Democratizing Produce Waste Reduction Using Hyperspectral Imaging

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Abstract

According to United Nations, a third of the food globally is lost or wasted every year which amounts to 1.3 billion tons per year. One of the UN Sustainable Development Goals is to, by 2030, reduce per capita global food waste by half at the retail and consumer levels which would also reduce the global emissions of greenhouse gasses. This research aims to provide a solution to democratize the reduction of produce waste by using hyperspectral imaging (HSI) to predict ripeness of vegetables and fruits. Providing capability of measuring ripeness on the mobile phones of retailers and consumers will enable them to reduce produce waste. HSI measures intensity or reflectance at several ('hyper') wavelength to resulting in spectrally abundant information to identify and distinguish unique properties of objects. This study answers a question – can spectral imaging be used to predict ripeness of fruits or vegetables on the continuum and a challenge - can spectral imaging be made economical or affordable since previous studies have been conducted using expensive hyperspectral cameras. This study investigates this question using machine learning (ML) models with data collected on hyperspectral images, RGB images from a smartphone camera, and ripeness measurement of tomatoes and focuses on two economical approaches. On average, the ML models based on results from these images achieve a RMSE on ripeness metric ranging from 3.6 Newtons to 7.7 Newtons. The predictions from the best fit ML model (with an RMSE of 3.8 Newtons) were further validated with ripeness measurement of ten tomatoes (not part of the ML model development) resulting in RMSE of 4.1 Newtons. This research demonstrates non-destructive, low cost and easy to use solutions to democratize the reduction of produce waste at the consumer, retail, and supplier level.

Keywords – Food Waste; Hyperspectral Imaging; Machine Learning; Computer Vision

Introduction

According to the Food and Agriculture Organization of the United Nations, a third of the food globally is lost or wasted every year which amounts to 1.3 billion tons per year. Food is wasted all the way from when it is grown and harvested by our farmers to when it is consumed at the household level. In the United States, consumers and households are responsible for 43% of the food waste, grocery stores for close to 13% and restaurants and food service industry around 26% of the food waste. Furthermore, decomposition of wasted food in our landfill emits greenhouse gasses that result in polluting our environment. Greenhouse gas emissions due to food waste is estimated to be about 8% of global emissions [Citation]. One of the UN Sustainable Development Goals is to, by 2030, reduce per capita global food waste by half at the retail and consumer levels which would also reduce the global emissions of greenhouse gasses.

This research aims to provide a solution to democratize the minimization of food waste of vegetables and fruits using hyperspectral imaging (HSI). HSI measures intensity or reflectance at several ('hyper') wavelength to resulting in spectrally abundant information to identify and distinguish unique properties of objects. This study answers a question and a challenge – A question is if the spectral imaging can be used to predict ripeness factor as a continuum for fruits or vegetables. We attempt to answer this question using machine learning (ML) models such as Ridge Regression (with cross-validation) and Convolutional Neural Networks and data collected on hyperspectral images, RGB images from a smartphone camera (and its spectral reconstruction), and ripeness measurements of tomatoes. The challenge is if we can make the spectral imaging economical or affordable. Previous studies that measure the ripeness of vegetables and fruits using hyperspectral imaging are scarce and these have been conducted using expensive (upwards of $25,000)[2] hyperspectral cameras that can only be purchased and utilized by research labs and commercial institutions. This study focuses on two economical approaches – first is by collecting spectral images using a low-cost self-built portable hyperspectral camera[2] and the second approach is via spectral reconstruction of RGB images taken with phone cameras[3]. We also collect hyperspectral images using a commercial camera (rented to us by a leading manufacturer for two months) to validate the results from this study. Finally, we use test data of ten tomatoes not used in the model development train and validation datasets and predict ripeness for these tomatoes using the best fit model (lowest root mean square error or RMSE).

This research makes significant contributions to the field of environmental science and engineering as well as to the field of hyperspectral imaging applications. Using the low-cost and user-friendly approaches demonstrated in this study, vegetable and fruit ripeness can be monitored by everyone at the retailer, food service and the household consumer levels. As a result, these approaches democratize the reduction of vegetable and fruit waste.

Previous studies have primarily used color feature of tomatoes to classify them in different ripeness stages. El-Bendary et. al. (2015) build machine learning classification algorithms to categorize whether a tomato is ripe or not with 90.8% classification accuracy. This does not measure ripeness factor as a continuum which is a better measure of days until use as opposed to two to three ripeness categories. It also uses RGB images as opposed to hyperspectral imaging that have finer spectral band with detailed intensity values that may help predict ripeness measured using a penetrometer.

Varga et. al. (2021) uses hyperspectral imaging to classify avocados and kiwis into unripe, perfect and overripe categories. They collect the hyperspectral images of these fruits using two expensive hyperspectral cameras - a Specim FX 10 and an INNO-SPEC Redeye 1.7 – that can only be used after receiving training on how to use these machines in research labs.

Hyperspectral Imaging

Hyperspectral Imaging Sensors (HSI) have been one of the most significant breakthroughs in solving problems in Remote Sensing, Food Analysis, Precision Agriculture, and others due to its non-destructive ability of analyzing food.

Hyperspectral imaging (HSI) is the combination of spectroscopy and digital imaging. A spectral image contains many spectra, one for each individual point on the sample's surface. Generally, hyperspectral imaging is referred to in the ultraviolet (UV) to near infrared (NIR) range as shown in Figure below. From among the different wavelength ranges, visible to near infrared (NIR) spectroscopy has been widely used for quality assurance purposes to analyze solid samples as they require minimal or no sample preparation and achieve a high signal-to-noise ratio

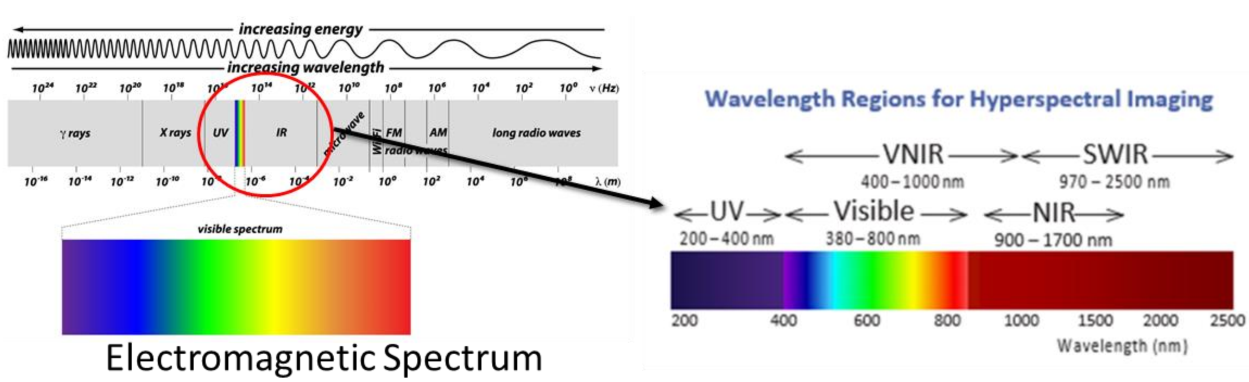

Figure 1: Wavelength regions for Hyperspectral Imaging

As shown in Figure 2, multispectral refers to several wavelengths like the RGB image from a typical digital camera is a type of multispectral image that uses the light intensity at three specific wavelengths: red, green, and blue, to create an image in the visible region, while hyperspectral refers to the complete wavelength region, i.e., the whole spectrum, is measured for each spatial point.

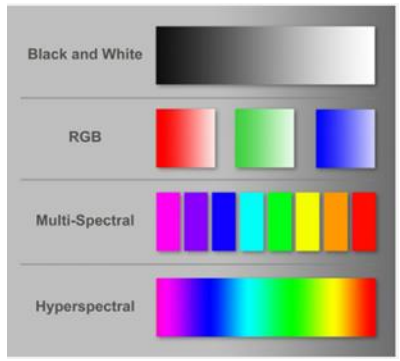

Figure 2: Different modes of Imaging

Hyperspectral imagery provides the potential for more accurate and detailed information extraction than possible with any other type of sensory data.

Methodology

First economical method: Low-cost Portable Self-built Hyperspectral Camera

Using the research conducted by JairoSalazar-Vazquez and AndresMendez-Vazquez, we developed a low-cost portable hyperspectral camera. The hardware was built based on the Bill of Materials and instructions referenced in the study Salazar et. al. (2020). As shown in Figure 3, some key aspects of the hardware included 3D printed parts of the camera housing, Edmund optics lens, Raspberry Pi camera and PCB and diffraction grating. The important assembly steps included:

1. Attaching the lens to the camera housing, followed by placing spacers and a +10mm concave lens. A 3D print of a separate mold for the concave lens to seat in the camera casing was needed.
2. Next, diffraction grating was added on top of the concave lens. A few more spacers were placed and then the lid was attached on the camera casing.
3. The raspberry pi was also inserted and attached to the pi camera. A 5.0V power cable was used to connect the camera to the computer for communication and capturing the images.
4. The raspberry pi with the camera is controlled by the command **raspistill -o myimage.jpg** to get an image. The raspberry pi will take an image that is captured

through the diffraction grating, concave lens, and lens and then outputs a spectral plane image.

5. This spectral plane image can be viewed in the pi root directory folder in file explorer. To convert this image into a hyperspectral image, the spectral plane image must be run through an analyses software where it is reconstructed into a hyperspectral image. Figure 4 further details the flowchart to convert a raw image into its hyperspectral components.

The hyperspectral setup and sequence of imaging steps are shown in Figure 5.

The total cost of this camera was approximately five hundred dollars. Using this camera, we take spectral images of the tomatoes. We will convert this spectral plane image to a hyperspectral image with several bands.

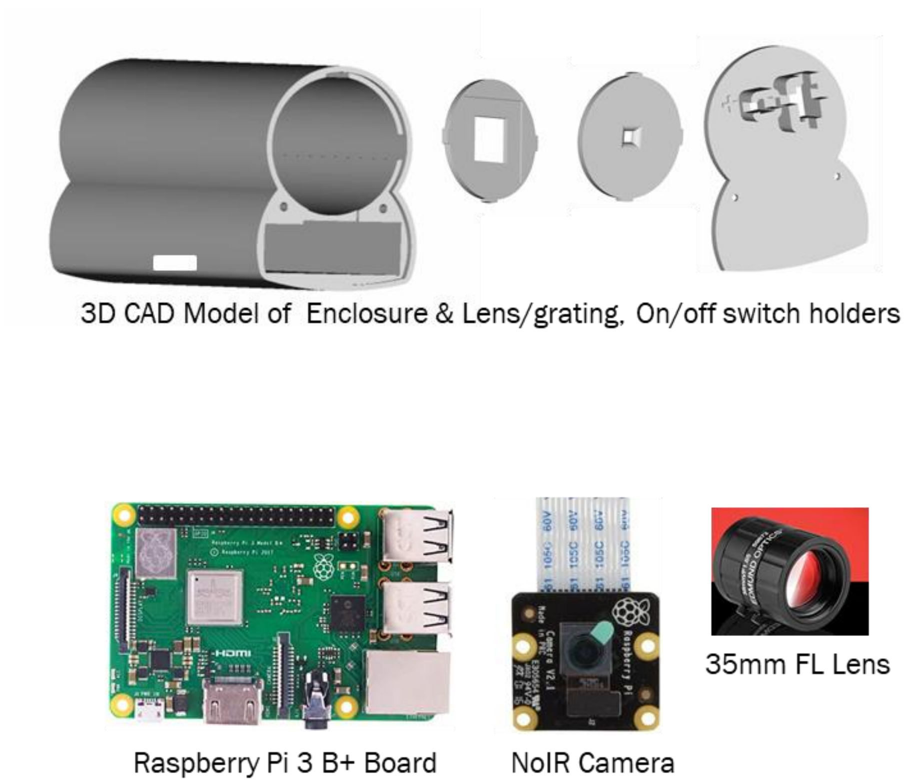

Figure 3: Various components used in the build of the Low-cost Hyperspectral Camera

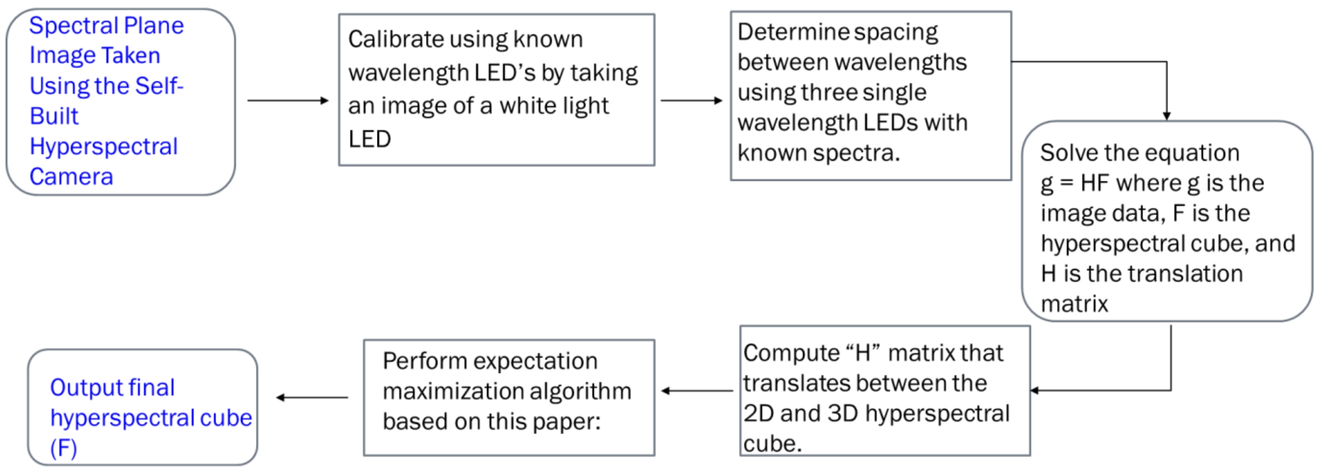

Figure 4: Flowchart to convert raw image from self-built camera into hyperspectral bands

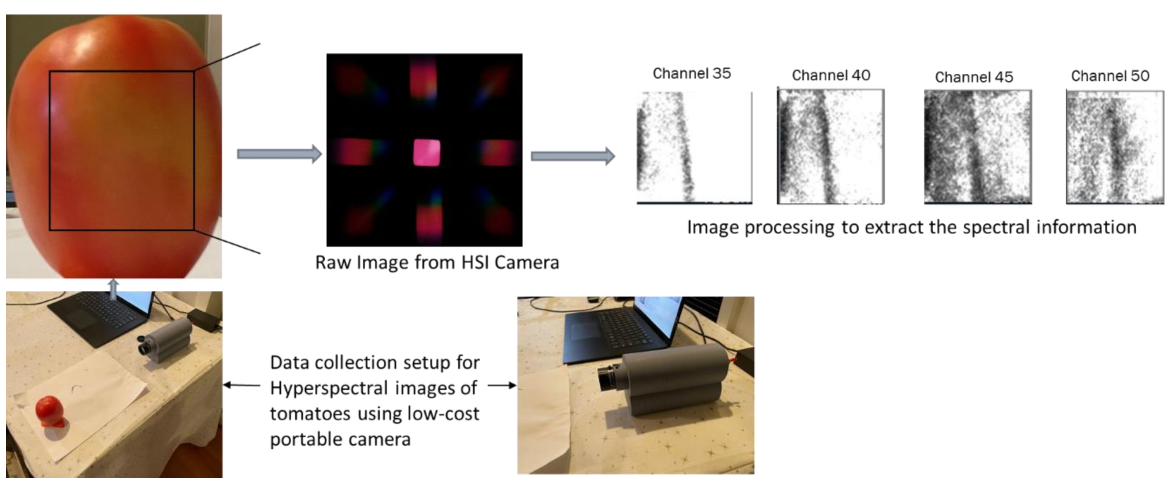

Figure 5: HSI setup in acquiring spectral plane images

Second economical method: Hyperspectral reconstruction of RGB image

Next, we take RGB image and convert that to its spectral reconstruction using a pre-trained network provided by Zhao et. al., 2020 (architecture shown in Figure 6). This research uses a multilevel Hierarchical Regression Network (HRNet) with PixelShuffle layer as inter-level interaction. It uses a training data consisting of 450 RGB-HSI pairs of different scenes. There are 31 spectral bands in the HSI, and they range from 400 nm to 700 nm.

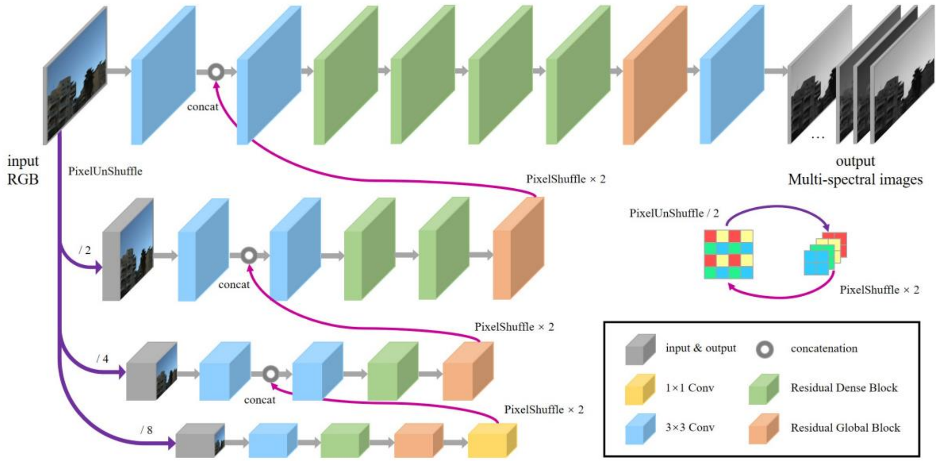

Figure 6: Architecture to convert RGB image into 31 hyperspectral bands [Ref: Zhao et al., 2020]

We start with three bands for each pixel in the image of the tomato and using the above research, we construct 31 bands for each pixel of the tomato image shown in Figure 7.

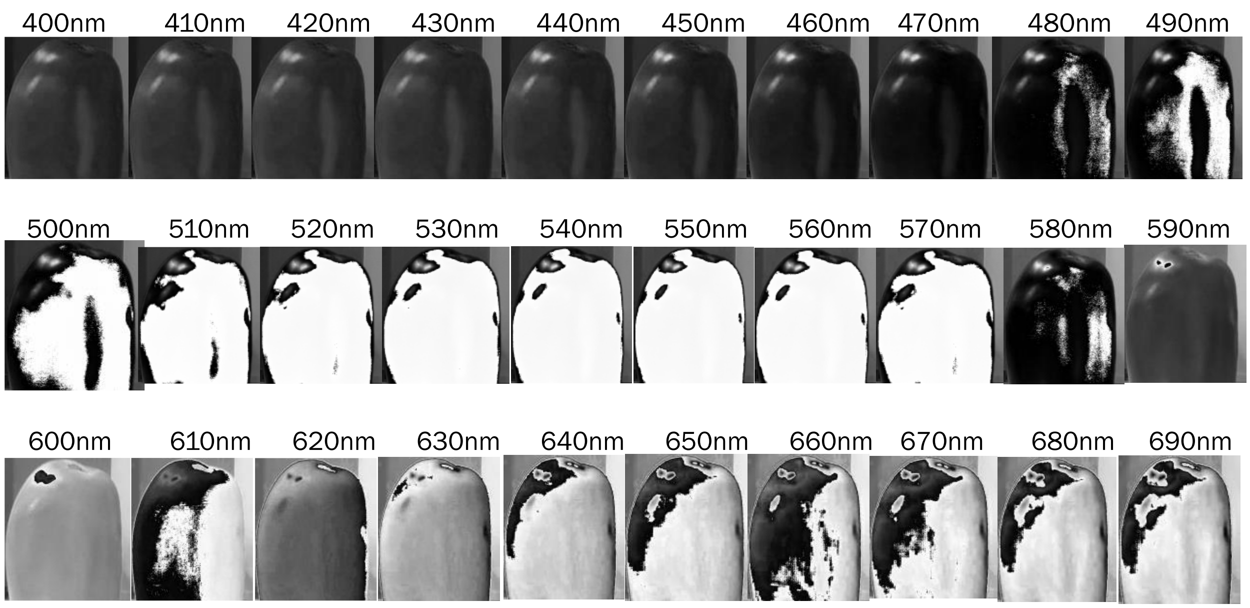

Figure 7: Hyperspectral reconstruction of a representative tomato from an RGB image

Ripeness measurement -

Next, we measure the flesh firmness ($N.cm^{-2}$) of the tomato using a penetrometer and measure the weight. A simple setup of the penetrometer is shown in Figure 8. Vegetable or fruit firmness metric is the most precise way to measure vegetable or fruit maturity[6] and can also be used to decide when to harvest, and transport from farm to food retail stores, so this methodology can also be used by farmers and distributors, however, this research specifically focuses on food service and retail industries and individual consumers can use low-cost hyperspectral cameras and smartphones to determine consumption of the vegetables and fruits. Using the above dataset, we will build a neural network to take a hyperspectral image or RGB image as input and predict how firm the tomato is in $N.cm^{-2}$. We plan to implement this prototype as an application software so any users can download it and use it to measure firmness of tomatoes.

Figure 8: Penetrometer setup to measure ripeness of Tomatoes

Data Collection -

Data was collected on 500 Roma tomatoes across the different methods discussed earlier - RGB Image Using Smartphone, Spectral plane image using self-built camera and converted to hyperspectral image with analysis program, spectrally reconstructed RGB image using existing research, Hyperspectral Image using a commercial hyperspectral camera, & ripeness metric on the continuum. Average ripeness for the data sample was around 14.4 Newtons (N) with a minimum of 0.8 N and a maximum of 50 N and the distribution is shown in Figure 9. Based on qualitative (softness, color, cutting it open and eating it) and percentiles of ripeness measurements, we categorize tomatoes below 8N as overripe, between 8N and 22N as ripe and above 22N as unripe. The unit of ripeness is Newtons/cm^2 but the area of the probe of the penetrometer is the same for all measurements and hence ripeness is reported in Newtons.

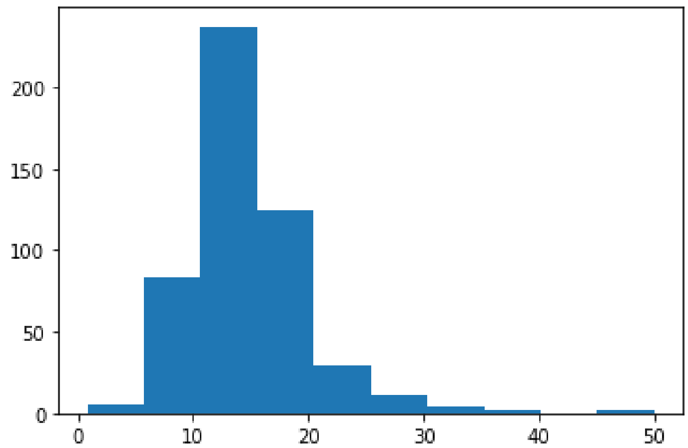

Figure 9: Ripeness distribution across 500 Tomatoes (Mean of 14.4N, Min=0.8N, Max=50N)

Experiments conducted –

Using the data collected, implemented 14 ML Models to predict ripeness factor – these models differed in the type of ML Model used and the data used to predict ripeness as shown in Table 1 below.

Table 1: ML Models implemented to predict ripeness

ML MODEL	RGB	Self-Built Hyperspectral	Reconstructed Hyperspectral	Commercial Hyperspectral
Linear Regression	✓	✓	✓	✓
Ridge Regression	✓	✓	✓	✓
Neural Network	✓	✓	✓	
Convolutional Neural Network	✓	✓	✓	

For Linear Regression and Ridge Regression with Cross-validation, aggregate metrics were used (mean, standard deviation, minimum and maximum values of pixel intensities by channel) – so 4 metrics per channel. For RGB images, this results in 12 features or independent (X) variables. For self-built camera, it resulted in 50*4 = 200 features and hyperspectral reconstruction of RGB images, it resulted in 31*4 = 124 features. Mean of pixel intensities by channel was used to account for the differences in the intensities across the pixel window sizes? Standard Deviation accounts for the variability of these intensities in this window. Max. & Min.?

For Neural Network and Convolutional Neural Network models use actual pixel intensities/reflectance (amount of light reflected from the tomato). These are 88x88 for the self-built camera (based on the filter used) and 256x256 for spectrally reconstructed RGB and the RGB images itself. *(Yes, the RMSE for models using the reconstructed HSI are better than that from the self-built HIS and this could be due to the lower resolution of the self-built images)*

The 4 types of input are – RGB images, hyperspectral images from self-built camera, hyperspectral reconstruction of RGB image, hyperspectral images taken from a commercial camera (individual pixel intensity data from commercial camera wasn't available).

For each model, the root mean square error (RMSE) was computed – this metric gives us the average distance between the actual and the predicted ripeness factor on a continuum. This is the formula used to compute the RMSE –

$$RMSE = \sqrt{\frac{\sum(Actual\ Ripeness - Predicted\ Ripeness)^2}{N}}$$

We selected the model with the lowest RMSE, to predict the ripeness factor on test data.

Results

On average, the ML models based on results from these images achieve a root mean squared error (RMSE between the predicted and actual ripeness metric) ranging from 3.6 Newtons to 7.7 Newtons for the 14 models implemented as shown in Figure 10. The lowest RMSE model with consistent results was 3.8 Newtons for Ridge Regression Cross-Validation using the hyperspectral reconstruction of RGB images as input. Using hyperspectral images from the self-built camera in a Ridge Regression Model achieved an RMSE of 4.8 Newtons. These models are validated using hyperspectral images collected from an industry standard camera (rented from Ximea) that estimate RMSE in the range of 3.2 Newtons to 3.4 Newtons which provide confidence to the results of this study. As a final step, the predictions from the lowest RMSE model were further validated with hyperspectral reconstruction of RGB images for ten random tomatoes. The RMSE for this test data was 4.1 Newtons which is in the range of RMSE observed using validation dataset for the best fit model.

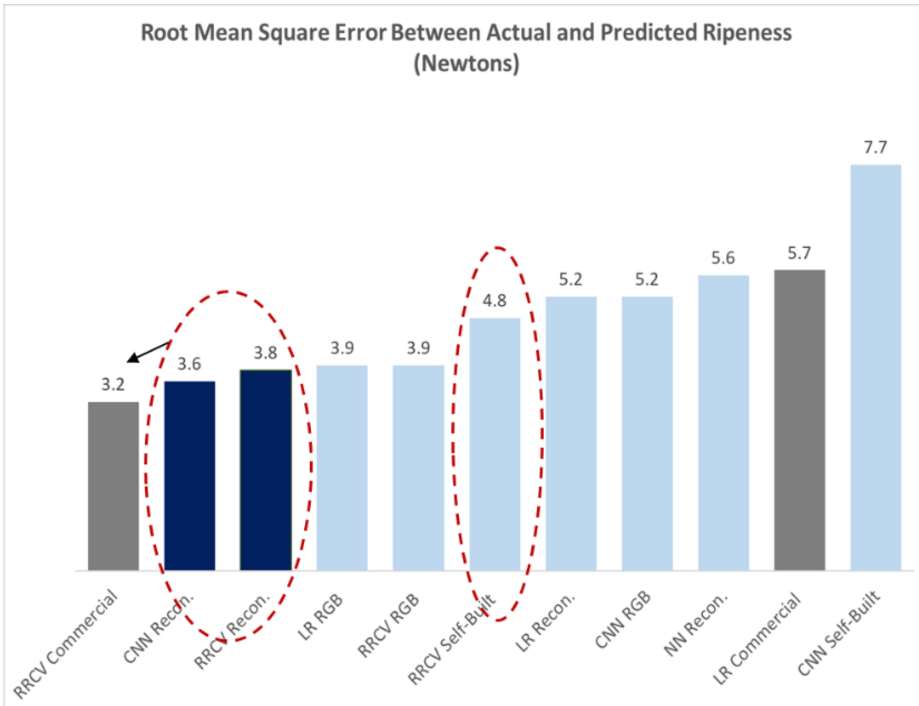

Figure 10: Ripeness results across 14 ML Models

Conclusion & Discussion

The key conclusions from the research are:

- Demonstrated that hyperspectral imaging can be used to predict ripeness factor of vegetables or fruits on the continuum using both aggregate metrics and pixel level intensities as inputs to different ML models.
- Research provides two economical approaches for collecting hyperspectral images
    - Self-built low-cost portable hyperspectral camera.
    - Spectral Reconstruction from a RGB image taken using a smartphone camera.

This research aids in democratizing reduction of produce waste at the consumer, retail, and supplier level by providing non-destructive, affordable, and easy to use solutions to predict ripeness on the continuum and hence consume tomatoes within the right time period.

A few key next steps for the research include:

- Expand ripeness metric to provide a 'best until use' date for a particular vegetable or fruit based on its current state as opposed to a generic date.
- Increase coverage to other most wasted vegetables and fruits (most common being bananas, apples, tomatoes, lettuce, sweet peppers, pears, and grapes). Based on research by Mattsson et al., 2018 these were measured in three categories -- economic loss to the retailer, climate impact, and total volume of waste.

- Optimize hardware configuration to focus hyperspectral pictures in near infrared region (600-800nm) – can it answer why self-built camera pixel intensities didn't result in the lowest RMSE of all models.

- Build an easy-to-use application for any user to download on their phone and use the phone camera to assess health of fruits and vegetables they intend to consume`

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