The Effect of Color Spaces and Spectra on a Strawberry Prediction Model

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Abstract

The purpose of this research is to reduce food waste by monitoring the ripening process of strawberries in order to optimize the harvesting time. To improve the moment of harvest, we need to know the ripeness of a strawberry. Using data from different color ranges and spaces we should be able to predict the ripeness of a strawberry on a 1-10 scale. We want to answer the question whether data from multiple color spaces can improve such a prediction model.

The prediction is performed on strawberry segments, using linear regression. The regression is performed based on the ripeness and the red and green pixel values in a segment. Each color space uses a slightly different metric.

We are able to show that the YCbCr and CIELab color space outperform RGB in such a linear regression. This is likely to come from the fact that these color spaces separate the luminance and chrominance. For the near-infrared range however, we do not have enough data to make such a conclusion as the available data only has ripeness levels 7-9.

1 Introduction

In 2014 Siu [1] showed that about 56 percent of strawberries are thrown away in all parts of the food chain on a farm in Ontario, between planting and getting them on the supermarket shelve. This is not uncommonly high as this is also seen in the United States and Europe [2, 3]. At the farm itself about 20 percent of this waste comes from untimely harvesting [4]. To reduce such food waste, the optimal moment of harvesting strawberries should be found. When harvested too early they will not ripen properly, lowering their market value [5]. When they are harvested too late, they will be rotten by the time they arrive in a supermarket.

The aim of this project is to build a prediction model for segmented images of strawberries and perform feature selection. From there the question will be if data from more color spectra such as the near-infrared range and data presented in other color spaces improve the performance of such a prediction model, in terms of accurate prediction of the ripeness.

By using computer vision and machine learning, it should be possible to predict the ripeness of a strawberry. This should help in finding the right time of harvesting. The creation of a fruit detection algorithm using a deep neural network was previously performed by Sa et al. [6]. Assessing the importance of different colors was also done before [7–10]. These however, mainly focused on looking at the ripeness based on three levels: ripe, mid-ripe and unripe. This research will go into more depth on creating a prediction algorithm on a 1-10 scale, and see if different color ranges and spectra can improve the accuracy of such an algorithm.

First, the methodology is explained in section 2. Then the color spaces and ranges are explained in section 3. After, the experiment setup and results are described in section 4 and 5. A short explanation of responsible research is given in section 6. Lastly a discussion is given in section 7 and the conclusion and future work are mentioned in section 8.

2 Methodology

In section 2.1 the research question is explained including a short description on how this will be answered. Then, the data is explained in section 2.2. Thereafter, the Design of a prediction model is explained in 2.3.

2.1 Formal Problem Description

To explain what problem this paper tries to answer, the exact research question will be explained. This is: 'Would data from more color spectra, such as the near-infrared range and data presented in other color spaces improve the performance of the prediction model, in terms of accuracy? To what extent?'.

Data from the near-infrared (NIR) range is explained in section 3.2 and multiple color spectra are explained in section 3.1. How the prediction model will look like is explained in section 2.3. The accuracy is measured in the method of least squares [11], which will be referred to as the mean squared error (MSE). The lower this is, the less the error. To answer this question, the different spaces and ranges will be put into this model and the results will be compared and discussed in section 7.

2.2 Data Exploration

In this section the relevant data that is provided for this research is explained. This data is contributed in two parts. The first one is the images which will be explained in section 2.2.1. The second part is about the labels of the strawberries and are explained in section 2.2.2.

2.2.1 Images

The provided images come from two different types of cameras. The first one is an RGB camera and is a standard to capture an image. An example image of a branch can be seen in figure 1. As can be seen in this figure, we can get the segment of the strawberry out of the image together with the labels. For this type the segments of the strawberries in the images have also been provided. These segmented images come from three cameras, and in total there are about 12000 segmented images.

The second type is an OCN camera. OCN stands for orange, cyan and near-infrared [12] and can capture wavelengths that the human eye cannot see. An image from the same branch as the other camera can be seen in figure 2. Together with these images, a json file is provided containing labels about the strawberries in combination with polygons to acquire each individual segment out of this image.

2.2.2 Labels

Next, the measurements of 305 strawberries are provided. In figure 1 the measurements of the that segment is shown. Each strawberry has an ID that refers to it. Marketable and waste mean whether that strawberry is marketable or it is a waste respectively. When one is true, the other must be false. The ripeness level shows the ripeness on a scale from 1 to 10,

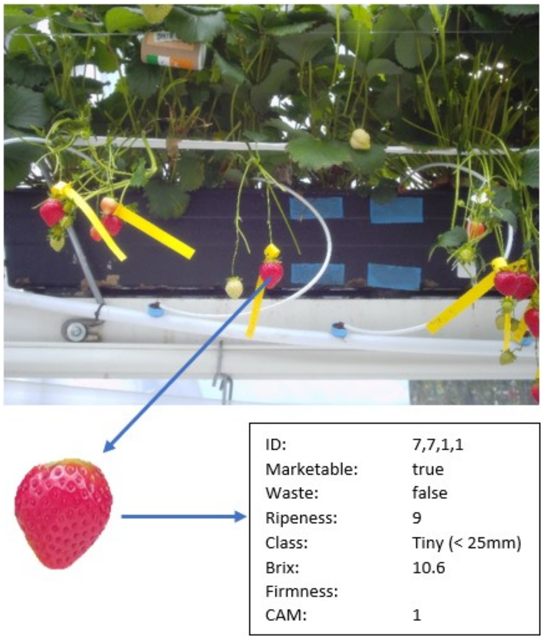

Figure 1: Strawberry data from a RGB camera together with a segment and the labels

where 1 means immature and 10 means over-mature. 7-8 are the optimal range for harvesting. The class shows the size of the strawberry. Brix shows the sweetness level of the strawberry. The unit is called [Brix]. Firmness is measured in [kg/mm2]. CAM means which of the cameras it comes from. Some strawberries have missing values, such as the firmness of this one, as measuring these might harm them. Therefore, these data are not available for all.

Lastly, the evaluation of ripeness of 254 strawberries is provided. For these, the month, day, hour and second the image for the strawberry is taken is given together with 3 different expert ripeness evaluations for that strawberry.

2.3 Designing a Prediction Model

For this research, the objective is to compare different color ranges and spaces. Therefore, a simple prediction model would suffice to make this comparison. This model should be easy to understand and have low time complexity to be able to run on multiple models.

Linear regression satisfies these requirements [13]. In addition, linear regression can be run on multiple variables and using different regularizes some noise in the data can be pruned. How the data is used and how the color from each color space is used is explained in section 4.

3 Color in Images

3.1 Color Spaces

In this section the different color spaces, that are discussed in this paper, are explained. This also includes the advantages and disadvantages for each color space.

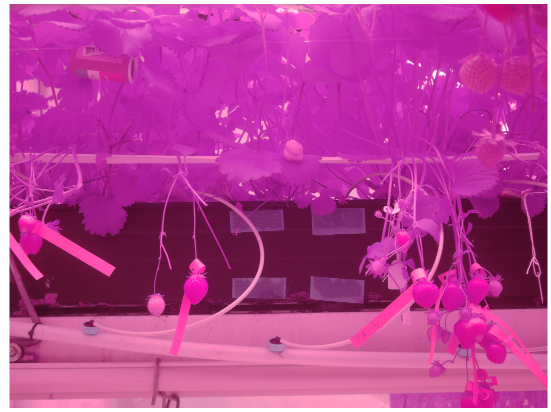

Figure 2: Strawberry branch in OCN

3.1.1 RGB

RGB is the most widely known color space. It is based on the amount of R (Red), G (Green) and B (Blue) in a single pixel.

The main disadvantage of the RGB color space, is that this color space is device dependent. That means that the same picture may look different, on different devices [8]. Another disadvantage is that it mixes chrominance and luminance, making it unfavorable for color-based recognition algorithms [14].

This last issue can be seen when looking at the value of red pixels in an image. The pixel values range from 0-255 and from figure 3 are shown in a histogram in figure 5. What can be seen is that there is a peek at 255 for the red pixels. When looking at the image, these are highlighted in figure 4, with a white circle around them. Since we can see that there is no peek for the other values (and thus are not white pixels), we can conclude that this peek comes from lightning rather than the pixels being actually completely red.

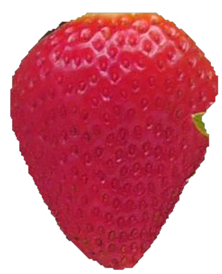

Figure 3: segment in RGB

Figure 4: High R value

In figure 6 an image is shown of a barn. A shows the visualization of the image and B, C and D show how the red, green and blue layers are saved, respectively.

3.1.2 YCbCr

As opposed to RGB, YCbCr has separate luminance and chrominance components, making this color space more usable for segmented image predictions. The same barn as above is show in figure 7.

Y' is the luma component, which represents the luminance and is computed from nonlinear RGB [14]. It can be obtained

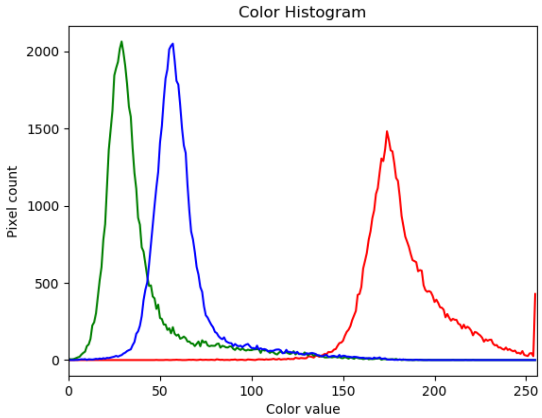

Figure 5: Histogram

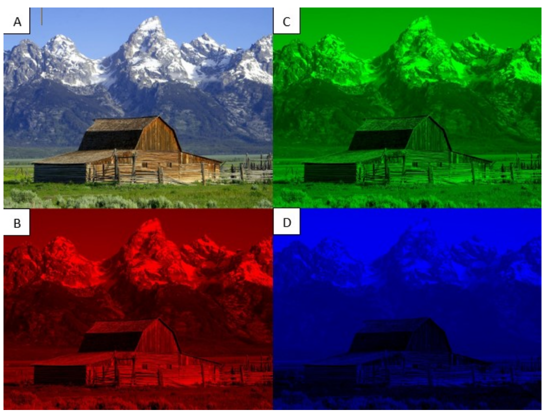

Figure 6: Barn in RGB[1]

from the weighted sum of the RGB values. Cb is the difference between the blue and luma component and Cr is the difference between the red and luma component [8]. The Cb and Cr represent the chrominance components in YCbCr.

3.1.3 CIELab

CIELab is a color space that is defined by the International Commission on Illumination (CIE) in 1976 [14]. The L represents the perceptual lightness, and a and b represent the red, green, blue and yellow values. Just like YCbCr, it is device-independent and has separate luminance and chrominance components. As this color space is a bit more difficult to depict, a three-dimensional representation is used in figure 8.

3.2 Near-Infrared Range

Next to our known color range (RGB), the only other color range that is used in this research is near-infrared. Therefore this is the only range that is explained.

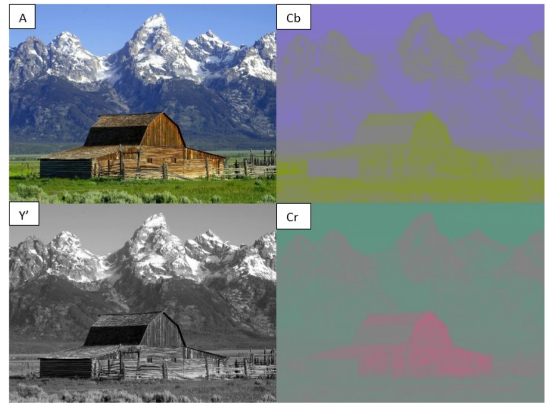

Figure 7: Barn in YCbCr[2]

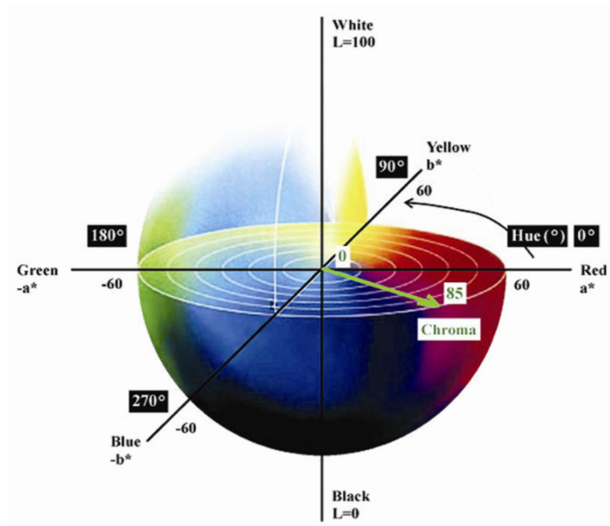

Figure 8: CIELab Color Space[3]

Near-infrared (NIR) sensors capture light that is invisible to the human eye [15]. A NIR camera captures red, green and NIR light. NIR can show problems in the growth of strawberries much sooner than the human eye can see, making this much more useful for identifying the value of a strawberry.

4 Experimental Setup

4.1 Linear Regression in Python

As explained in section 2.3, a linear regression model will be used to estimate the ripeness of a strawberry based on the colors in an image. For the environment, Python 3.7.3 and Conda 4.12.0 were used. The linear regression model was based on Python's Seaborn library [16].

First, the ripeness evaluations are read as a pandas dataframe. This makes it easier to work with Seaborn. Then, the rows without ripeness evaluation are dropped as they do not contain any relevant information. Then, the mean of each row is calculated from the three estimated ripenesses. We will assume this ripeness is the true ripeness value of that strawberry.

[1] https://en.wikipedia.org/wiki/RGB_color_model
[2] https://en.wikipedia.org/wiki/YCbCr
[3] www.dnaphone.it/en/wine-color-analysis-cielab-social/

Next, the segments are read, using the OpenCV library [17] as a BRG image, which is the complement of RGB. From this it is converted to the corresponding color space.

From here, the data is split in a 80/20 train/test set. This means that there are no overlapping strawberries from the train and the test set. Then, each color space uses a slightly different metric for the color in the regression. Each is explained in section 4.2. Once that is calculated, we move on to the regression part. Using Seaborn's linear regression, the slope and intercept can be calculated using the lowest standard error. With this, the results are plotted and saved.

Now the slope and intercept are known, we can calculate the estimated ripeness for each strawberry in our test set. Then the last step is to calculate the MSE based on the difference between the estimated and the true ripeness.

4.2 Color Metrics

4.2.1 RGB Metric

The mean pixel values for each layer can show the ripeness in a fruit ripeness prediction model [18]. For strawberries, we are mainly interested in the amount of red and green in a RGB image. Therefore, we use the difference between the amount of red and the amount of green in a segment. To calculate this, we use the following formula:

$$\frac{\sum r - \sum g}{n * 255} * 100 \tag{1}$$

Here, r and g are the red and green pixel value between 0-255 respectively. n shows the number of nontransparent pixels in a segment. A result of 100 would mean that all pixels have a value of 255 in R and 0 in G and -100 would be the opposite.

4.2.2 CIELab Metric

For CIELab a more straightforward metric is used. Since we are interested in the red and greenness of a strawberry, the a-axis can be solely used. This axis directly depicts the amount of red and green in an image. The mean value of all pixels in a segment is calculated as a result.

4.2.3 YCbCr Metric

Just like CIELab, YCbCr uses a more direct approach than RGB. For YCbCr, we are mainly interested in the red chrominance. The mean pixel value of Cr is calculated per segment and used.

4.2.4 NIR Metric

The information in a near-infrared is mainly about wavelength. Therefore, it is read as a grayscale image. With that, the mean value of the pixels is calculated.

5 Results

As mentioned in section 2.1, we use the MSE to calculate the loss. With the linear regression of section 4.1, the slope and intercept are known to us. These results are shown in figures 9-12. Using these lines, we can calculate the MSE for each color space and spectra. The MSE results are shown in table 1. In this table, we can see that RGB has a higher, thus worse, MSE than CIELab and YCbCr. NIR seems to have a different looking regression from the color spaces, but does give a better MSE.

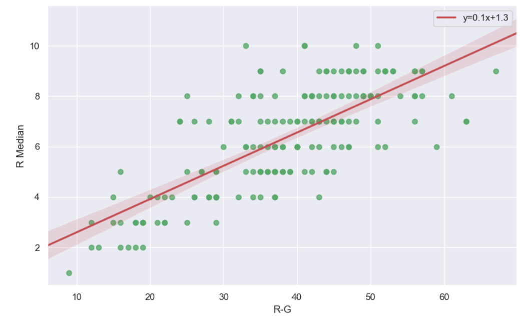

Figure 9: Linear regression of RGB

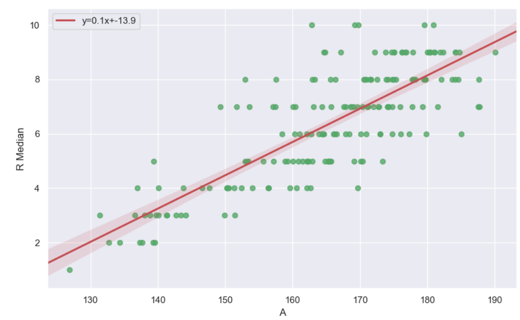

Figure 10: Linear regression of CIELab

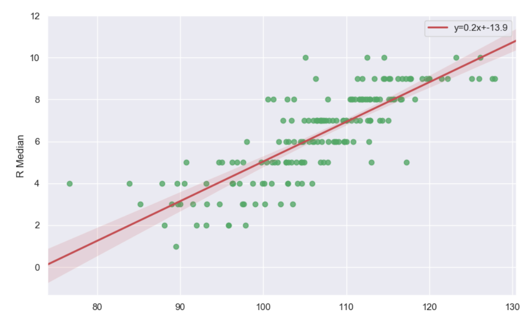

Figure 11: Linear regression of YCbCr

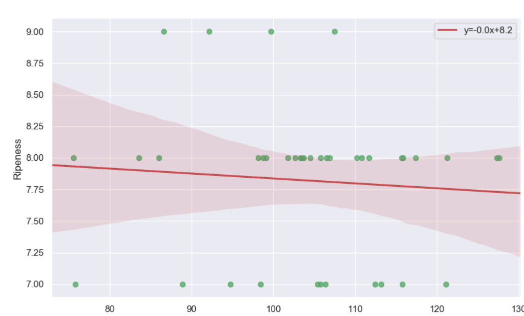

Figure 12: Linear regression of NIR

Results of Linear Regression				
Color Space	RGB	CIELab	YCbCr	NIR
MSE	2.33	1.76	1.35	0.35

Table 1: MSE of Linear Regression

6 Responsible Research

6.1 Data Risk

The strawberry images are provided by Delphy[4], a consulting company for farming. These images only contain data about the strawberry and therefore have no harmful information. These image along with all cited papers are the only data used in this research. Therefore, there is no risk in the data used in this project.

6.2 Reproducibility

All code used to create the described results is on GitLab[5] and is shared with my supervisor. The code comments in a way that each individual part is understandable. In this way, this research can easily be understood and reconstructed.

7 Discussion

From previous research, we could see that different color spaces can be used to predict the ripeness of a strawberry on a ripe, mid-ripe and unripe maturity level. In this research a scale of 1-10 was used to predict the ripeness. We were able to perform linear regression on multiple color spaces.

From the results, we can see that in the color spaces, RGB is outperformed by CIELab and YCbCr. This is probably caused by the combined chrominance and luminance in RGB, which we can see since only the chrominance was used for the other color spaces, and they gave a better result.

The estimation for NIR does not seem reliable. The estimation seems to always predict the ripeness around ripeness level 8. This is likely to come from a shortage in ripeness range from the OCN data, as these only contain ripeness level 7-9.

8 Conclusions and Future Work

8.1 Conclusion

The goal of this research was to answer the question if data from more color spectra and spaces could improve the accuracy of a ripeness prediction model for strawberries. The accuracy is measured as the mean squared error.

We implemented a linear regression prediction model to predict the ripeness based on colors. This regression was run on RGB, giving a result of 2.33. The CIELab and YCbCr color spaces then gave a result of 1.76 and 1.35 respectively. Based on these results, we can conclude that both these color spaces can improve the prediction model. A significant part of this improvement comes from the color spaces that separate the chrominance and the luminance. For the NIR however, the regression gave a poor estimation, since we only had ripeness data ranging from 7-9. Therefore, the low MSE of 0.35 does not tell us whether color spectra can improve this prediction model.

8.2 Future Work

Future research should look into the effect of NIR and other color spectra on such a prediction model, when more data is available. These data should then cover ripeness levels between 1-10. This could be done if the ripeness of strawberries in OCN images is monitored more frequently throughout the ripening process.

Secondly, in the prediction model we build, only color data was used to estimate the ripeness level. Linear regression can however use multiple features to train a prediction model. In later research more features, like brix, firmness and size could be used next to color data to improve this prediction model.

Lastly, a greater variety of color spaces could be used. This could give a better understanding on what parts in each color space causes an improvement of the prediction model.

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[5] https://gitlab.tudelft.nl/

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