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Machine Learning and Neural Network Approach to Fruit Quality Assessment Using Polarization Features of the Image

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***Abstract*— The project titled "Machine Learning and Neural Network Approach to Fruit Quality Assessment Using Polarization Features of the Image" aims to generate a non-destructive and non-invasive technique for determining the freshness and quality of apples by leveraging image polarization characteristics. Images of apples are captured using a smartphone camera, resized to 256X256 pixels, and cropped to highlight the fruit's edges. These images are then polarized at four specific angles 0°, 45°, 90°, and 135° from which Stokes parameters are computed to extract features like Degree of Linear Polarization (DoLP) and Angle of Polarization (AoP). Following the application of demosaicking to refine color precision, these features are analyzed by a "Radial Basis Function Neural Network (RBFNN)", which is trained to accurately estimate the apple's age with perfect precision based on real-world data. This method facilitates the early identification of apples that might not be fit for consumption before external signs of decay are visible, offering a means to evaluate fruit quality without causing any harm to the fruit and establishing a standardized approach for assessing apple edibility. The technology offers possibilities for use in retail and consumer environments to select fresher apples and in production and quality control settings, with future opportunities for scaling, adapting the approach for other types of fruit, and developing user-friendly applications.**

Keywords*— *"Radial Basis Function Neural Network (RBFNN)", Polarization Features, Degree of Linear Polarization(DoLP), Angle of Polarization(AoP), Mean Square Error (MSE).

I. INTRODUCTION

Effective fruit quality assessment is crucial for producers, retailers, and consumers, influencing key processes such as preservation, processing, packaging, and distribution. Traditional methods for evaluating fruit quality like visual inspection, Brix measurement, and gas chromatography can be complex and sometimes damaging to the fruit. Non-destructive techniques, including acoustic resonance, ultrasonic testing, electronic noses, and optical spectroscopies, are increasingly preferred due to their minimal impact on the fruit sample and cost-efficiency.

Among non-destructive methods, optical techniques utilizing Polarization light have proven particularly effective. Polarization involves examining light that vibrates in a single plane, which can unveil notable aspects of the fruit's structure and quality. This method is advantageous as it avoids causing any harm to the fruit and is straightforward to apply.

The project titled "Machine Learning and Neural Network Approach to Fruit Quality Assessment Using Polarization Features of the Image" focuses on using polarized images to scrutinize the freshness and quality of apples. Apples are photographed with a smartphone camera, and these images are resized to 256x256 pixels. The images are then polarized at angles of 0°, 45°, 90°, and 135°, from which the Degree of Linear Polarization (DoLP) and Angle of Polarization (AoP) are derived. These polarization features are essential for assessing the fruit's condition as they indicate changes in its external and internal properties over time. To improve image accuracy, demosaicking is applied, and the extracted polarization data are interpreted through various neural network algorithms. The aim is to discover which model delivers the most accurate forecast for the apple's age with high precision. As apples mature, their surface texture, color, and polarization attributes change, which can be leveraged to assess their freshness and ripeness. This model provides a way to identify apples that are nearing the endpoint of their edible period before any visible spoilage occurs. It enhances sorting and grading processes by offering a reliable, non-destructive method to evaluate fruit quality based on polarization features. This approach helps in quality assurance, reducing waste, and ensuring consumers receive fresh fruit. Future enhancements may involve expanding the technology intended for other fruits, calibrating Machine Learning algorithms for better accuracy, and integrating the system into broader quality management practices. This project represents a significant advancement in non-invasive fruit quality assessment, combining optical polarization techniques with Machine Learning to improve fruit quality management.

II. METHODOLOGY

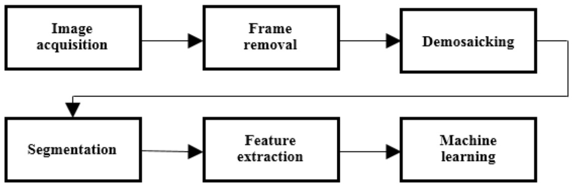


Fig.1Block diagram of proposed methodology

The block diagram for the fruit quality assessment system illustrates the process from image acquisition to Machine Learning, encompassing stages such as frame extraction, demosaicking, segmentation, feature extraction, and Machine Learning algorithms.

a. Image acquisition

The system starts with an image of an apple, captured with a smartphone camera as depicted in Fig. 2(a) The image may contain one or more apples. To ensure clear boundary detection for segmentation, avoiding overlapping of apples over one another is important. Fig. 2(b) demonstrates how multiple apples can be captured in one frame.

Fig.2(a) Image acquisition   Fig. 2(b) Input image data

b. Frame removal

To standardize the image and prepare it for segmentation and further processing, the frame surrounding the object (in this case, the fruit) is removed, as shown below. The cropped image is then converted from RGB to gray.

Fig.3(a) Frame Removal

Fig.3(b) RGB to gray conversion

c. Demosaicking

Demosaicking transforms unprocessed sensor inputs into full-colour images by reconstructing RGB values from a Bayer-filtered sensor. It uses interpolation methods like bilinear and advanced algorithms (e.g., AHDD) to estimate missing colours and ensure accurate, high-quality images. This process is crucial for achieving clear and precise colour representation in various imaging applications.

Fig.4(a) shows the demosaicking process. The image after the demosaicking process is depicted in Fig.4(b).

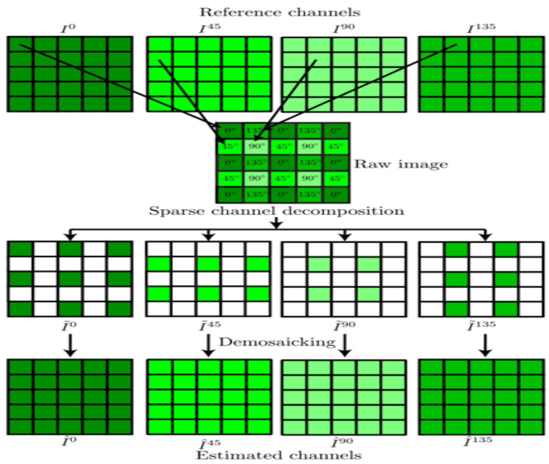


Fig.4(a) Demosaickig process

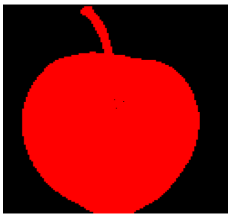


Fig.4(b) Demosaicked image

d. Segmentation

After demosaicking, the image is segmented using Otsu's method, which involves analyzing the histogram and selecting a threshold to classify pixels as either foreground or background. This process generates a binary image where pixels below the threshold are set to black (representing the background) and those above are set to white (representing the foreground). The Region of Interest (ROI) is then defined within this binary image, with pixels marked as Zero (0) for the background and One (1) for the foreground, thereby highlighting the object's Region of Interest(ROI).

Fig.5 (a) Segmented image

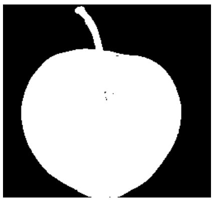


Fig.5 (b)Object's Region of Interest(ROI).

e. Feature extraction

The polarization state of light is characterized using Stokes parameters, four parameters that illustrate how light waves oscillate in different directions. Introduced by Sir George Gabriel Stokes in the 19th century, these parameters are fundamental in optics and polarimetry. They are commonly denoted as (*I, Q, U, V*), where:
I = Intensity or total intensity, *Q* and *U* = These parameters describe linear polarization, *V* = Circular Polarization.
The Stokes parameters are derived mathematically using the four full-resolution intensity images as follows:

$$S_0 = I_0 + I_{90} \quad (1)$$

$$S_1 = I_0 - I_{90} \quad (2)$$

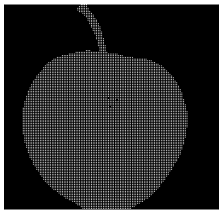
$$S_2 = I_{45} - I_{135} \quad (3)$$

$$S_3 = I_{RCP} - I_{LCP} \quad (4)$$

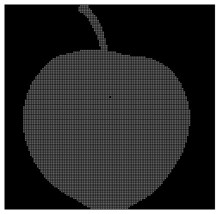
Degree of Linear Polarization (DoLP) and Angle of Polarization (AoP) are fundamental terminology employed in the analysis of polarized light, especially in fields like optics, remote sensing, and machine vision that are fed as source data to the Machine Learning model.

$$DoLP = \sqrt{\frac{S_1^2 + S_2^2}{S_0^2}} \quad (5)$$

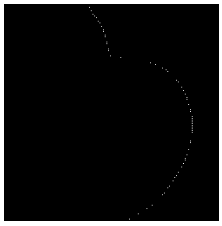
$$AoP = \frac{1}{2}atan(\frac{S_2}{S_1}) \quad (6)$$



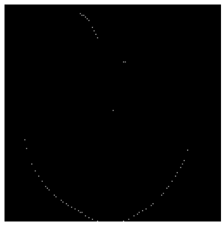
(a)



(b)



(c)



(d)

Fig.6 Polarized images: (a)0-degree polarized image; (b) 45-degree polarized image; (c)90-degree polarized image; (d)135-degree polarized image.

f. Machine Learning

Machine learning, a subset of Artificial Intelligence, revolves around formulating algorithms that are able to learn from data and make decisions or predictions. In our project, the goal is to determine the function *f(DoLP,AoP)*, which predicts the age of an apple in terms of days. The process involves two main phases within the Machine Learning model: The Training phase and the Testing phase, as illustrated in Fig.7(a) and 7(b) respectively.

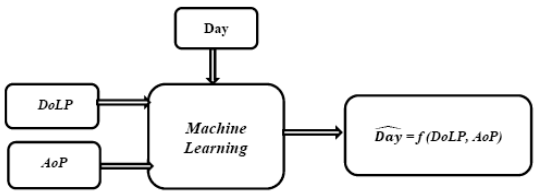


Fig.7(a)Machine LearningTraining phase

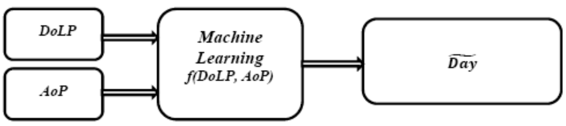


Fig.7(b)Machine LearningTesting phase

Training phase:

In the training phase, we use a "Radial Basis Function Neural Network (RBFNN)" to predict the age of apples derived from their polarization features: Degree of Linear Polarization (DoLP) and Angle of Polarization (AoP). The process begins by extracting these features from segmented grayscale images and forming feature vectors paired with age labels. The RBFNN, which employs Gaussian functions in its hidden layer, adjusts parameters like centres and spreads through clustering algorithms. During training, supervised learning approaches like backpropagation are served to optimize the network's weights. The dataset is divided into 80% for training and 20% for testing to assess the model's performance.

Testing Phase:

After training with the "Radial Basis Function Neural Network (RBFNN)", 20% of the dataset is reserved for testing to evaluate the model's accuracy and effectiveness. The process starts with a user selecting a JPEG image of a fruit, which is resized to 256x256 pixels and converted to grayscale. Boundary detection is performed using convolution to identify significant intensity changes, aiding in isolating the fruit by removing the frame. Otsu's method helps to binarize the grayscale image, creating a mask that marks the fruit as the Region of Interest (ROI). Polarization features, including Degree of Linear Polarization (DoLP) and Angle of Polarization (AoP), are calculated for four polarization angles (0°, 45°, 90°, 135°) within the ROI. These features are consolidated into vectors representing the fruit's quality characteristics. The pre-trained RBFNN then uses these vectors to estimate the fruit's quality index. This automated approach provides a standardized method for assessing fruit quality, improving efficiency and accuracy in agriculture, food processing, and retail.

III. RESULTS AND DISCUSSION

This study investigates the ripening and rotting process of apples over a 12-day period to assess their quality. The experimental procedure involves capturing an aggregate of 120 images from day 3 to day 14, with images featuring both individual and multiple apples to avoid overlap and aid in boundary detection. The dataset is split into training (80%) and testing (20%) sets, with the division being randomized each time the script is executed. A "Radial Basis Function Neural Network (RBFNN)" is utilized for training, with the count of neurons and epochs dynamically determined based on data complexity to reduce the Mean Square Error (MSE). Model performance is evaluated using the testing set, with accuracy measured by MSE, where reduced MSE reflects improved model accuracy. The approach ensures robust assessment of apple quality, and additional validation methods and comprehensive metrics are recommended to further refine model performance and reliability.

The model's effectiveness concerning to the complexity of the dataset and the count of neurons is demonstrated in the Table No. 1.

Magnitude of dataset (Collection of images)	Mean Square Error (MSE) for 0 neurons	Mean Square Error (MSE) for 50 neurons	Mean Square Error (MSE) for 100 neurons
30	0.120687	0.00171437	-
40	0.106018	0.00109761	-
50	0.106689	0.00186583	-
60	0.109131	0.00316152	-
70	0.107457	0.00660079	-
80	0.109131	0.00221992	-
90	0.09	0.0204681	-
100	0.0897812	0.0101958	-
110	0.0826446	0.0216004	0.000402284
120	0.0763889	0.023877	0.00207395

Table No.1 Proficiency of the model

In the "Radial Basis Function Neural Network (RBFNN)", the program script does not explicitly set the count of neurons in the hidden layer. Instead, 'newrb' function automatically determines this number by the image data's complexity. The 'newrb' function employs the K-means clustering algorithm to adjust the neuron count in response to the distribution of the training data, aiming to minimize the Mean Square Error (MSE). As illustrated in Table No. 1, datasets with 30 to 100 images use between 0 and 50 neurons, while datasets with 110 or 120 images require over 100 neurons. This increase in neuron count generally results in a lower MSE, enhancing the model's accuracy and reliability.

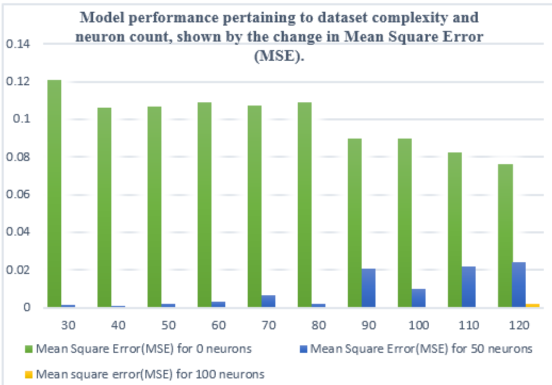


Fig.8 Model performance concerning dataset complexity and neuron count, shown by the change in Mean Square Error (MSE).

The performance graph displayed in Fig.8 visualizes the data from Table No. 1, demonstrating how the Mean Square Error (MSE) varies with data complexity and the count of neurons. This graph aids in the interpretation of how changes in neuron count and dataset complexity impact the model's accuracy.

To evaluate the efficiency of the configured model, the dataset is initially trained using a “Radial Basis Function Neural Network (RBFNN)”, which employs a single hidden layer, as the network architecture inherently consists of only one hidden layer. After training, a confusion matrix is generated to assess performance. The classification error is computed from this matrix, and precision is derived from the error, which determines the model's accuracy and reliability.

A confusion matrix is a tabular representation which evaluates the performance of a classification model. In our project, which classifies these fruits on the basis of their age in days, the confusion matrix is derived to handle 12 classes, one class designated for each of the day from day 3 to day 14. Each row of the matrix represents an actual class, with rows corresponding to the days on which the images were captured—day 3 images are in the first row, day 4 images in the second row, up to day 14 in the 12th row. Each column represents a predicted class, with columns corresponding to the days predicted by the model—column 1 for predicted day 3, column 2 for predicted day 4, and till the column 12 for predicted day 14. This setup enables us to compare the actual and predicted classifications to assess the model's accuracy.

The confusion matrix stemmed after training the model with the “Radial Basis Function Neural Network (RBFNN)” is:

$$\begin{bmatrix} 10 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 10 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 10 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 10 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 10 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 10 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 10 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 10 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 10 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 10 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 10 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 10 \end{bmatrix}$$

In this confusion matrix, all the diagonal entries are 10(10 images in each class) and all non-diagonal entries are zero. Indicating that each class from 1 through 12 is correctly classified 10 times and no image in this dataset is misclassified. Hence the classification error for the above confusion matrix is zero.

Classification error = 0

Performance of RBFNN (%) = (1- Classification error) *100

= 100%

Performance of RBFNN: 100.00%

The “Radial Basis Function Neural Network (RBFNN)” achieves correct classification for the real time dataset with an accuracy of 100%.

IV. CONCLUSION

This project aims to establish a non-invasive and non-destructive method for assessing apple fruit quality by extracting polarized features such as Degree of Linear Polarization (DoLP) and Angle of Polarization (AoP) from images taken with a smartphone camera. These polarized image features are applied to a Machine Learning model trained over a “Radial Basis Function Neural Network (RBFNN)” to predict the apples' age over time. Tests with real data indicate that this method is capable of predicting apple age with 100% accuracy, enabling the identification of apples that are no longer suitable for consumption before visible signs of rot appear. The goal is to standardize a reliable, non-invasive solution for determining the edibility of apples.

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