CSCE 5222: Feature Engineering
Project Proposal - Group 4

[https://github.com/csce5222/traffic_light_color_detection]

Project Proposal Description (Abstract)

The "Traffic Light Color Detection" project is dedicated to the development of a robust system designed to accurately identify and categorize traffic signal colors, including Green, Yellow, and Red. This endeavor encompasses an extensive exploration of diverse color-based image processing models, a comprehensive evaluation of their performance, and the adept handling of challenges related to feature engineering in image data.

At its core, this research project places a significant emphasis on achieving real-time traffic light detection using various objective detection and image processing algorithms. Additionally, the project leverages a diverse array of datasets and color models to facilitate adaptation to different real-world scenarios and ensure the precise categorization of detected colors.

The overarching goals of this project can be concisely summarized as follows:

- Primary Objective: The primary goal of this project is to establish a robust system capable of accurately identifying and classifying traffic signal colors, specifically Green, Yellow, and Red. This system is intended for practical use in applications such as traffic management.

- Methodology: The project's fundamental approach revolves around advanced image processing techniques, enabling the analysis of images or video frames captured by traffic cameras. These techniques empower the system to achieve precise recognition and categorization of the colors displayed by traffic lights.

- Exploration of Color-based Image Processing Models: The project extensively investigates various color-based image processing models, each carefully designed to efficiently process and interpret visual data, ensuring real-time and accurate color recognition.

- Performance Evaluation: A significant focus is placed on the rigorous evaluation of the performance of these image processing models. This evaluation assesses the system's accuracy, speed, and reliability in distinguishing between the essential traffic light colors.

- Addressing Feature Engineering Challenges: The project dedicates considerable attention to overcoming the intricacies of feature engineering in image data. This includes the development and implementation of algorithms and techniques aimed at enhancing image quality, mitigating noise, and correcting for variations in lighting conditions, each of which can significantly impact color detection accuracy.

- Utilization of Diverse Datasets and Color Models: The project thoughtfully incorporates a diverse range of datasets and color models, underscoring the importance of adaptability to diverse real-world scenarios. This diverse data landscape ensures the system's ability to effectively categorize colors with precision.

In summary, the project represents an innovative research initiative driven by the overarching objective of creating a dependable system for the precise identification and categorization of traffic light colors. The project's multifaceted approach encompasses advanced image processing techniques, performance evaluation, and the adept management of feature engineering challenges. With the integration of Convolutional Neural Network (CNN) algorithm for real-time traffic light detection and the utilization of a wide range of datasets and color models, the project holds the promise of significantly enhancing road safety and enabling the integration of this technology into applications such as autonomous vehicles and advanced traffic management systems.

1. Project Title and Team Members

Project Title: Feature Engineering Optimization for CNN-Based Traffic Light Color Detection

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2. Idea description

At its core, this project aims to establish a system capable of highly accurate detection and classification of traffic light colors. The significance of this endeavor is underscored by its applicability in autonomous vehicles, advanced driver assistance systems, and traffic management.

The central concept of the project is to create a system with the ability to precisely detect and categorize traffic light colors, including Green, Yellow, and Red, achieving a high level of accuracy.

The importance of this endeavor is highlighted by its broad applicability across crucial areas. Primarily, it has a significant role in autonomous vehicles, where accurate recognition of traffic signal colors is essential for safe and effective self-driving operations. Moreover, the project is relevant to advanced driver assistance systems (ADAS), enhancing driver safety through real-time color recognition.

Additionally, the project holds relevance in the field of traffic management. Here, precise detection and classification of traffic light colors are vital for optimizing traffic flow, reducing congestion, and improving road safety. The data generated by this system informs decisions related to signal timing, lane assignments, and traffic control strategies.

In summary, the fundamental idea of the project is to develop a system that excels in accurately identifying and categorizing traffic light colors. Its potential applications span autonomous vehicles, advanced driver assistance systems, and traffic management, with the promise of enhancing safety, efficiency, and overall transportation effectiveness [1], [2].

3. Goals and Objectives

From the myriad of goals and objectives within the project, our main focus is to identify the most crucial ones, which are as follows:

- Traffic Light Detection: To formulate a resilient algorithm for identifying traffic lights in images and video streams, with a particular emphasis on achieving real-time processing capabilities.

- Systematic Labeling: Since this project will utilize a supervised machine learning algorithm we will be labeling the dataset as we will be utilizing images from a variety of data sources using a variety of localized positions, orientation, and other image criteria for the traffic signal.

- Color Classification: To implement a classification system that precisely determines the color state of the detected traffic light (Green, Yellow, or Red).

- Image Processing Techniques Comparison: To evaluate the efficacy of gray image processing against at least two other color-based image processing models, including but not limited to RGB, YUV, and HSV, in order to ascertain the most effective approach.

- Address Feature Engineering Challenges: To thoroughly investigate and mitigate common challenges and pitfalls associated with feature engineering for image data, including issues such as noise, variations in illumination, and occlusions.

- Datasets: To leverage multiple datasets, including the Bosch Small Traffic Lights Dataset, MIT self-driving car course dataset, Traffic Signal - Open Data DC, and DriveU

Traffic Light Dataset (DTLD), for the purpose of ensuring the model's robustness and ability to generalize [9], [10], [11], [12].

- Color Model Evaluation: To assess the performance of a variety of color models, including but limited to RGB, CMY, YUV, YIQ, YCbCr, HSV, and HLS, in the context of traffic light color detection [3], [4].

4. Motivation

Our motivation for embarking on the project stems from our involvement in previous research and a deep commitment to advancing the precision and effectiveness of traffic light color detection. We understand the vital role this technology plays in applications such as autonomous vehicles, advanced driver assistance systems, and traffic management. Here are certain facets of our drive:

- Enhancing Road Safety: Accurate detection of traffic light colors is paramount for road safety, as it plays a pivotal role in the decision-making processes of autonomous vehicles and driver assistance systems.

- Optimizing Traffic Management: Efficient traffic management systems have the potential to alleviate congestion and enhance traffic flow. Reliable traffic light detection contributes significantly to achieving this objective.

- Advancing Research: This project contributes to the advancement of computer vision and image processing by delving into various color models and addressing feature engineering challenges within the domain of traffic light detection.

- Real-world Applications: The outcomes of this research hold the promise of benefiting a wide array of applications, ranging from self-driving vehicles to smart city initiatives. These applications have the potential to revolutionize transportation systems and reduce road accidents.

The project aspires to surmount the technical hurdles associated with detecting and categorizing traffic lights. By comparing diverse image processing techniques and integrating real-time detection techniques, this research endeavors to elevate the capabilities of traffic management systems and autonomous vehicles, ultimately contributing to safer and more efficient roadways [13].

5. Significance

The significance of this project is to make an extensive study on the effect of color spaces in the classification of Traffic signals with CNN.

The variable lighting conditions outdoors, can cause the image or videos to capture the information with inconsistencies in brightness, contrast and color information. Which could create misclassifications, in case of autonomous vehicles this could cause a serious threat to the passengers in the vehicle and pedestrians in case of wrong classification of traffic lights.

To tackle this issue, our project aims to find a color space that has limited sensitivity to the outdoor lighting conditions. In this project our primary objective is understanding the effect of different color channels in image classification with CNN and suggest the color space that has limited sensitivity for variable lighting conditions.

In case of autonomous vehicles this project will have significant impact in:

Enhanced Road Safety: Precise traffic light color recognition is paramount for road safety, ensuring vehicles respond appropriately to signals, thus reducing the risk of accidents caused by disobeying or overlooking traffic lights.

Empowering Autonomous Vehicles: The project's success is pivotal for the safe integration of autonomous vehicles. Self-driving cars rely on accurate traffic light interpretation to make informed driving decisions, including halting at red lights and proceeding at green lights.

Elevating Driver Assistance Systems: Advanced Driver Assistance Systems (ADAS) benefit from real-time traffic light recognition, enhancing their capacity to provide drivers with valuable insights and support. This leads to reduced collision risks and heightened road safety.

In summary, this project will suggest the best color spaces that will be less sensitive for variable outdoor lighting conditions and have minimal impact on the classification error.

6. Literature Survey

Traffic light classification is one of the important tasks within the field of autonomous vehicles. For a safe autonomous navigation of vehicles, an accurate and efficient recognition of traffic lights is crucial. Convolutional Neural Networks (CNNs) have been the main choice in image classification as they are very good at automatic extraction of image feature extraction and classification [8].

Research by Yuan et al. [18] has explored alternative methods of enhancing the accuracy of traffic light classification by integrating the features of Histogram of Oriented Gradients (HOG) alongside CNN-derived features. HOG is a feature descriptor that has the information of the local shape and structure of objects within an image. Combining this feature with the feature vector from CNN will provide the model with more information about the image. The main contribution of this research is to incorporate these HOG features and the CNN feature vector into a Support Vector Machine (SVM) for classification. They chose SVM because of its proven capability to classify multidimensional data effectively. By utilizing CNN-based feature vectors and HOG features, this approach improved traffic light classification accuracy from 88.25% to

91.36%. While the quantitative improvements achieved by this approach may not be considered substantial, they represent a step toward refining traffic light classification in autonomous vehicles. This integration of multiple feature types, such as HOG, alongside CNN-derived features, enriches the classification framework.

The significance of the image color space in classification accuracy has garnered increasing attention in recent research. One noteworthy study, conducted by Nazirah et al. [19], explores the conversion of images into the HSV (Hue, Saturation, Value) color space and its subsequent use in conjunction with a CNN. This particular method claims to have achieved an impressive accuracy of 93.25%, signifying a substantial advancement in the field of image classification.

In a separate investigation, Shreyank N et al. [20] undertook a comprehensive comparison of the effect of different color spaces on image classification using the CIFAR-10 dataset. Their study aimed to assess how variations in color space influence classification results. While the research observed that altering the color space did indeed produce diverse outcomes, the reported accuracies remained relatively consistent. This finding suggests that, in certain contexts, the choice of color space may have a limited impact on classification performance.

Most of the existing research in Traffic light classification is based on building CNN models in single color spaces or adding additional features to make their model robust. Yet, limited research works are addressing the effect of classification based on different color channels. In the real-world application of traffic light classification, the outdoor environment and varying weather conditions can play a significant impact in the classification results. Our project addresses this gap by comparing the classification performance of CNN models on various color channels and reporting the optimal color channel or channels that are suitable for traffic light classification in outdoor environments.

7. Objectives

Feature Extraction: Feature extraction in our project is converting the image input into different color spaces and making use of the different features captured by each color channel.

The list of color spaces we will be working on are: (note: Our research will not be bound to the listed color spaces, the list can increase or decrease according to complexity)

- RGB
- HSV
- YCbCr
- CIELAB
- YUV
- HED
- YIQ

Model Training: Train and tune multiple CNN models and fit them on all the color spaces that we will be working on [14], [15], [16], [17].

Evaluation Metrics: We will evaluate all the models based on the following metrics.

- Accuracy
- Recall
- Precision
- F1-Score

Results Comparison: We will compare the classification results of all the models as per the metrics listed above and provide a detailed analysis.

Color space suggestion: Based on the results and its analysis we will suggest the best color space suitable for image classification in an outdoor environment.

8. Features

The system that will be developed will predict the color or type of traffic-light signal in the image. The system will be designed in a way that will allow various feature vectors as input to be passed into the model chosen based on the image processing algorithm configured for the prediction in question. In other words, the same underlying model will be used for prediction with varying feature vectors [5], [6], [7],[18].

The end-user will iteratively provide various images to the system in order to predict the type of image. The Traffic Light Color prediction application programmable interface (API) will expose a simple python interface where the end-user configures each type of feature vector for the specific execution. Then the prediction API will determine the traffic signal color of the image. If the image is unable to be classified then a message will be sent to the end-user indicating that it was unable to classify the image (not an image of a traffic light, poor image quality, etc…) along with a null value for prediction.

```
yhat = model.predict(x, image_proc=ImageProcessing.YCbCr)
<TrafficSignal.RED>

yhat = model.predict(x, image_proc=ImageProcessing.YCbCr)
Unable to detect the traffic signal
<TrafficSignal.UNKNOWN>
```

Below is a list of the enums that will be utilized in the project. Note, this list may expand and contract based on the execution of the project.

```python
from enum import Enum

class ImageProcessing(Enum):
	CIE_RGB = "CIE_RGB"
	CIE_XYZ = "CIE_XYZ"
	RGB = "RGB"
	CMY = "CMY"
	YUV = "YUV"
	YIQ = "YIQ"
	YCbCr = "YCbCr"
	HSV = "HSV"
	HLS = "HLS"
```

In early years of computing research scientists would use creative techniques to exercise the scientific and mathematical models on digital and/or analog systems. However, with evolution of more commoditized compute and storage computer vision is seeing an unprecedented period of exponential growth. More specifically image processing was mostly performed using black and white images using a single color vector (black → white). Today, color image processing is becoming more ubiquitous in order to improve the accuracy of many image and video models. There are many color image processing techniques available today. But, this research paper will focus on a subset of methods available. In particular, our research will attempt to analyze and process the color space models using perception, additive and subtractive, luminance and chrominance, and additive perceptual luminance and chrominance models [22].

Perception models sort out colors according to the similarities we perceive and they were developed by experiments aimed at establishing measurable links between colors. *Additive and Subtractive* models describe colors according to the way they are used in reproduction systems (eg. printing and displaying). *Luminance and Chrominance* models look for separating the brightness from the hue (ie. pigment). Lastly, *Additive Perceptual Luminance and Chrominance* models create a perceptual organization by rearranging the color of other models by using a color transformation with the aim to create a more intuitive and interpretive representation of the image.

The Commission Internationale de l'Éclairage or CIE created standards for a color space model. It is also known as the CIE XYZ color space or the CIE 1931 XYZ color space [23]. According to the tristimulus theory it explains how the human eye can perceive certain colors and not others based on our biology in the color spectrum. It is modeled using a three-dimensional linear space using color components or weights of [c1, c2, c3] and primary colors of [A1, A2, A3]. Therefore the colorimetric equation is a linear combination of color components and primary colors:

C = $c_1A_1 + c_2A_2 + c_3A_3$

Perception-based Color Models:
We will explore two types of Perception models. They are CIE RGB and CIE XYZ.

Both Perception models are based on what the human eye can perceive. However, each model uses different primary colors. For example, the CIE RGB uses realistic colors whereas CIE XYZ uses theoretical colors. The equations for both models are defined as follows. ,

Additive and Subtractive Color Models:
The two *Additive and Subtractive* models we will explore are RGB and CMY. These two models differ in the way in which colors are created but both are popular in reproduction systems (eg. printing). RGB is an *Additive* while CMY is *Subtractive*. In RGB the colors are based on black and color intensities are added. On the other hand, CMY the colors are based on white and then intensities are subtracted. Note, CMY has been extended to CMYK by adding black to the base colors [19].

Luminance and Chrominance Color Model:
Luminance and Chrominance are popular for video processing, which is nothing more than images strung together to give the illusion of motion. The big difference between images and videos is that brightness for each color depends on all components in images. However, from a historical perspective, brightness is a separate component in video to represent perceived brightness. The YUV colorspace was used for the European analog TV standard, PAL, while YIQ was used for the North American and Japanese standard, NTSC [21]. The YCbCr standard is for digital video.

Additive Perceptual Luminance and Chrominance Color Model:
Additive Perceptual models are created by transformation that rearranges colors defined by the RGB color model making their components easier to understand. This is accomplished by combining features such as hue, brightness, and saturation. Two of the more popular *Additive Perceptual* models that will be used are Hue Saturation Value (HSV) and Hue Lightness Saturation (HLS). Both HSV and HLS define hue and saturation of a color but they use different concepts to define the bright component.

The input feature vector will be either gray images from 0 (black) to 255 (white) intensity values. In addition, for color images each image will consist of three channel RGB values with each color with color intensity values from 0 to 255.

The project encompasses a set of crucial elements, each serving a distinct role in achieving its goals. These elements include:

9. Expected outcome

Null Hypothesis H_0 $\rightarrow$: Color-scale image processing techniques will provide higher accuracy (precision, recall, etc..) than gray-scale image processing techniques.

Alternative Hypothesis H_1 $\rightarrow$: Grey-scale image processing techniques will provide higher accuracy (precision, recall, etc..) than color-scale image processing techniques.

Due to the commoditization of Open Source software algorithms, compute, and storage color image processing is more common than it was many years ago. As a result, even training thousands of color images is cost and time effective in order to produce the desired results. If compute and storage does become a limitation on local computers there are several public cloud vendors (AWS, GCP, and Azure) that provide commoditized virtual machines that can easily be spun and down based on computing resource needs.

10. References

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