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DETECTION AND IDENTIFICATION OF ARTIFICIALLY RIPENED FRUITS USING MATLAB

G Sivabharahi[1], V Sowndarya[2]

[1]Assistant Professor, [2] PG Student, Department of Computer Science

Mangayarkarasi college of arts and science for women, Paravai, Madurai

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Abstract

The detection of fruit maturity levels is crucial in ensuring their quality and safety for consumers. To achieve this, the utilization of advanced image processing techniques such as texture and colour analysis has become increasingly popular. In this study, we propose the use of the Gray Level Co-occurrence Matrix (GLCM) method for texture analysis of tomato images, based on its high recognition capabilities in terms of contrast, correlation, homogeneity, and energy. By extracting features from the GLCM calculations, the influence of external light intensity can be minimized, thereby improving the accuracy of maturity level detection. The K-Nearest Neighbour (K-NN) classification method is employed to classify the results of GLCM calculations, utilizing the distance (k) as a measure of similarity between images. K-NN is chosen due to its simplicity and efficiency in dealing with a wide range of image classification problems. Overall, this proposed method has the potential to improve the detection of maturity levels in fruits, specifically in tomatoes, which can ultimately contribute to enhancing the quality and safety of produce for consumers.

Keywords: GLCM, KNN, correlation, energy, homogeneity

INTRODUCTION

Artificial ripening of fruits is a common practice in the fruit industry, as it helps to increase the shelf life of fruits and allows them to be transported over long distances. However, this practice has raised concerns among consumers about the potential health hazards of consuming artificially ripened fruits. Artificial ripening is often achieved by exposing fruits to ethylene gas, which is a natural plant hormone that triggers the ripening process. But, excessive exposure to ethylene gas can lead to over-ripening, decay, and loss of nutritional value in fruits [1].

To address these concerns, there is a growing need to develop reliable methods for detecting and identifying artificially ripened fruits. This is where MATLAB, a powerful software platform for numerical computation and data analysis, can play a crucial role. With its image processing and machine learning capabilities, MATLAB can be used to develop algorithms for identifying and classifying fruits based on their ripeness levels.

By analyzing the color, texture, and other visual features of fruits, MATLAB algorithms can differentiate between naturally ripened and artificially ripened fruits. This can help consumers to make informed choices about the fruits they buy, and can also help regulatory authorities to enforce regulations on the use of ethylene gas for artificial ripening. Overall, the use of MATLAB for detecting and identifying artificially ripened fruits has the potential to improve food safety and quality, and to promote consumer confidence in the fruit industry.

The identification of fruit species can be a laborious and time-consuming process due to the large number of existing fruit types worldwide. This task can prove particularly challenging for non-expert stakeholders, including land managers, foresters, agronomists, and amateur gardeners, among others. To address this issue, an automatic fruit disease identification tool has been proposed to streamline the plant species identification process. This tool has the potential to be of significant benefit even to experienced botanists [2].

Fruit identification is typically based on the observation of a fruit's physical characteristics, such as its size, color, and shape. In this study, our focus is on the shape of the fruit. To describe the shape of a leaf, it is possible to develop a specific approach or adapt a generic shape retrieval method to the particular case of fruits. By applying this approach to the identification of fruit species, we aim to improve the accuracy and efficiency of the fruit identification process.

The proposed method has the potential to simplify the task of fruit identification, enabling non-expert stakeholders to accurately and efficiently identify various fruit species. This, in turn, can have positive implications for the management and preservation of fruit crops, ultimately contributing to the improvement of agricultural practices.

LITERATURE REVIEW

Over the past few years, there has been a growing interest in developing automated systems for plant recognition and classification using leaf images. Researchers have proposed various approaches and techniques, ranging from geometrical and morphological parameters to image and data processing, as well as artificial neural networks. In 2013, Kue-Bum Lee [3] proposed a leaf recognition system that utilized the leaf vein and shape for plant classification. The proposed approach extracted 21 leaf features, including distance feature between centroid and all points on the leaf contour, and frequency domain data by using Fast Fourier Transform methods.

Similarly, in 2013, Pallavi P [4] highlighted the need for setting up a database for plant protection due to the risk of extinction faced by many plant species. In 2015, Sapna Sharma [5] emphasized the challenge of analyzing plant leaf images due to the presence of minute variations and a large dataset for analysis. Artificial neural networks were found to be successful in addressing these issues in pattern recognition, classification, and image analysis. Additionally, in 2015, Sachin D Chothe [6] presented a computer-based automatic plant identification system that extracted geometrical parameters and morphological features based on leaf structure and vein feature. Finally, in 2014, Ekshinge Sandip Sambhaji [7] proposed a leaf recognition algorithm using easy-to-extract features and a high efficient recognition algorithm based on Multilayer Perceptron with image and data processing techniques. Overall, these studies demonstrate the potential of automated leaf recognition systems for plant classification and protection, utilizing various approaches and techniques to extract features and improve recognition accuracy.

METHODOLOGY

In order to extract a uniform portion of banana bunches from images, a segmentation technique was employed to isolate the relevant area. This resulted in a grayscale image of the bananas, which was then used to extract various imaging features. These features were extracted both spatially and through the use of the KNN algorithm.

Spatial feature extraction involves analyzing the arrangement and characteristics of the pixels within the image. This can include measurements of texture, color, and shape, among other parameters. These spatial features can then be used to classify and distinguish between different banana varieties or levels of ripeness [8].

Alternatively, the KNN algorithm is a machine learning technique that utilizes a labeled dataset to identify patterns in the data and make predictions about new, unlabeled samples. By training the KNN algorithm on a dataset of banana images with known features and classifications, it can be used to predict the characteristics of new images based on their similarity to the training data [9].

In either case, the extracted imaging features provide a wealth of information that can be used to identify and classify banana bunches. This information can be used to improve the accuracy and efficiency of quality control processes in the fruit industry, helping to ensure that consumers receive high-quality produce.

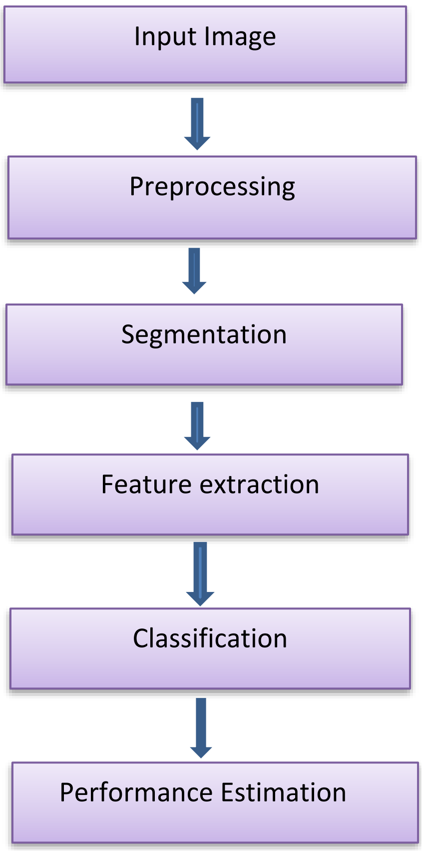

Fig 1 Proposed Methodology

Input Image

The fundamental data structure in MATLAB is the array, which is a collection of ordered real or complex elements. Arrays are particularly well-suited to representing images, which are essentially ordered sets of color or intensity data. Complex-valued images can also be represented using arrays [10].

In MATLAB, images are typically represented as two-dimensional arrays (matrices) in the workspace. In this representation, each element of the matrix corresponds to a single pixel in the displayed image. For instance, an image consisting of 200 rows and 300 columns of differently colored dots would be stored as a 200-by-300 matrix.

In some cases, such as for RGB images, a three-dimensional array is required. In this representation, the first plane in the third dimension represents the red pixel intensities, the second plane represents the green pixel intensities, and the third plane represents the blue pixel intensities. This enables the representation of full-color images in MATLAB, allowing for advanced image processing techniques to be applied to a wide range of real-world image data.

The array-based representation of images in MATLAB provides a powerful and flexible framework for analyzing and manipulating image data, enabling researchers and practitioners to explore and extract insights from image data with great precision and accuracy.

Preprocessing

Image resizing is a common technique used to alter the size and dimensions of an image by adding or removing pixels. This process, known as resampling, is typically accomplished using software and can result in changes to both the width and height of the image. There are several methods for resizing images, including cropping the image to a smaller size or adjusting the number of rows and columns to change the overall dimensions of the image. However, the most common method involves resampling the image by adding or subtracting pixels [11].

When resizing a vector graphic image, such as those created using geometric primitives, the image can be scaled without any loss of image quality by using geometric transformations. However, when resizing a raster graphics image, a new image must be generated with a higher or lower number of pixels. This can result in a loss of image quality, as the software must approximate the new pixel values based on the original image data [12].

Despite the challenges associated with resizing raster graphics images, advances in image processing software have made it possible to achieve high-quality results with minimal distortion or degradation of image quality. As a result, resizing continues to be an important technique for manipulating and enhancing digital images in a variety of applications, from web design to medical imaging and beyond.

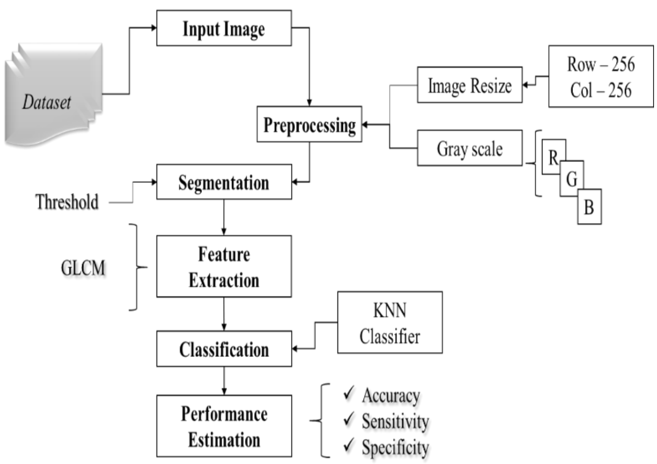

Fig 2 Overall Process of Proposed methodology

Feature extraction (GLCM)

In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image.

According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second-order and higher-order statistics [13].

The Gray Level Co-occurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. GLCM introduced by Haralick. contains information about the positions of pixels having similar gray level values

The basic GLCM algorithm is as follow:

- Count all pairs of pixels in which the first pixel has a value i, and its matching pair displaced from the first pixel by d has a value of j.
- This count is entered in the i^{th} row and j^{th} column of the matrix Pd[i,j]
  Note that Pd[i,j] is not symmetric, since the number of pairs of pixels having gray levels[i,j]does not necessarily equal the number of pixel pairs having gray levels [j,i].
- The elements of Pd[i,j]can be normalized by dividing each entry by the total number of pixel pairs.
  Normalized GLCM N [i,j], defined by

$$N[i,j] = \frac{P[i,j]}{\sum_i \sum_j P[i,j]}$$

Classification

In pattern recognition, the k-nearest neighbors algorithm (k-NN) is a non-parametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression. In k-NN classification, the output is a class membership. An object is classified by a plurality vote of its neighbours, with the object being assigned to the class most common among its k nearest neighbours (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbour. In k-NN regression, the output is the property value for the object. This value is the average of the values of k nearest neighbour. k-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The k-NN algorithm is among the simplest of all machine learning algorithms.

RESULT

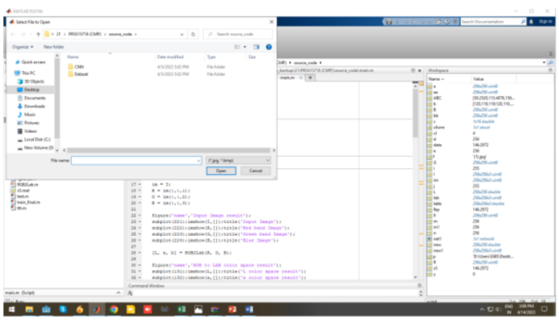

Fig 3 Image Dataset

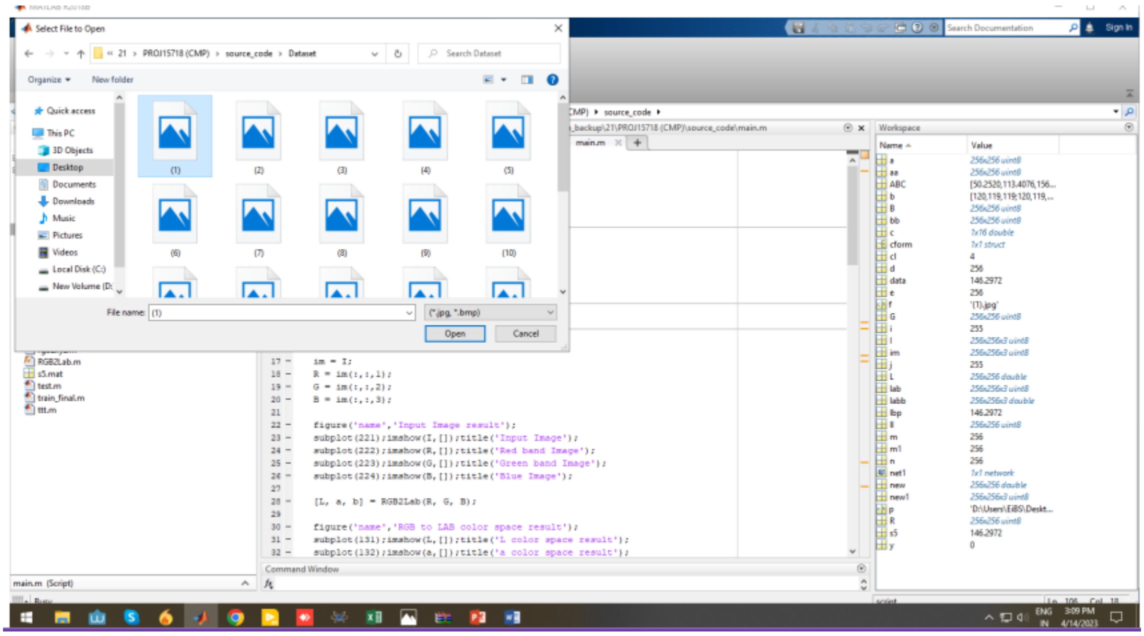

Fig 4 Input Image Selection

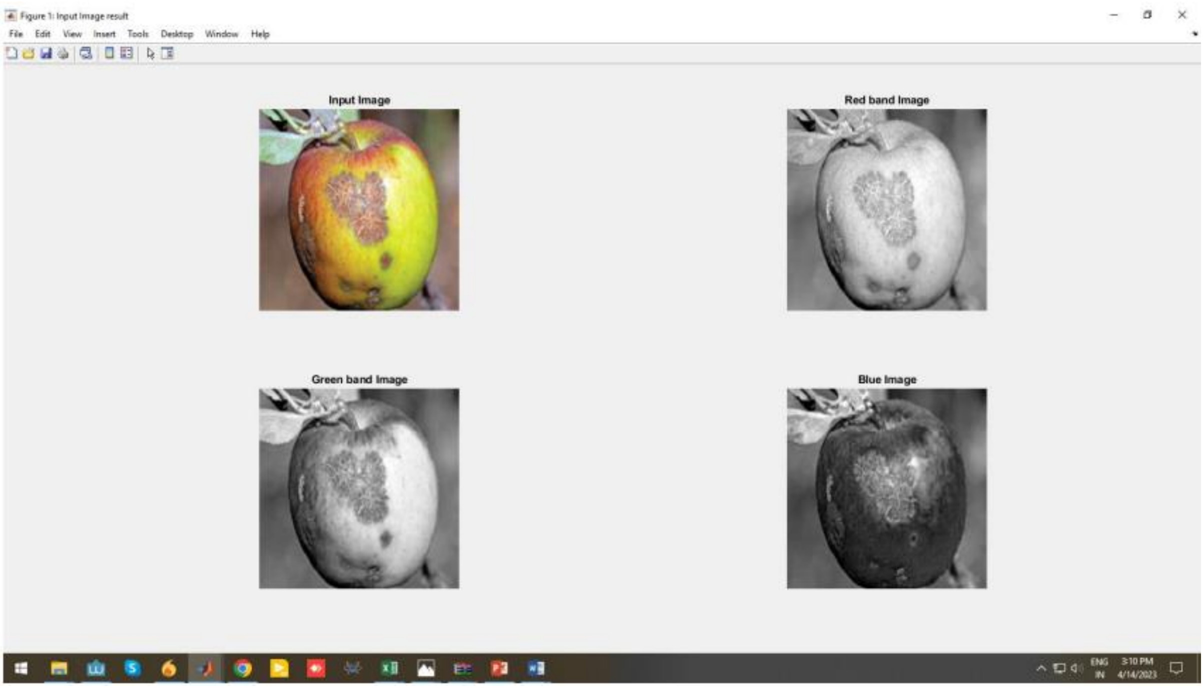

Fig 5 Pre-Processing(1)

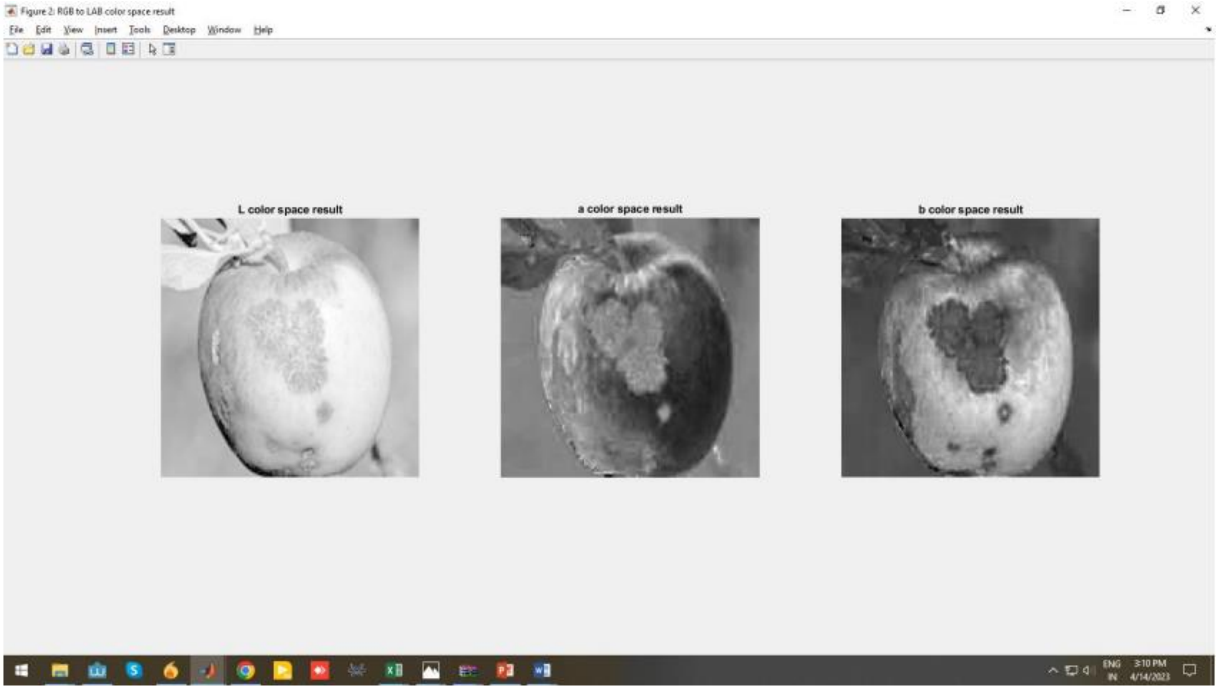

Fig 6 Pre-Processing(2)

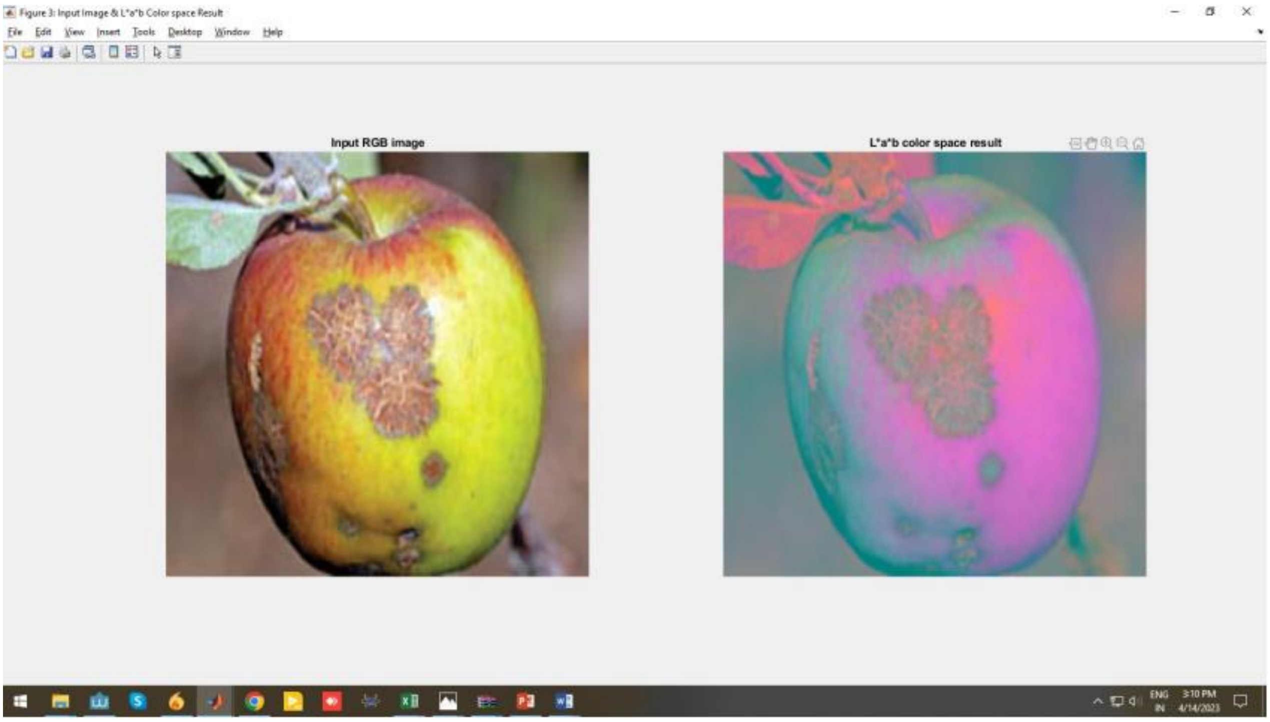

Fig 7 Segmentation-1

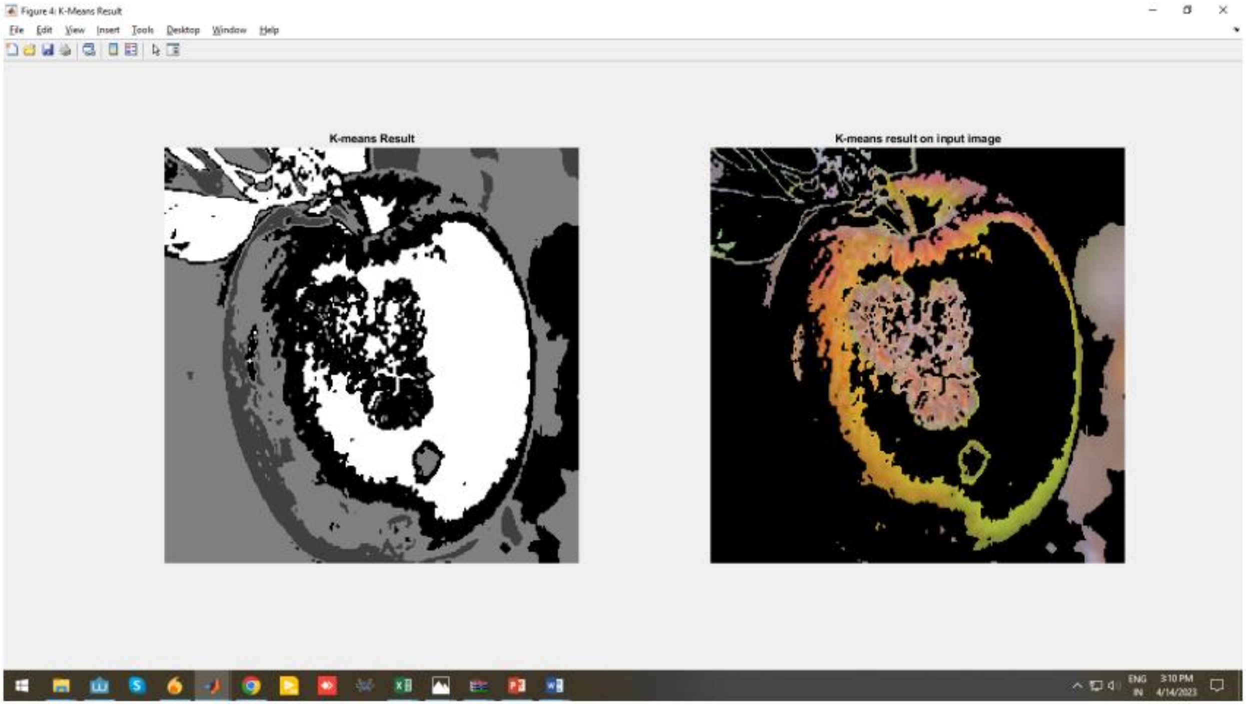

Fig 7 Segmentation-2

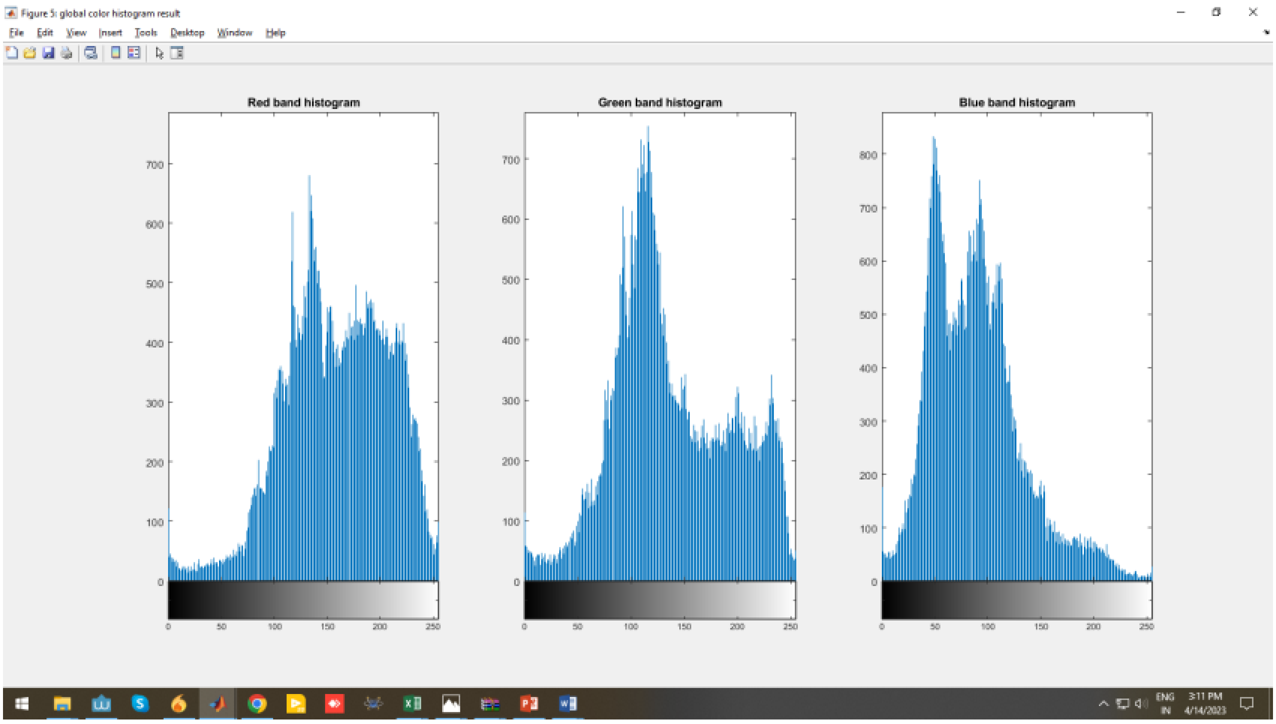

Fig 8 Performance

Fig 9 Identification

CONCLUSION

The proposed method endeavors to create an Android application that is capable of detecting artificially ripened and naturally ripened fruits with high accuracy. The application employs the smartphone camera to capture an image of the fruit, which is then subjected to advanced image processing techniques, specifically histogram analysis. Subsequently, the application employs a threshold-based classification methodology to effectively distinguish between naturally ripened and artificially ripened fruits. This approach leverages the power of cutting-edge technologies and intelligent algorithms to deliver a highly efficient and user-friendly solution for fruit ripeness detection. By accurately identifying the ripeness of fruits, this application has the potential to enhance food safety, reduce waste, and improve the overall quality of produce for consumers.

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