Color Classification and Recycling Bin Detection

Amitash Nanda

Department of Electrical and
Computer Engineering
University of California San Diego
La Jolla, USA
ananda@ucsd.edu

***Abstract*—Data is essential while dealing with any Machine Learning approach and concepts. One of the crucial aspects of data is color. It is an important characteristic of an object because of its significant influence on value. Hence, getting the color parameter into consideration is an utmost priority while dealing with classification models. This project involves developing a color classification model and drawing the concept from later to detect recycle bins using Gaussian Discriminant Analysis. Our contribution is a probabilistic color classification model that distinguishes among different colors and recognizes recycling bin blue color. Our model for color classification gives an accuracy of 100%. Where, for the bin detection shows an accuracy of 90% on the validation data set, while the unknown test dataset has a score of 7.18/10.**

Keywords—Open CV, Gaussian Discriminant Analysis, Bayes Decision Rule, roipoly, Scikit-Image, Maximum Likelihood Estimate

I. INTRODUCTION

The enormous growth in population leads to massive waste generation in the current society. The traditional municipal system of tracking waste containers or recycling bins in municipalities is rigid and inefficient. To track recycling bins in real-time by human labour is not cost-effective. Following the current shift towards smart cities, there have been attempts to implement innovative technology solutions to urban areas. Much work has been done in this field, and one of the highly discussed solutions is radio frequency identification (RFID). This system requires manual installation with interaction locally, which incurs flexibility, environmental impact, and cost problems. Motivated by this problem, we propose a tracking system for the recycling bin. This system's primary goal is to successfully identify the recycling bin in a reliable manner.

Our main contribution is an end-to-end probabilistic color classification model that distinguishes among different colors and recognizes the blue color of the recycling bin. In the project's first phase, we trained a probabilistic color model from the pixel data to distinguish between red, green, and blue pixels. The data consists of training and validation sets of red, blue, and green images. Each training data set consists of around 3700 (28*28) images and validation sets around 100 (28*28) images with a single RGB value at all of its pixels. We trained the data using a generative learning algorithm called Gaussian Discriminant Analysis based on the red, green, blue label. In the second part of the project, we used the same Gaussian Discriminant Analysis as previously used to train the color model to recognize recycling bin blue color and segment unseen images into the blue region. We detected the blue recycling bin and drew a bounding box around them, considering the blue areas.

II. PROBLEM FORMULATION

A. Red, Green, Blue Color Classification

Consider we have given a labelled training dataset. Representing $X \in \mathbb{R}^3$ as the RGB values and $y = \{1,2,3,)^n$ representing Red, Blue, Green as 1, 2, 3 respectively and n is the no of examples. The data consists of training and validation sets of red, blue, and green images. Each training data set consists of around 3700 (28*28) images and validation sets around 100 (28*28) images with a single RGB value X at of all pixels.

The challenge is to train a probabilistic color model for the parameters the best represents our data (X, y). It means that we need to find some parameter θ, ω that maximises the probability distribution of our data given by $P(\boldsymbol{y}, X|\omega, \theta)$.

B. Blue Recycling Bin Detection

Consider we have given blue recycling bin images in form of training and validation datasets. Training set and validation set consists of 60 and 10 images respectively. After implementing roipoly, we have a set of labelled RGB value as examples. Consider the given dataset represents in the form of $X \in \mathbb{R}^3$ as the RGB values and $y = \{1,2,3,4)^n$ representing bin blue, non bin blue, dark and light as 1, 2, 3, 4 respectively and n is the no of examples.

The challenge is to train a probabilistic model for the parameters the best represents our data (X, y). It means that we need to find some parameter θ, ω that maximises the probability distribution of our data given by $P(\boldsymbol{y}, X|\omega, \theta)$. We need to segment unseen images into blue regions, provided the above parameters. Then given the blue regions, we need to detect the blue recycling bin by drawing the boundary box around them and find the bounding box coordinates (x_1, y_1, x_2, y_2) that represents the top-left and bottom-right corner of the boundary boxes.

III. TECHNICAL APPROACH

Machine Learning models can be classified into two types of models. Discriminative and Generative models. Discriminative models make prediction on the unseen data based on conditional probability and can be used for classification and regression problems. Generative model focuses on the distribution of a data sets to return a probability for a given example. In this project the main objective is to

build a probabilistic color classification model. For this we must use a single Gaussian generative model. This type of model can approximate the required unknown data generating probability density function. By which it can generate new example (x, y) by sampling from the optimal distribution $p(x, y)$. Thus, it makes very effective to classify new examples. This project involves the use of Gaussian Discriminant Analysis model. We have not considered Gaussian Naïve Bayes model because it generates a model without any conditional independence assumption on $p(x_i|y_i, \omega)$. Thus, it makes our prediction more accurate.

Gaussian Discriminant Analysis uses a generative model $p(\boldsymbol{y}, X|\omega, \theta)$ for discrete labels $y \in \{1,2, \ldots., K\}$ where θ is a set of parameters that model the marginals $p(y)$ and ω is a set of parameters that models the conditional $p(\boldsymbol{x}|y, \omega)$. The following expression needs to be maximised to get the optimal distribution.

$$p(y, X \mid \omega, \theta) = p(y \mid \theta)p(X \mid y, \omega) \quad (1)$$

$$p(y, X \mid \omega, \theta) = \prod_{i=1}^{n} p(y_i \mid \theta)p(x_i \mid y_i, \omega) \quad (2)$$

Where,

$$p(y_i \mid \theta) := \prod_{k=1}^{k} x\theta_k^{1\{y_i=k\}} \quad (3)$$

$$p(x_i \mid y_i = k, \omega) := \varphi(x_i; \mu_k, \Sigma_k) \quad (4)$$

By solving the following constrained optimization, we obtain the MLE parameter for this model.

$$max_{\theta,\omega} \log p(y, X \mid \omega, \theta) \quad (5)$$

Where,

$$\sum_{k=1}^{K} \theta_k = 1$$

The MLE estimates of θ and ω are:

$$\theta_k^{MLE} = \frac{1}{n}\sum_{i=1}^{n} 1\{y_i = k\} \quad (6)$$

$$\mu_k^{MLE} = \frac{\sum_{i=1}^{n} x_i 1\{y_i = k\}}{\sum_{i=1}^{n} 1\{y_i = k\}} \quad (7)$$

$$\Sigma_k^{MLE} = \frac{\sum_{i=1}^{n}(x_i - \mu_k^{MLE})(x_i - \mu_k^{MLE})^T 1\{y_i=k\}}{\sum_{i=1}^{n} 1\{y_i=k\}} \quad (8)$$

Give any new example we can get the class it belongs to using our trained model.

$$y_* = argmax_y \log p\left(x, y \middle| \theta^{MLE}, \omega^{MLE}\right) \quad 9$$

A. Red, Green, Blue Color Classification

We have given the labelled training images, using the data we trained our model through Gaussian Discriminant Analysis as discussed above. We found the parameters for θ, μ, Σ and using these parameters we define the Bayes Decision Rule as shown in the Equation 9. We classify the images based on the BDR. As we successfully identified all classes for red, green, blue correctly on the validation set with accuracy 100 % and obtained a score of around 9.934/10 when tested on unknown images.

B. Blue Recycling Bin Detection

We have given the training set of images containing blue recycling bin with other objects. Then we used the roipoly function in python to label multiple sets of RGB pixels extracted from these images into four classes. blue_bin for recycling bin blue (class 1), non_bin_blue for other shades of blue (class 2), dark_color for brown, black, red (class 3) and light_color for white, yellow and green (class 4). We implemented the same Gaussian Discriminant Analysis model as in color classification, but now with four classes. Using the trained parameters we segment the recycling-bin blue like regions from the validation images to get binary masks of blue-bin and nonblue-bin regions. Then we detect the recycling bins using the regionprops and label functions from scikit-image. We did this by drawing boundary boxes on the segmented regions while considering a similarity index. We checked the area of the box to be greater than 5550 pixels in order to avoid smaller patches of blue regions.

IV. Results

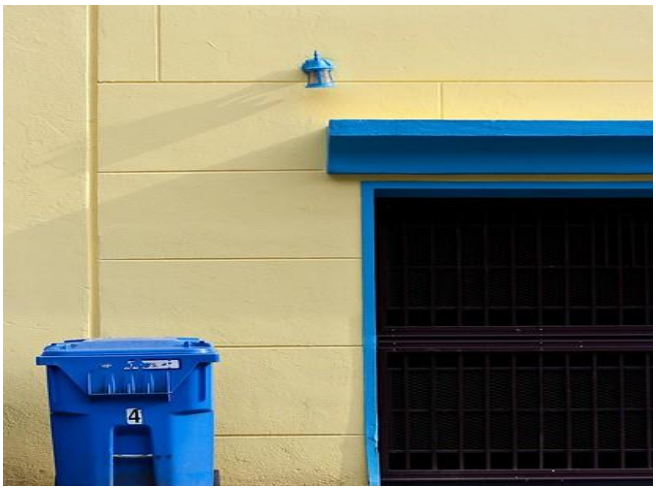
A. Red, Green, Blue Color Classification

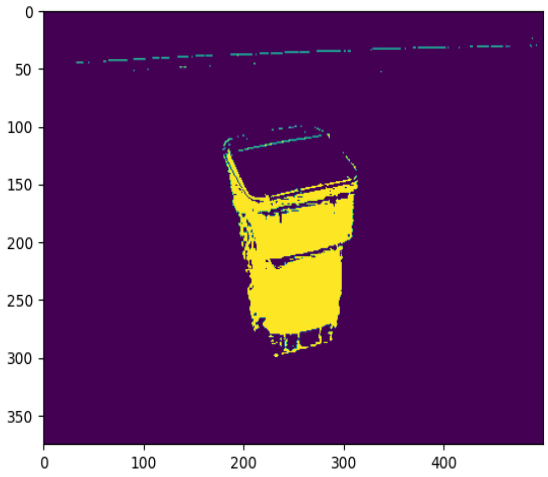
We implemented our model on classifying the blue pictures on the validation dataset with an accuracy of 100 % (precision = 1). While on the unknown images we obtained a score of 9.934/10.

B. Blue Recycling Bin Detection

On successful implementation of our model on bin detection for the ten validation datasets, we get an accuracy of 90%. While tested on the unknown images gives a score of 7.18/10. The inaccuracy on the unknown images can be attributed to the cases where some images may contain blue colour bin like object but not exactly the blue bin region. So, this may be too big as we did not set any bounding box on the maximum area of the bounding box.

Figure 1 to Figure 30 shows the original ten images in the validation set, masked images of the same, and boundary box respectively.

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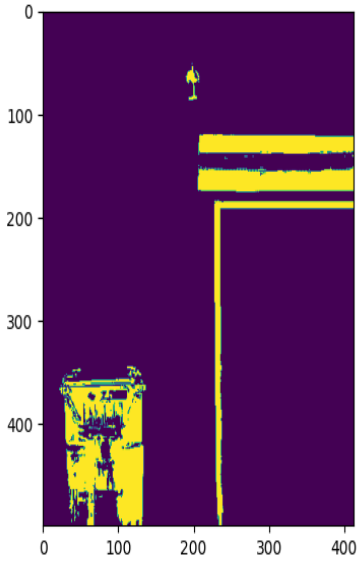
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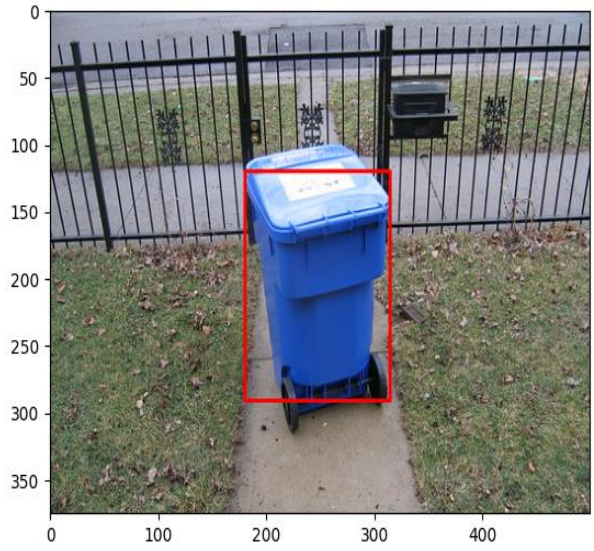
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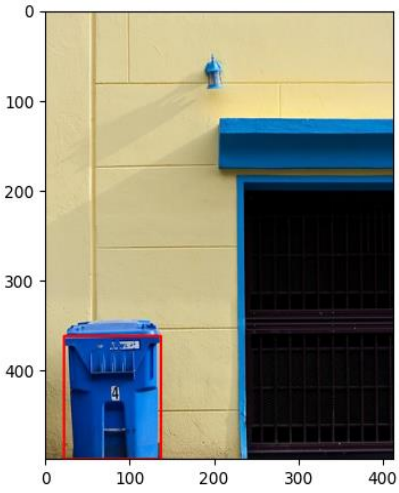
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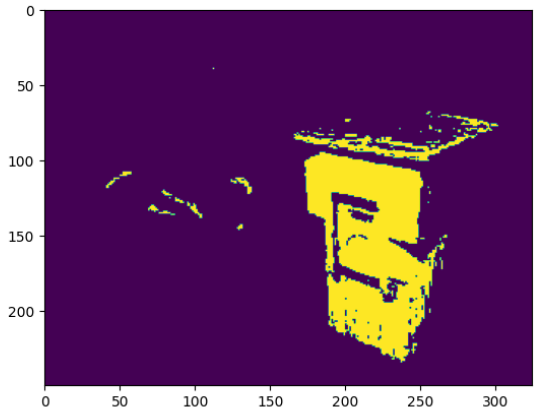
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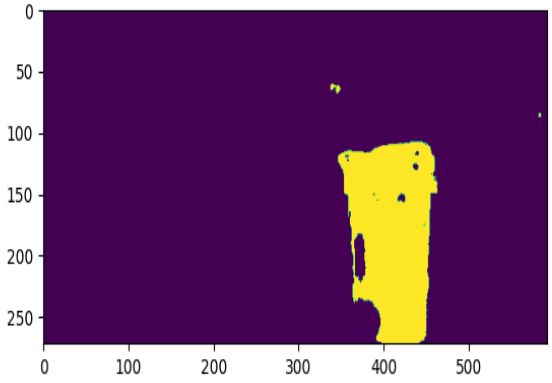
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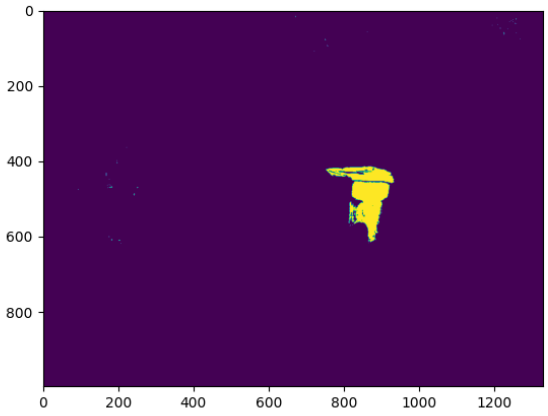
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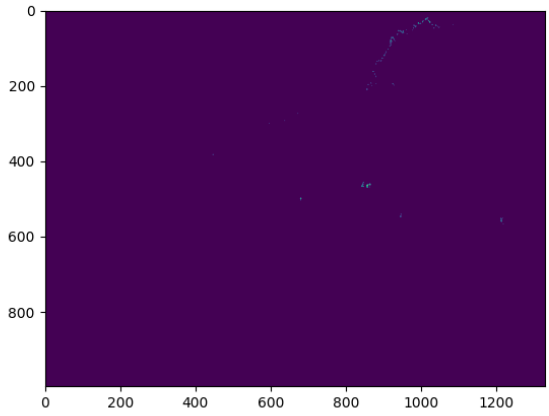
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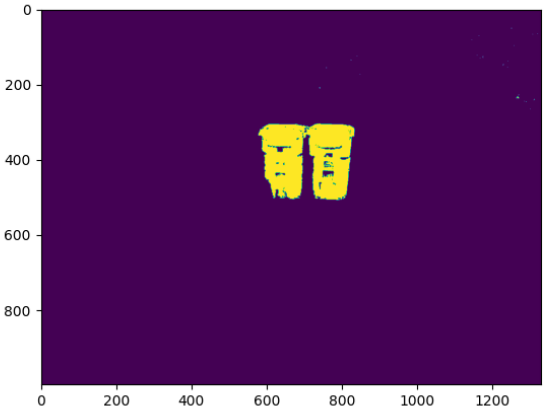
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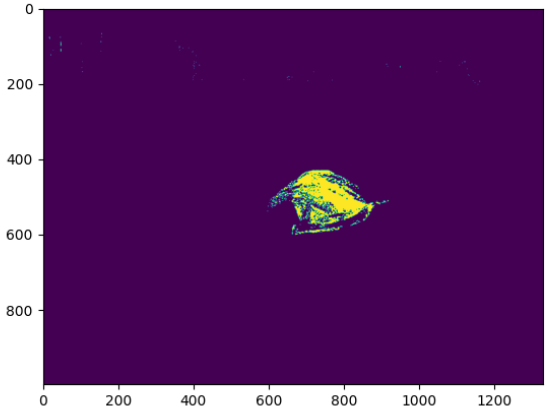
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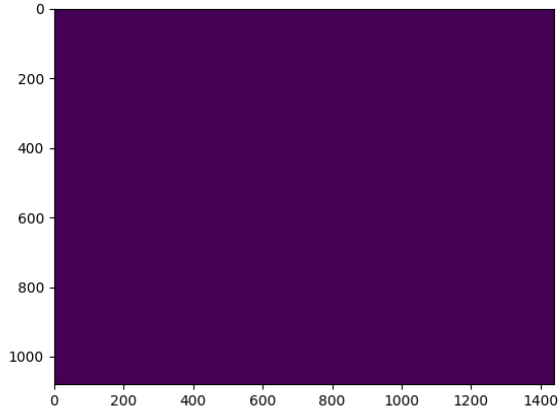
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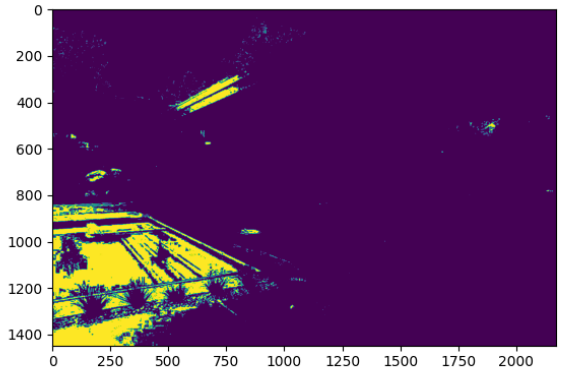
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