradable, solid waste and wet waste as well as metal wastes. In order to differentiate these different types of the wastes a Convoluted Neural Network (CNN) is used. In this project we will first design the convoluted neural such that the designed network gives lesser error and greater accuracy in the process of classification. In this process a dataset containing all the possible inputs i.e.; the dataset contains all the possible images required for the classification. Both input and output will be given while training the machine since is CNN comes under Supervised Learning where the machine is trained by giving both input as well the output. The images are given as the input for the classification. The dataset will be divided into two parts one is training set and the other one is testing set. The dataset will be divided based on the split ratio which will be initialized while defining the program. Now after training the machine by training dataset, it will be tested using testing dataset to calculate the accuracy of the machine. If the obtained accuracy is not sufficient for the given process the same process will repeat from designing the CNN to getting the precise output. That output is given to the microcontroller and is classified as biodegradable and non-biodegradable waste.

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# IV. FLOW CHART

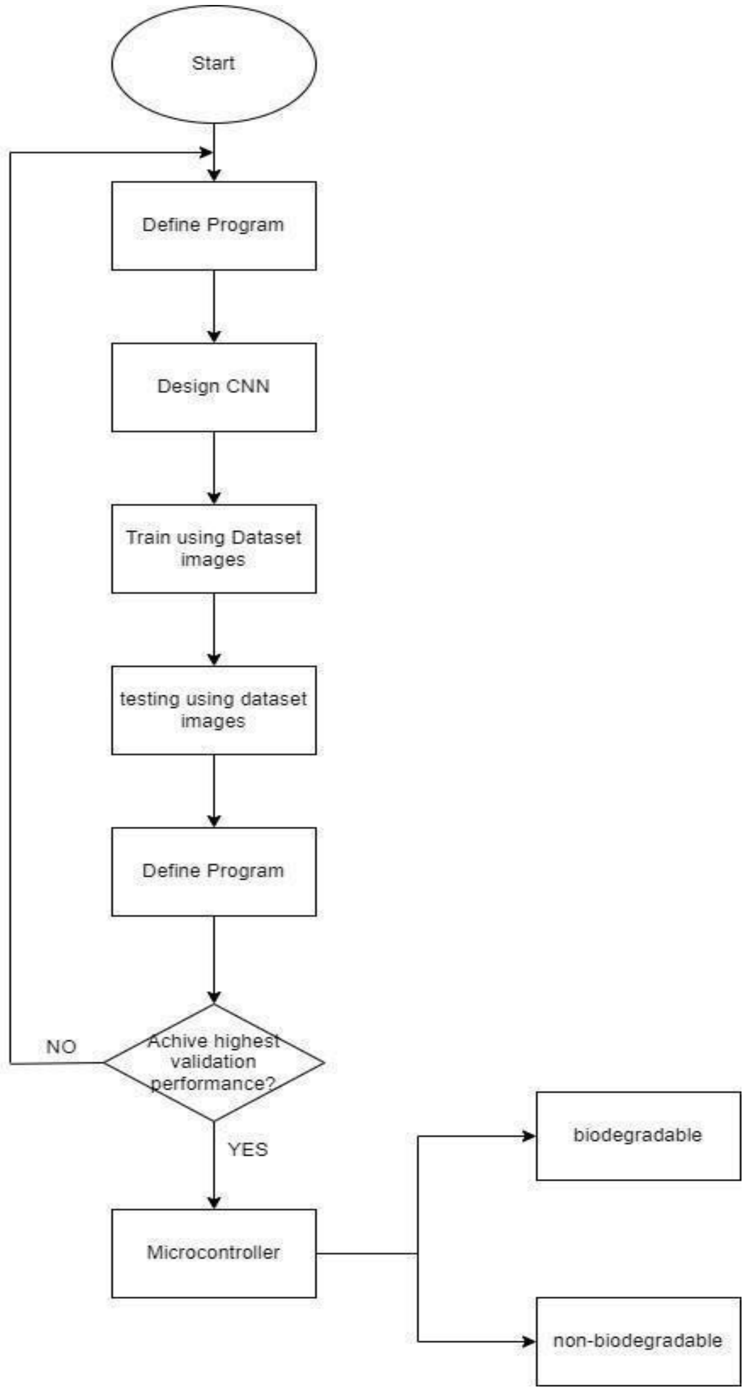


**Fig:1 Flow chart**

# CNN:

## About Image Processing Using CNN:

Image processing refers to the manipulation and analysis of digital images using algorithms and techniques to enhance, modify, or extract information from the images. It involves a wide range of operations, including filtering, enhancement, restoration, segmentation, and feature extraction. Let's explore the key steps and concepts involved in image processing:

Image Acquisition: The process begins with capturing or obtaining a digital image from a source such as a camera, scanner, or sensor. The image is typically represented as a grid of pixels, where each pixel contains color and intensity information.

Preprocessing: This step involves preparing the acquired image for further analysis and processing. It may include operations such as resizing, cropping, and color space conversion. Preprocessing techniques are applied to remove noise, correct lighting conditions, and enhance the image quality.

Filtering: Filtering techniques are used to modify the frequency content of an image. Common filters include:

Smoothing Filters: These reduce noise and blur the image using operations like Gaussian smoothing or median filtering.

Sharpening Filters: These enhance edges and fine details in the image to improve its clarity and definition.

Frequency Filters: These manipulate the image's frequency domain representation, enabling operations like high-pass filtering or low-pass filtering.

Enhancement: Image enhancement techniques aim to improve the visual quality or extract specific features from an image. Some common enhancement operations include:

Contrast Adjustment: Modifying the image's contrast to make it visually more appealing or enhance details.

Histogram Equalization: Adjusting the image's histogram to improve its overall brightness and contrast.

Color Correction: Modifying color balance, saturation, or intensity to correct color casts or enhance specific color features.

Noise Reduction: Applying algorithms to suppress or remove noise from the image while preserving important details.

Restoration: Image restoration techniques are used to recover or improve the quality of degraded or damaged images. This may involve removing blur, reducing noise, or enhancing images affected by motion, atmospheric conditions, or sensor artifacts. Restoration techniques often rely on mathematical models to estimate and restore the original image based on observed degradation characteristics.

Segmentation: Image segmentation involves partitioning an image into meaningful regions or objects. It is used to separate foreground from background, identify distinct objects, or extract specific features. Segmentation algorithms can be based on color, texture, intensity, or a combination of these factors. Common techniques include thresholding, region growing, edge detection, and clustering.

Feature Extraction: Feature extraction is the process of capturing relevant information or characteristics from an image. These features can be used for further analysis, classification, or recognition tasks. Examples of extracted features include edges, corners, textures, color histograms, or more complex descriptors like scale-invariant feature transform (SIFT) or histogram of oriented gradients (HOG).

Object Recognition and Analysis: Once the relevant features have been extracted, they can be used for tasks such as object recognition, object tracking, or image classification. Machine learning algorithms, including deep learning approaches like Convolutional Neural Networks (CNNs), are often employed for these tasks. These algorithms learn patterns and relationships from labeled training data and can make predictions or classifications on new, unseen images.

Image processing finds applications in various fields, including medical imaging, satellite imaging, surveillance, robotics, quality control, and more. The techniques and algorithms used in image processing continue to evolve, driven by advances in computer vision, machine learning, and computational power, enabling us to extract valuable information and insights from digital images.

## About Data Set:

In image processing, a dataset refers to a collection of digital images that are used for various purposes such as training, validation, and testing of image processing algorithms and models. Datasets play a crucial role in the development and evaluation of image processing techniques, as they provide the necessary input for algorithm training, parameter tuning, and performance assessment. Let's delve into the key aspects of image datasets:

Image Collection: Creating an image dataset involves collecting a representative set of images that align with the specific goals and requirements of the image processing task. The images can be obtained from various sources such as cameras, sensors, online repositories, or manual annotation.

Image Annotation: An important step in building an image dataset is annotating the images with relevant information or labels. Annotation involves assigning metadata or tags to images to indicate specific characteristics, such as object classes, object locations, pixel-level segmentations, or other relevant attributes. Accurate and consistent annotation is crucial for supervised learning tasks, where labeled data is used to train models.

Training, Validation, and Testing Split: Once the dataset is collected and annotated, it is typically divided into three subsets: training set, validation set, and testing set. The training set is used to train the image processing algorithms or models, the validation set is used for hyperparameter tuning and model selection, and the testing set is used for unbiased evaluation of the trained models.

Data Augmentation: Data augmentation techniques are often employed to artificially expand the dataset and improve the generalization capability of the models. Augmentation involves applying various transformations to the images, such as rotation, scaling, cropping, flipping, or adding noise. By introducing these variations, the models become more robust to different image conditions and variations encountered during inference.

Dataset Size and Diversity: The size and diversity of an image dataset can significantly impact the performance and generalization of image processing algorithms. A larger dataset with diverse images helps the model capture a wide range of patterns and variations, leading to better performance on unseen data. It is essential to strike a balance between dataset size and computational resources while ensuring sufficient representation of the real-world data distribution.

Benchmark Datasets: In many image processing tasks, benchmark datasets are commonly used for fair comparisons and evaluation of different algorithms or models. These benchmark datasets are widely adopted by the research community and often come with pre-defined training, validation, and testing splits. Examples of well-known benchmark datasets in image processing include ImageNet, COCO, PASCAL VOC, and CIFAR-10/100.

Data Privacy and Ethics: Image datasets may contain sensitive information, and it is crucial to handle them with proper care and adhere to ethical guidelines. Anonymization techniques can be employed to remove personally identifiable information from the images. In cases where explicit consent is required, obtaining consent from the individuals or subjects appearing in the images is necessary.

Data Bias and Fairness: Image datasets can sometimes exhibit biases or imbalances, leading to potential biases in the trained models. Careful examination and mitigation of bias are important to ensure fairness and prevent discrimination. Bias detection techniques, diverse data collection strategies, and bias mitigation methods can be employed to address these issues.

In summary, an image dataset in image processing comprises a collection of labeled images used for training, validation, and testing of algorithms and models. Datasets play a critical role in developing and evaluating image processing techniques, and factors such as dataset size, diversity, annotation quality, and ethical considerations impact the performance and fairness of the resulting models.

# V. CONCLUSION

the use of Convolutional Neural Networks (CNNs) for the segregation of solid waste into biodegradable and non-biodegradable categories offers significant advantages in waste management. By leveraging computer vision techniques, CNNs can automate the waste segregation process, reducing the reliance on manual labor and improving efficiency.

The training of a CNN involves using a dataset of labeled images to teach the network to recognize and classify waste items. The CNN architecture, consisting of convolutional, pooling, and fully connected layers, extracts feature from the input images and makes predictions based on learned patterns. The training process, driven by backpropagation, adjusts the weights of the network to minimize the prediction error.

Once trained, the CNN can be deployed in various applications, such as mobile or web-based platforms, allowing users to capture images of waste items and receive instant classification results. This technology can significantly streamline waste management operations, enabling efficient segregation, recycling, and proper disposal of solid waste.

The utilization of CNNs for waste classification not only improves waste management practices but also contributes to environmental sustainability. Accurate segregation of biodegradable and non-biodegradable waste ensures that organic matter is appropriately processed through composting or anaerobic digestion, reducing landfill usage and greenhouse gas emissions. It also enables effective recycling and resource recovery from nonbiodegradable waste, promoting a circular economy and minimizing the environmental impact.

Furthermore, CNN-based waste segregation systems have the potential to scale and adapt to different waste management settings. With advances in computer vision and machine learning, these systems can continually improve their accuracy and performance, leading to enhanced waste sorting capabilities and optimized resource allocation.

However, it's important to note that the successful implementation of CNN-based waste segregation requires careful consideration of factors such as dataset quality, image preprocessing, model training, and deployment infrastructure. Collaborations between waste management experts, data scientists, and technology developers are crucial to developing robust and reliable CNN models tailored to specific waste management contexts.

In summary, the integration of CNN techniques for the segregation of solid waste into biodegradable and nonbiodegradable categories offers immense potential for improving waste management practices. By automating waste segregation, these systems contribute to efficient resource utilization, environmental sustainability, and a cleaner and healthier living environment.

# VI. RESULTS

In ConvNet architecture with twenty epochs, an accuracy of 100% was achieved. For the model, a loss of 0% was obtained on training the model for twenty epochs. **Figure 2** shows the accuracy and loss Evaluation

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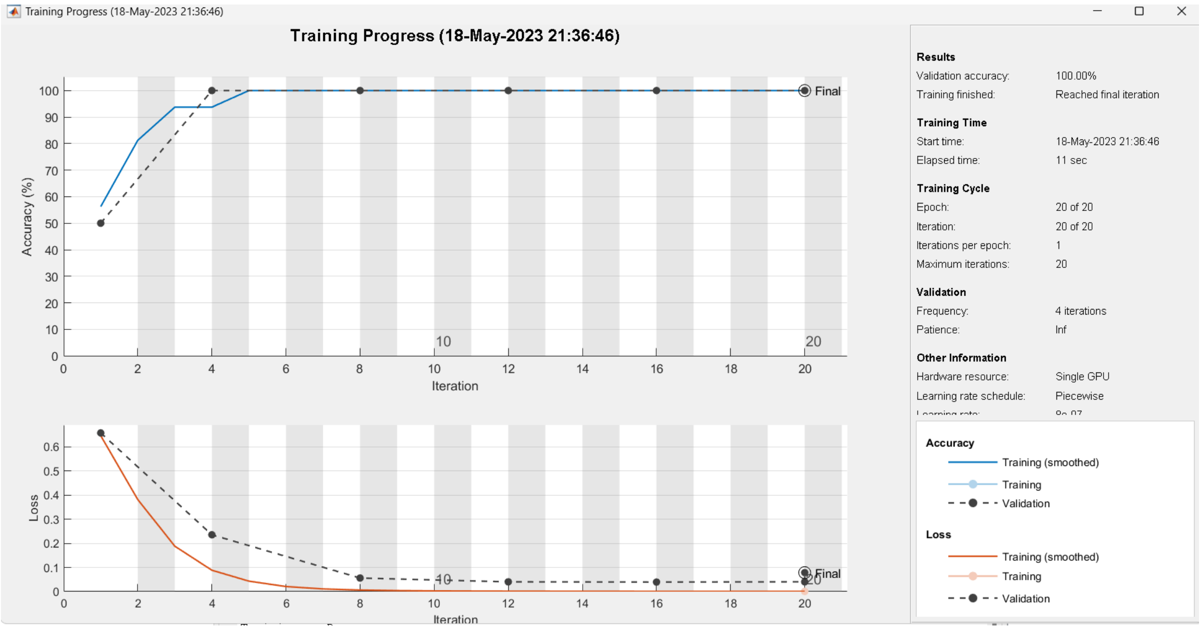


**Fig:2 Evaluation of accuracy and loss function of model.**

**FIGURE 3** illustrates the result of putting a given waste of cardboard in front of a camera during the testing process and showing that it is degradable

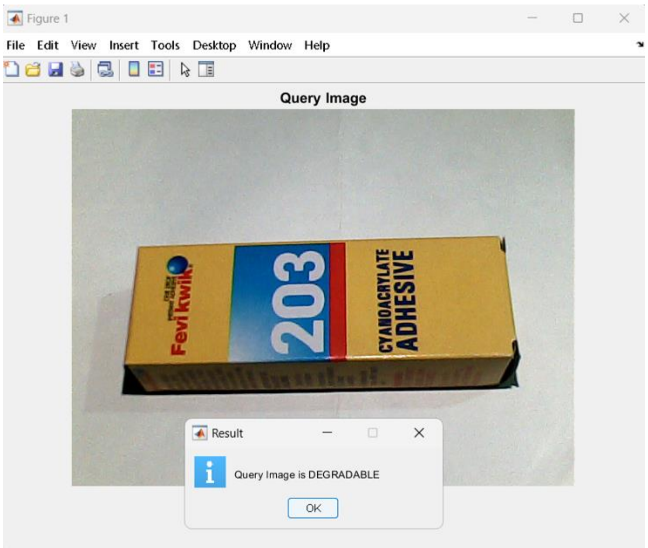


**Fig:3 Result as Degradable**

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