HS-ENEV-0165: Tackling Food Waste Using Hyperspectral Imaging

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Motivation & Background

- According to the UN, a third of the food (~1.3 billion tons/year) globally is lost or wasted every year
- In the US, households are responsible for 43% of the food waste, (grocery stores ~13% and food service industry ~26%). In addition, food waste contributes to 8% of global greenhouse gas emissions
- UN Sustainable Development Goals is to, by 2030, reduce per capita global food waste by half at the retail and consumer levels
- Previous studies[1] attempted to tackle food/produce waste using hyperspectral imaging (HSI) by measuring ripeness of vegetables and fruits and these studies were conducted using expensive hyperspectral cameras utilized only by research labs and commercial institutions. In addition, ripeness of these fruits and vegetables was a binary metric as ripe or unripe
- HSI have been one of the most significant breakthroughs in solving problems in Food Analysis due to its non-destructive ability of analyzing food. HSI measures intensity or reflectance at several ('hyper') wavelength bands resulting in spectrally abundant information to identify and distinguish unique properties of objects.

[Source: blogspot.com]

Reference
1 - Nashwa El-Bendary, Esraa El Hariri, Aboul Ella Hassanien, Amr Badr, Using machine learning techniques for evaluating tomato ripeness, Expert Systems with Applications, Volume 42, Issue 4, 2015.

Research Objective

Study answers a question and a challenge –

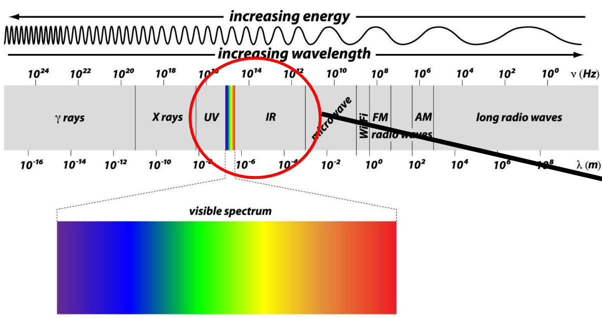
- ❑ QUESTION: Can spectral imaging be used to predict ripeness factor of vegetables or fruits on the continuum?
  - This study investigates this question using data collected on hyperspectral images and ripeness factor of tomatoes using a penetrometer.

- ❑ CHALLENGE: Can spectral imaging be made economical or affordable?
  - Previous studies[1] have been conducted using expensive hyperspectral cameras that can only be purchased and utilized by research labs and commercial institutions. Approx. price ~$20-25K
  - Can we make an economic version of hyper spectral camera $500 ?
  - Can we use a smartphone camera for this task? (via spectral reconstruction of RGB images)

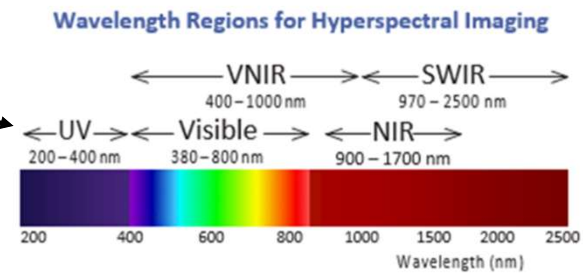
Reference

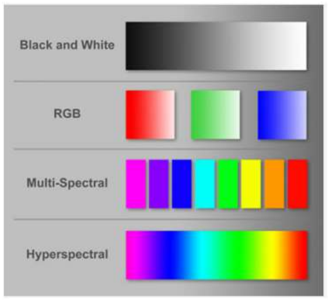
1 - Varga, Leon Amadeus, et al. "Measuring the Ripeness of Fruit with Hyperspectral Imaging and Deep Learning." ArXiv.org, 20 Apr. 2021, https://arxiv.org/abs/2104.09808.

What is Hyperspectral Imaging (HSI) ?



Electromagnetic Spectrum





Different modes of imaging

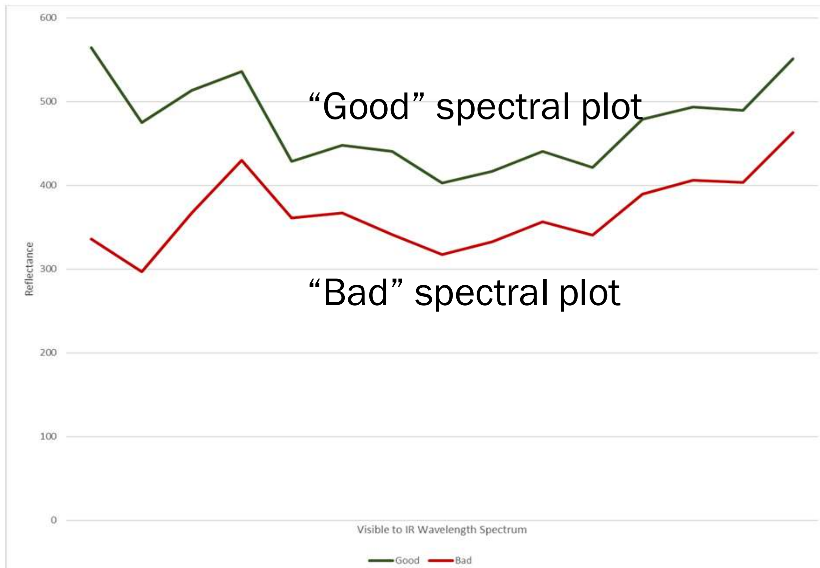
- HSI is the combination of spectroscopy and digital imaging.
- Generally, HSI is referred to in the ultraviolet (UV) to near infrared (NIR) range
- Visible to near infrared (NIR) spectroscopy has been widely used for quality assurance purposes to analyze solid samples as they require minimal or no sample preparation and achieve a high signal-to-noise ratio

- Multispectral - several wavelengths are measured
- 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
- Hyperspectral - complete wavelength region, i.e., the whole spectrum, is measured for each spatial point.

[Source: middletonspectralvision.com]

Comparison of Reflectance using Commercially Available Hyperspectral Camera

Bad (Overripe) Tomato

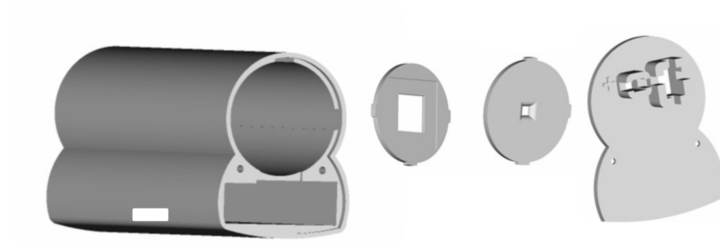


Commercially available hyperspectral camera show significant differences in spectral signatures between Good and Bad (Overripe) Tomato across the different wavelengths in the Visible to Infrared spectrum

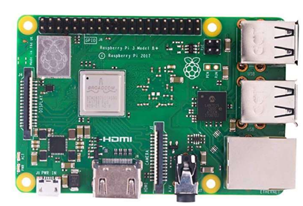
Good Tomato

Self-Built Low-Cost Portable Hyperspectral Camera

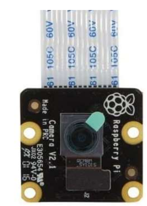
- This low-cost camera was invented by Salazar-Vazquez, Jairo, and Andres Mendez-Vazquez and referenced in their paper on “A Plug-and-Play Hyperspectral Imaging Sensor Using Low-Cost Equipment.” HardwareX, Elsevier, 22 Nov. 2019.
- Build-up of camera included
  - Solid modeling & 3D printing of Camera enclosures & holders for lens/grating and Raspberry Pi board (~$30)
  - Purchasing all components from Amazon.com / Edmund Optics like Raspbery Pi control Motherboard, Camera, Power supply connector, On/Off switch, Lens etc (~$450)
  - Self-building including soldering all the key cables from Raspberry MB, to power cable and on/off switch in my garage with the help of the procedure outlined in Salazar-Vazquez’s paper.
- Some relevant specs of the Self-built Camera include:
  - Visible/Near Infrared spectra over 300nm-700nm range of the electromagnetic spectrum50 spectral bands
  - Raspberry Pi NoIR V2 Camera 8 Megapixels; Edmundoptics Model 59872 lens
  - Data acquisition and storage was achieved with a PC running in-house software developed by SUNY Binghamton



3D CAD Model of Enclosure & Lens/grating, On/off switch holders



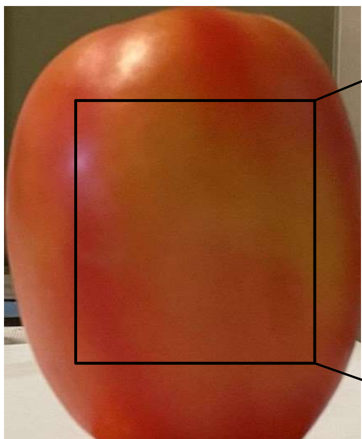
Raspberry Pi 3 B+ Board

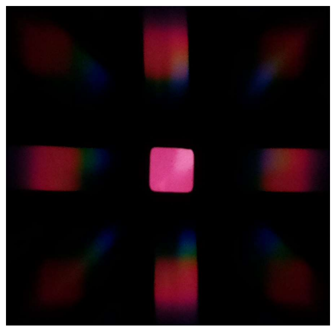


NoIR Camera

35mm FL Lens

Representative Hyperspectral Images from Self-Built Camera for a Specific Tomato





Raw Image from HSI Camera

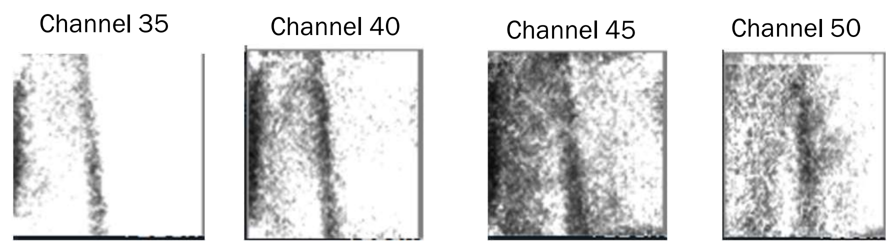
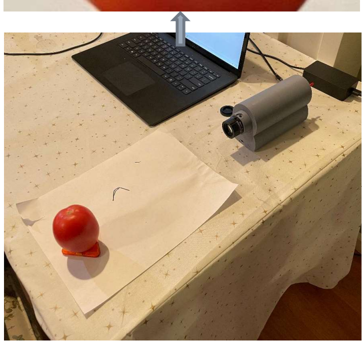
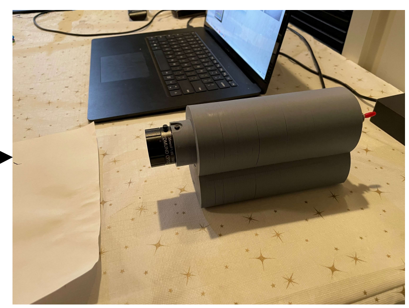


Image processing to extract the spectral information

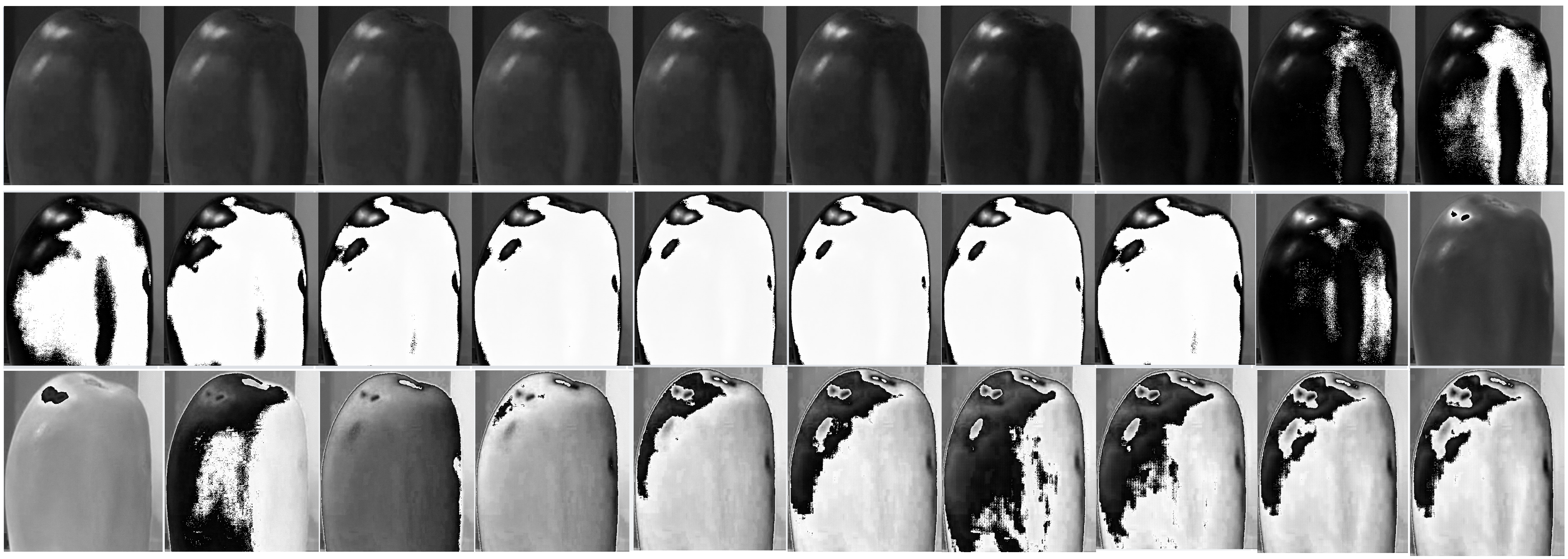


Data collection setup for Hyperspectral images of tomatoes using low-cost portable camera



Spectral Reconstruction of RGB Image

- Images of 31 channels for a particular tomato



Reference: Zhao, Yuzhi, et al. "Hierarchical Regression Network for Spectral Reconstruction from RGB Images." ArXiv.org, 10 May 2020

Data Collection

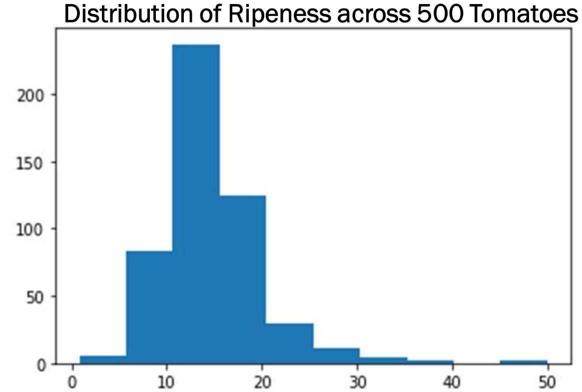
Collected following data on 500 Roma tomatoes -

- ❑RGB Image Using Smartphone (specs in appendix)
- ❑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
  - ➢ 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

500 Roma Tomatoes

Measuring Ripeness w/ Penetrometer

Distribution of Ripeness across 500 Tomatoes



Methodology

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

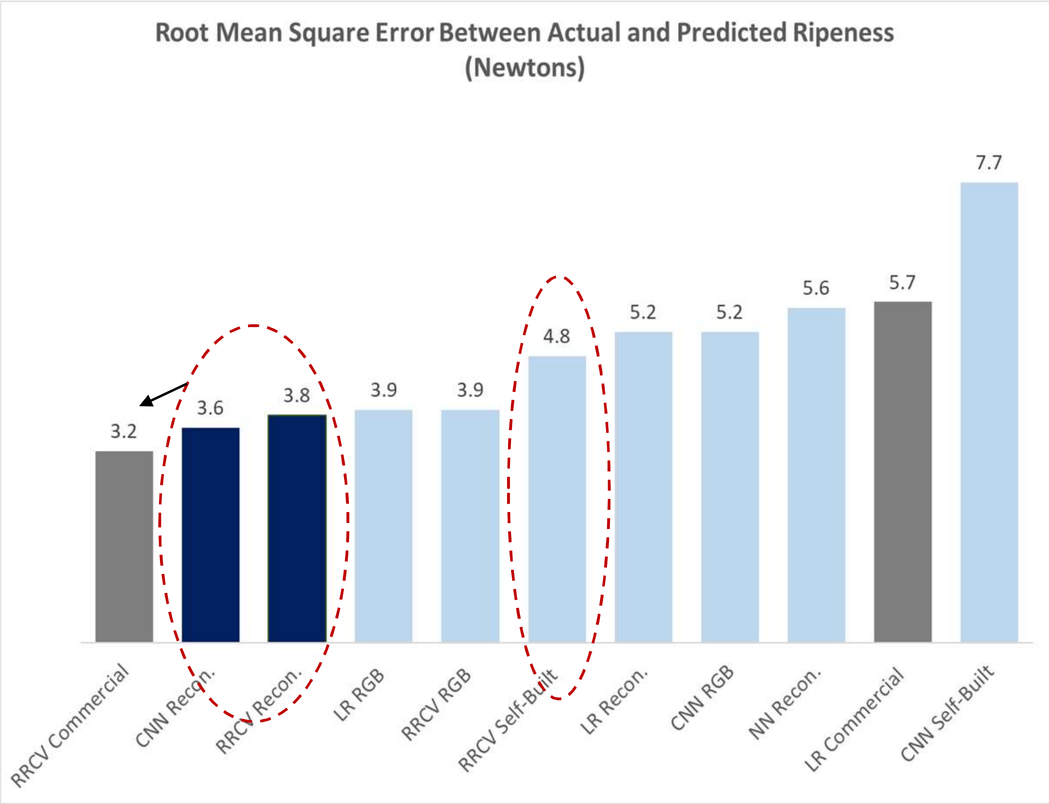
- Using the data collected, implemented 14 ML Models to predict ripeness factor – these models differed in the type of ML Model used and the data used to predict ripeness as shown in the matrix above.
- For Linear Regression and Ridge Regression with Cross-validation, aggregate metrics were used (mean, standard deviation, minimum and maximum values of image pixel intensities by channel) – so 4 metrics per channel. For RGB images, this results in 3*4=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.
- 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.
- 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.
- 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 –

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

Lower the RMSE, the better a particular model may be used to fit a test/validation dataset

Results & Conclusions

- Graph to the right shows the RMSE for the ML Models –
  - Gray bars are RMSE of models using commercial hyperspectral images
  - The best fit or lowest RMSE models are the CNN and the Ridge Regression with cross-validation using the spectral reconstruction of RGB images (3.6 to 3.8 N)
  - RMSE from Ridge Regression using commercial hyperspectral images is 3.2 N which provide confidence to the results of this research
- Demonstrated that HSI 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
- Democratize reduction of produce waste at the consumer, retail, and supplier level by provide non-destructive, affordable, and easy to use solutions to predict ripeness on the continuum and hence consume tomatoes within the right time period



Path Forward

1. Next steps for this research include using this 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.
2. Test with other most wasted vegetables and fruits (most common being bananas, apples, tomatoes, lettuce, sweet peppers, pears, and grapes)
   - Based on research by Lisa Mattsson, Helén Williams, Jonas Berghel, “Waste of fresh fruit and vegetables at retailers in Sweden – Measuring and calculation of mass, economic cost and climate impact”, Resources, Conservation and Recycling, Volume 130, 2018 (https://doi.org/10.1016/j.resconrec.2017.10.037)
   - These were measured in three categories -- economic loss to the retailer, climate impact, and total volume of waste.
3. 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.
4. 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`