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Deep Learning-Based Non-Invasive Approach to Grade Multi-Spectral Images of Apples Based on Sweetness

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Abstract: This abstract introduces a research project to develop an affordable solution for grading apple fruit using non-invasive multi-spectral imaging. The study investigates the potential correlation between sugar content and multi-spectral images obtained from the non-invasive imaging chamber. Using a handheld refractometer, the sugar content of apple samples is determined, and then the corresponding multi-spectral image of the apple fruit is analyzed. This research aims to uncover insights into the feasibility of estimating sugar content using non-invasive techniques. The research methodology entails the construction of a prototype multi-spectral imaging chamber, acquiring a diverse set of apple samples, capturing multi-spectral images, and applying advanced image processing techniques to analyze the images. With the help of the refractometer, the apple fruit will be evaluated to quantify the apple samples' sugar content. Correlation studies will scrutinize the relationship between the processed multi-spectral images and the measurements of sugar content. Anticipated outcomes involve developing a functional grading system based on non-invasive multi-spectral imaging and insights into the potential correlation between sugar content and spectral characteristics. AppleNet uses convolutional neural networks using Matlab, and the images are processed via AppleNet to achieve an accuracy of 65 %. To sum up, this research project aims to propose a cost-effective solution for grading apple fruit through non-invasive multi-spectral imaging and to explore the correlation between sugar content and multi-spectral images. The findings of this study could enhance quality control measures and improve efficiency in the apple industry, ultimately benefiting fruit producers, distributors, and consumers.

Keywords: *Multi-spectral imaging, Non-invasive, Apple fruit, AppleNet, Convolutional Neural Network, Grading, Sweetness, Deep learning*

1. Introduction

Multi-spectral imaging refers to capturing images at different wavelengths spanning the electromagnetic spectrum. This encompasses the visible range (400-700 nm) and extends to wavelengths beyond, including infrared and ultraviolet. The emergence of light-emitting diodes (LEDs) capable of emitting diverse colors, such as red, green, and blue (RGB), has significantly contributed to the widespread adoption and progress in multi-spectral imaging.

Multi-spectral imaging allows for extracting valuable information to classify and evaluate the quality of fruits and vegetables. This capability empowers exporters to ensure the shipment of high-quality fruit products, bolstering a country's reputation as a dependable exporter. Furthermore, exploring multi-spectral imaging within fruits and vegetables holds promise for disease prohibition/avoidance, irrigation management, and enhanced yield.

Moreover, multi-spectral data is the foundation for analyzing various characteristics and factors of fruit, vegetable, and tree species, fostering further exploration in these domains. The main objective of this paper is to investigate any potential correlation between the sugar content of apple fruit and the multi-spectral images obtained from the imaging chamber.

Figure 1 illustrates the configuration of multi-spectral imaging. A light source emitting various wavelengths, covering both visible and non-visible spectra, passes across a multi-spectral filtered disk to create specific wavelengths of light. A fruit specimen, such as an apple, is exposed to a particular wavelength, and a camera records a photo of the specimen. The multi-spectral filter disk is then rotated to capture images in other colors. A computer uses a Convolutional Neural Network Algorithm to process the multi-spectral image to determine the fruit's grading. Notably, the camera lacks an infrared filter to monitor all wavelengths of light. This project uses five types of apples: Red Delicious USA, Royal Gala, Red Delicious New Zealand, Washington, and Kinnaur. First, the apple juice is taken from all five apples, and then, by using a refractometer, the sugar content is noted for each of the four apples of one category. The Lookup table shows the sugar content reading in % brix. After using the Multispectral chamber, the multispectral image of apples of all five categories is captured. Then, the multi-spectral images of apples are concatenated. These concatenated images are processed through AppleNet using the convolutional neural

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network algorithm. After processing the images through AppleNet, the accuracy achieved is 65 %.

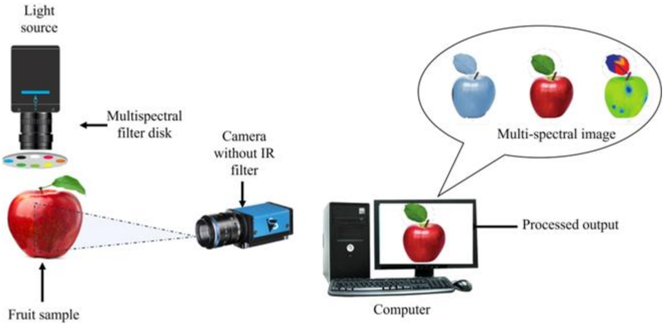

Fig. 1. Setup of multi-spectral imaging

2. Literature Review

The evaluation of fruit quality holds significant importance from the perspective of consumers. While human experts can traditionally inspect fruit quality, manual sorting through visual examination proves to be labor-intensive, slow, inconsistent, and prone to errors [1]. The introduction of multi-spectral imaging techniques has enabled the automation of the grading process, thereby reducing labor costs and enhancing the efficiency and accuracy of classifying. Fruit quality encompasses both internal and external attributes. Internal fruit quality comprises aroma, taste, texture, firmness of the fruit skin, presence of diseases, and organic residues [2]. It also encompasses nutritional quality, including sugar content, titratable acidity (TA), starch, pH, organic acids, and total soluble solids (TSS) value, among others [3]. External fruit quality is influenced by size, color, shape, and bruises on the fruit skin [4]. The critical features for evaluating fruit quality include ripeness and skin flaws. Internal factors, ripeness, and yield must be evaluated to assess fruit quality. Utilizing an automated fruit and vegetable grading technique can benefit farmers and consumers by ensuring the availability of high-quality fruits in the market. This technological advancement streamlines the grading process and contributes to delivering superior products to consumers. Bin Yan et al. (2021) introduced a lightweight apple target detection technique designed for a picking robot to automatically identify graspable and ungraspable apples in an apple tree image using an improved version of YOLOv5s [5]. The proposed approach involved several modifications to the original YOLOv5s network. First, the existing BottleneckCSP module was enhanced and transformed into the BottleneckCSP-2 module, replacing the original YOLOv5s network's backbone structure. Additionally, the SE module, part of the visual observation technique network, was incorporated into the enhanced backbone network. The feature maps bonding fusion mode and feed into the target detection layer of medium dimension in the original YOLOv5s network were also enhanced. Lastly, the initial anchor box dimensions of the original network were enhanced. Test outcomes demonstrated the effectiveness of the proposed enhanced network model in recognizing graspable apples, including those that were unblocked or only partially blocked by tree leaves, as well as ungraspable apples that were blocked by tree branches or obscured by other fruits. The study utilized a dataset of 1214 apple images, encompassing various scenarios such as apples blocked by leaves and branches, diverse occlusion, overlapping apples, different natural light angles, rear illumination angles, and side illumination angles. The recognition results achieved using the improved YOLOv5s network were as follows: a total recall of 91.48 %, precision of 83.83 %, mean average precision (mAP) of 86.75 %, and F1 score of 87.49 %. The mean detection speed was 0.015 seconds per photo. Chunxiao Tang et al. (2018) devised a multiple linear regression model to estimate the sugar level of Fuji apples by utilizing multispectral imaging [6]. Visible/near-infrared (NIR) spectroscopy spanning a wavelength range of 350-1200 nm was employed to optimize the multispectral imaging system and select the most suitable wavelengths. The spectral information was evaluated using backward interval partial least squares, identifying a section comprising various sensitive wavelengths. Through step-wise multiple linear regression, four optimal wavelengths (461 nm, 469 nm, 947 nm, and 1049 nm) were chosen from this section. Based on these effective wavelengths, a multispectral imaging technique was developed. The scattering region of the multispectral photos was extracted by analyzing the image histogram and camera response function. Subsequently, the scattering outlines were obtained by performing radial averaging on the selected scattering regions. The revised Lorentzian distribution function was employed to match the scattering profiles, and the factors of the Lorentzian functions served as the dataset for multiple linear regression to construct the prediction prototype. The multiple linear regression prototype exhibited a strong correlation between the predicted sugar content and the actual values, with a correlation coefficient (r) of 0.8861. The Root Mean Square Error of Calibration (RMSE) was found to be 0.8738°Brix, indicating the accuracy of the prediction prototype. Jin Wang et al. (2022) proposed an automated method for grading and quality detection of "Red Fuji" apples [7]. By leveraging image processing and machine vision techniques, grading models for apple flaws, shape, and dimension were developed. Classifier thresholds were selected to determine the aspect ratio (λ), defective pixel ratio (t), and cross-sectional diameter (Wp) of the apple photo. Spectral data of the apples within the wavelength limit of 400 nm to 1000 nm was taken. The collected spectral reflectance information underwent multiple scattering correction (MSC) and standard normal variable (SNV) alteration techniques. The competitive adaptive re-weighted sampling (CARS) algorithm and successive projections algorithm (SPA) were utilized to capture specific wavelength points containing Brix information. The CARS-PLS (partial least squares) algorithm established a Brix prediction standard. The grading factors were combined, including apple flaws, shape, size, and Brix. A medium for online classification detection of apple quality was developed, along with a complete classification detection algorithm and computer software. The results demonstrated high accuracy in apple flaw, shape, and dimension grading detection, with average accuracies of 96.67 %, 95.00 %, and 94.67 %, respectively. The accuracy for grading apple flaws, shape, size, and Brix was 96.67 %, indicating the feasibility of the detection technique for classifying" Red Fuji" apples in Luochuan. Khodabakhshian et al. (2016) proposed a multi-spectral imaging technique for assessing the quality of pomegranate fruits [8]. Visible/NIR spectroscopy in the 400–1100 nm limit was employed to determine the Total Soluble Solids (TSS) level, pH, and titratable acidity (TA) value. The results of the multi-spectral imaging technique were evaluated using a multiple linear regression design. The obtained TSS exhibited a high correlation coefficient (r) value of 0.97, a Ratio Performance Deviation (RPD) of 6.7, and a Root Mean Square Error of calibration (RMSEC) of 0.21 or Brix. The findings demonstrated accurate prediction of pH and TA using the developed models. Lianou et al. (2019) presented an online feature selection classification method for investigating the quality of vanilla cream using a multi-spectral photo technique [9]. The dataset comprised 245 spectra of cream samples. The study inspected two micro-biological quality classes: fresh samples with total viable counts (TVC) 2 CFU/g (Colony Forming Units per gram) and spoiled samples with TVC 6 CFU/g. The overall classification accuracy for model validation of the two classes reached 91.7 %. Liu et al. (2014) investigated a multi-spectral imaging technique for determining strawberry fruits' quality factors and ripeness phases [10]. A total of 210 fruits were considered in the study. The results showed that the Back Propagation Neural Network (BPNN) model outperformed the Partial Least Squares (PLS) and Support Vector Machine (SVM) models in predicting firmness and Total Soluble Solid (TSS) content using multi-spectral imaging. The SVM model achieved a perfect classification accuracy of 100 % for fruit maturity stage classification. Santoyo et al. (2019) proposed a method for estimating the ripeness of bananas using a multi-spectral photo technique [11]. Using the Hotelling transform, the technique accurately identified brown marks on the banana peel. Visible optical filters in the range of 410-690 nm and NIR filters in the limit of 820-910 nm were employed. Texture homogeneity criteria were used to monitor the development of brown spots during the ripening operation through the fusion of spectral images. Lohumi et al. (2021) designed a real-time method for identifying foreign materials (FMs) jumbled with fresh-cut vegetables using fluorescence and color photo techniques [12]. The design included a multi-spectral fluorescence imager and a Liquid Crystal Tunable Filter (LCTF) to catch desired band photos of fresh-cut vegetables sequentially. The average detection accuracy of FMs in cabbage and green onion specimens was evaluated, and the overall detection accuracy exceeded 95 % in four repetitions. The developed real-time detection method was further experimented in an industrial surrounding, demonstrating comparable performance. Naeem et al. (2021) utilized a multi-spectral photo technique, texture feature extraction, and a Multi-Layer Perceptron (MLP) grader to classify medicinal plant leaves using five wavelength bands ranging from 460 nm to 1560 nm [13]. The study considered six medicinal plant leaves. The grading accuracies achieved were as follows: Tulsi (99.10 %), peppermint (99.80 %), Bael (98.40 %), lemon balm (99.90 %), catnip (98.40 %), and Stevia (99.20 %) using the multi-layer perceptron grader. The MLP method demonstrated a high accuracy of 99.01 % compared to other methods employed in the study. Liu et al. (2016) employed a fusion of multi-spectral photo technique and chemometric information to determine the varieties of rice seeds [10] non-invasively. The investigation involved multi-spectral imaging techniques to differentiate rice seeds based on their varieties. Morphological and spectral characteristics were extracted from the multi-spectral photo data. Various chemometric techniques, including Partial Least Squares Discriminant Analysis (PLS-DA), Least Squares-Support Vector Machine (LS-SVM) prototypes, and Principal Component Analysis-Back Propagation Neural Network (PCA-BPNN), were utilized. The discrimination performance of these methods was evaluated to categorize the rice seeds into five different classes. The spectral information compassed various features of the rice seeds. Finally, the spectral and morphological data were merged, and the discrimination results were assessed. Differences in the varieties of rice seeds were observed, and they could be successfully classified based on their variety. The LS-SVM prototype achieved a classification accuracy of up to 94 %, PLS-DA achieved 62 %, and PCA-BPNN achieved 84 %.

3. Methodology

The proposed algorithm, named AppleNet, adopts a Convolutional Neural Network (CNN) architecture, illustrated in Figure 2. The main aim of this algorithm is to tailor CNN for multi-spectral images, departing from the conventional focus on RGB images found in existing networks such as AlexNet, GoogleNet, VGG, and DenseNet, which primarily emphasize object detection within RGB images.

CNNs consist of multiple layers designed to process and extract features from input data. The CNN AppleNet architecture encompasses the following layers:

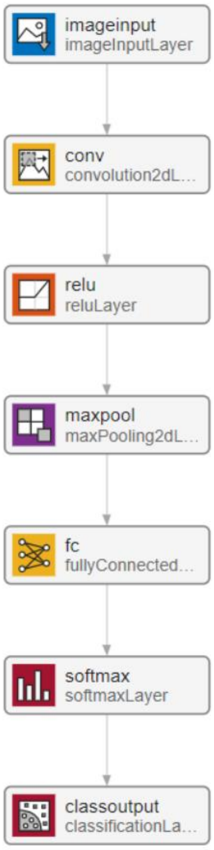

Fig. 2. Proposed network of AppleNet

Image Input Layer: The AppleNet model employs an input layer to receive RGB images with dimensions of 128 × 128 × 3 pixels.

Convolution Layer: The CNN incorporates convolutional layers with multiple filters for convolution operations [14]. The input data, presented as a 3D array, undergoes convolution using a 5x5 filter.

Rectified Linear Unit (ReLU) Layer: CNNs typically include ReLU layers to apply element-wise operations, resulting in rectified feature maps [15]. These rectified feature maps are then forwarded to the pooling layer.

Pooling Layer: This layer conducts down-sampling operations to reduce the size of the feature maps [16]. The pooling operation involves flattening the resulting 2D arrays from the pooled feature maps into a single, long, continuous, linear vector.

Max Pooling Layer: The max pooling layer diminishes image dimensionality by selecting the maximum valued element within each region the filter captures across different feature maps [17]. This process further reduces the number of pixels in the output compared to the preceding convolutional layer.

Fully Connected Layer: Following the pooling layer, the flattened matrix serves as input to a fully connected layer, which is responsible for classifying and identifying the images. The output of the max pooling layer is connected to this fully connected layer, which comprises three output layers for image classification and identification [18].

Softmax Layer: The Softmax layer allocates decimal probabilities to each class in a multi-class problem, ensuring the probabilities sum up to 1.0 [19]. This additional constraint aids in expediting training convergence. The Softmax layer is typically implemented as a neural network layer preceding the final output layer.

Final Classification Layer: Affixed after the Softmax layer and Fully Connected layer, this layer categorizes the given images into one of the four output classes of apples: Class 10, Class 12, Class 13, and Class 15. It is the concluding stage of the neural network's classification process [20].

4. Hardware setup

Figure 3 shows the design and constituent elements of the Multispectral Imaging Chamber. The experimental setup for capturing the Multispectral image of the Apple Fruit is depicted in Figure 4, while Figure 5 offers an overview of the diverse components composing the Multispectral Imaging Chamber.

The hardware configuration encompasses the following components:

1. Logitech Digital HD Portable 1080p Webcam C615 with Autofocus – cost of which is 3300 Rs.
2. RGB LED Soft Ring Light MJ26 has eight wavelengths, costing 800 Rs.
3. Wooden Enclosure with a door (dimensions: 30×45×45 cm) – cost of 3500 Rs.
4. A computer for processing.

These components constitute the essential elements of the hardware setup, contributing to the practical functionality of the Multispectral Imaging Chamber.

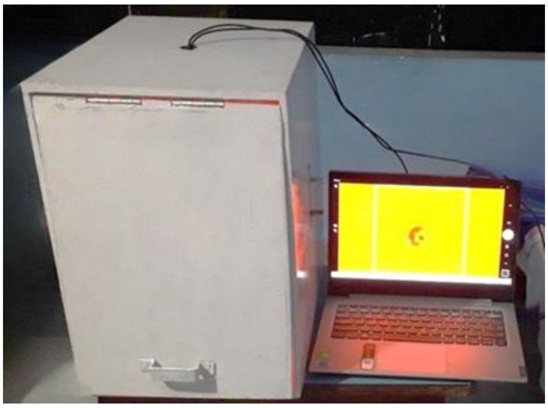

Fig. 3. Multi-spectral Imaging Chamber.

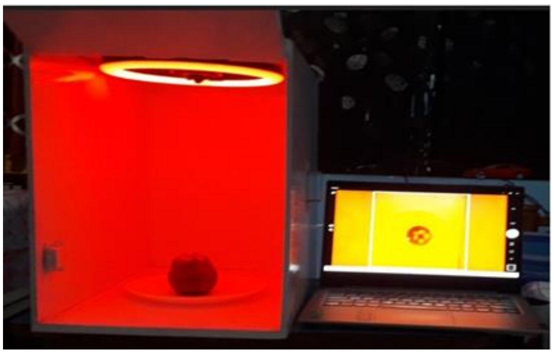

Fig. 4. Experimental setup for capturing the Multi-Spectral image of Apple fruit.

Fig. 5. Components of Multi-spectral Imaging Chamber (RGB LED Ring, USB Camera, Wooden Enclosure with Door).

4.1. Multi-spectral imaging Chamber

To carry out the imaging procedure, follow the steps outlined below:

1. Place the apple fruit on a plate or inside the chamber. 2. The chamber has an LED Ring on the top, and a webcam is affixed to the fixed top plate. 3. Perform each imaging session at least three times.4. Position the apple within the chamber, ensuring it stays stable and stationary. 5. During imaging, make sure the fruit remains still. 6. Securely close the chamber to create an airtight and light-tight environment. 7. Connect the two USB ports from the chamber to your computer—one for the camera and the other for internal lighting.8. Power on the LED Ring to initiate illumination inside the chamber. 9. Press the color change button to adjust the color and capture the image. 10. open the camera application on your computer by pressing the Windows button. The screen will appear black due to the darkness inside the chamber. 11. Take the first photograph to start the imaging sequence. 12. Press the power button to activate the white light exposure after capturing the initial black image. This allows you to see the fruit inside the chamber. 13. Capture the first image, then change the RGB button to modify the color and capture the second image. 14. Repeat this process eight times, ensuring each color change stabilizes before capturing the image. 15. When you reach the last image, the red color will reappear, signifying the endpoint of the sequence. 16. The process outlined above pertains to the automatic mode. For manual mode, turn off the power between each image capture. 17. In subsequent images, turn off the power, click to capture the following image, then turn on the power for the following image. 18. Repeat the process for nine images, including eight color shades and one black image. 19. Each fruit should be examined in at least three orientations—horizontally, vertically, and lying down. 20. Repeat the entire procedure thrice to account for potential noise or miscalculations.

After completing the imaging sessions, verify that the thumbnail and main images correspond accurately. You should have 27 photos in the designated folder, consisting of three sets, each containing nine. The red color indicates the fourth image and serves as the stopping point. Review the folder to ensure no photos were missed.

Upon completion, remove the apple from the chamber, considering the minimum of three orientations, as earlier mentioned. It is crucial to repeat the process three times to minimize errors caused by noise.

4.2. Concatenation of Multi-spectral Image of Apple Fruit

To concatenate the multispectral images of the apple fruit using MATLAB, follow the steps outlined below. Begin by creating a folder named "Merger" in MATLAB and arranging all nine images in sequential order within this folder. Select all the images by pressing Ctrl+A, then right-click on the first image and rename it "a(1)". The subsequent images will be automatically renamed as "a(2)", "a(3)", "a(4)", "a(5)", "a(6)", "a(7)", "a(8)", and "a(9)".

Afterward, utilize the provided MATLAB code to read the images "a(1)" to "a(9)" and assign them to variables "i" through "i8," respectively, ensuring the correct path to the "Merger" folder is specified. Subsequently, concatenate all the images from "i" to "i8" and store the result in the variable "i9" using the MATLAB code provided. Lastly, display the concatenated image "i9" using MATLAB's "show" command. This process facilitates the concatenation of all the photos in MATLAB, culminating in the visual presentation of the final concatenated image. Figures 6 (a), (b), and (c) showcase the concatenated images of Red Delicious USA, Royal Gala, and Washington Apple, respectively.

(a)

(b)

(c)

Fig. 6. Concatenated image of (a) Red Delicious USA Apple, (b) Royal Gala Apple, and (c) Washington Apple.

4.3. Dataset Preparation

The goal is to create an extensive dataset consisting of 81 multispectral images for each type of fruit, focusing specifically on apples. Eight specific wavelengths will be selected, and 27 photos will be taken for each fruit, including a black reference image, across the specified wavelengths. As a result, the dataset will consist of 81 images for an individual fruit, covering eight unique wavelengths. A spectrometer will be employed for manual measurement to evaluate the sweetness of each fruit, and the fruits will be classified according to established grading methodologies. For grading by sweetness, the following five types of apples were considered: Red Delicious USA, Royal Gala, Red Delicious New Zealand, Washington, and Kinnaur.

4.4. Refractometer

The handheld refractometer, as shown in Figure 7, is easy to use; it will read apple juice sweetness in % brix. First, cut the apple into 5 or 6 pieces and take the apple juice using a mixer. Then, sieve the apple juice with the help of Silver and pour it into a glass. Then, using a dropper, put one or two drops of the apple juice on the prism and close the flap. After this, hold the refractometer toward the light to read the apple sweetness through the eyepiece accurately.

Fig. 7. Refractometer

After repeating the above procedure for all five types of apples, the Lookup table for sugar content in apples is obtained, as shown in Table 1.

Table 1. Sugar Content Measurement in % Brix for Different Types of Apples.

Sr. No	Name of the Apple	Apple	Sugar Content (% Brix)
1	Kinnaur Apple	Apple 1	10
2	Kinnaur Apple	Apple 2	10
3	Kinnaur Apple	Apple 3	15
4	Kinnaur Apple	Apple 4	12.5
5	Red Delicious NZ	Apple 1	12.8
6	Red Delicious NZ	Apple 2	13.8
7	Red Delicious NZ	Apple 3	12.1
8	Red Delicious NZ	Apple 4	10
9	Red Delicious USA	Apple 1	10
10	Red Delicious USA	Apple 2	12
11	Red Delicious USA	Apple 3	10
12	Red Delicious USA	Apple 4	10
13	Royal Gala	Apple 1	10
14	Royal Gala	Apple 2	12
15	Royal Gala	Apple 3	13
16	Royal Gala	Apple 4	13
17	Washington Apple	Apple 1	10
18	Washington Apple	Apple 2	12.5
19	Washington Apple	Apple 3	10
20	Washington Apple	Apple 4	10

5. Results and Discussion

To get the results, first, make the Sweetness folder, which consists of the readings of the sugar content of apples. In our case, we have to make four folders and then put the images of the apples with that particular reading in the corresponding folder. For example, according to the readings, a folder named 10,12,13 and 15 were obtained using a refractometer. Once the folder is ready, divide the dataset into 80% for training and 20 % for validation and process the images to the AppleNet in MATLAB, which uses the CNN algorithm. After processing the images through AppleNet, the accuracy achieved is 65 %—the Accuracy vs. Iteration and Loss Vs graphs. Iterations are shown in Figure 8. Figure 9 depicts the Number of observations vs. class labels.

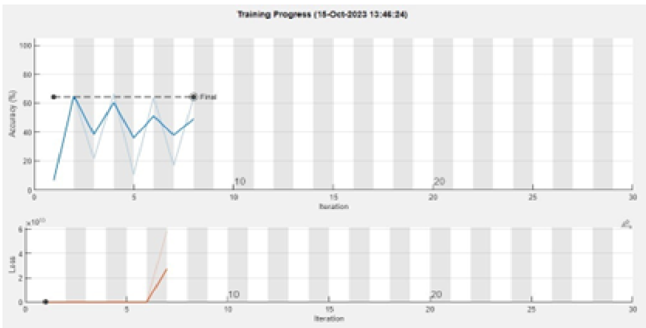

Fig. 8. Accuracy and Loss Vs Iteration.

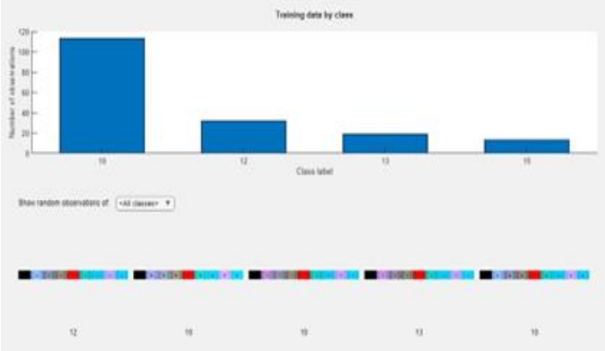

Fig. 9. Number of Observations and Loss Vs. Class Labels.

The results of this study demonstrate the effectiveness of multispectral imaging, coupled with the novel AppleNet Convolutional Neural Network (CNN) architecture, in the sweetness grading of apple fruit. Achieving a 65% accuracy in sweetness classification is a significant stride towards non-invasive, automated grading systems. The correlation studies between sugar content and multispectral images, as measured by a refractometer, reveal nuanced variations across different apple types. However, it's essential to acknowledge the inherent challenges in establishing direct correlations, as sweetness involves complex factors beyond spectral features. The performance of AppleNet, explicitly designed for multispectral images, indicates the potential of tailoring CNNs to the unique characteristics of fruit grading. Nevertheless, the modest accuracy highlights the need for a more extensive dataset to improve the model's generalization ability across diverse apple varieties.

The limitations of this study, particularly the relatively small dataset size and the associated impact on model accuracy, open avenues for future research. Enhancements in accuracy could be achieved by expanding the dataset to include a broader range of apple types, considering variations in environmental conditions, and refining the imaging process to mitigate potential noise sources. The practical inference of this research for the Apple industry is noteworthy, offering a possible shift toward automated grading systems that can enhance efficiency and reduce labor costs. As multispectral imaging technology evolves, this study contributes to the broader understanding of its application in fruit quality assessment. It motivates further exploration of innovative solutions in agricultural practices.

6. Conclusion

In summary, this study employs the Multispectral imaging technique to assess sweetness and grade apples, explicitly focusing on five varieties: Red Delicious USA, Royal Gala, Red Delicious New Zealand, Washington, and Kinnaur. The initial phase involves the construction of a Multispectral chamber, facilitating the capture of multispectral images of the apples. Subsequently, these images are amalgamated, and the concatenated dataset undergoes processing through the developed prototype AppleNet, utilizing Convolutional Neural Networks (CNN). The achieved accuracy in this process is 65%. However, it is noteworthy that the potential for increased accuracy exists, mainly through the enlargement of the dataset, a limitation acknowledged in this project. Future endeavors will concentrate on augmenting the dataset size to enhance the accuracy of the grading system. Secondary data has been collected for this study.

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