Traffic Sign Detection and Recognition

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I. INTRODUCTION

Traffic sign detection and recognition is a critical task in computer vision and intelligent transportation systems, potentially enhancing road safety and optimizing traffic management. In recent years, significant progress has been made in this field, thanks to advancements in machine learning algorithms and the availability of large-scale annotated datasets. This paper focuses on implementing Traffic Sign Detection and Recognition using MATLAB, leveraging machine learning techniques and masks to improve accuracy and robustness. The objective of this project is to investigate the effectiveness of machine learning algorithms for traffic sign detection and recognition, in combination with the use of masks in MATLAB. By leveraging the power of machine learning, we aim to develop a robust and accurate system capable of detecting and recognizing traffic signs from images or video streams. Additionally, the utilization of masks helps to improve the localization accuracy by focusing on the relevant regions of interest within the image. We will explore various stages of the detection and recognition pipeline, including preprocessing, feature extraction, training, and classification. Moreover, we will address the challenges associated with this task, such as variations in lighting conditions, occlusions, and complex backgrounds, by implementing these techniques using MATLAB.

The outcomes of this research will contribute to the advancement of intelligent transportation systems, efficient traffic management, and the development of autonomous vehicles. Based on the road accident statistics released by United states Road Safety Collaboration 1.29 million people are killed globally as result of road accidents. Most of the accidents are occurred due to drivers do not focus on the road by using mobile or they ignore road signs, also the weather may Obscures vision especially during early morning. The road signs give valuable information to the control system of the vehicles preserve the live of the driver and the others, these road signs are categorized into colors to be easy for identification. These road signs decrease the number of accidents on the road. So the identification of road signs stands as a crucial step in mitigating traffic accidents and fatalities. Employing image processing technology to build road sign detection and recognition systems ensures that drivers are well-informed about road regulations and potential hazards, fostering the expectation of a decline in accidents and fatalities. The system's development contains two primary objectives: 1- Segmentation of road signs through color information extracted from real images using the color thresholding technique. 2-Classification of road signs based on the region of interest identified during the color segmentation stage. In this paper ,the first section is about sign detection, the section is about Random Forest, the third section is about the results of the random forest classifiers and the last section is about the Conclusion.

II. Methodology

<u>Detecting and recognizing road signs:</u>

In the following section, we'll illustrate the process of detecting and recognizing road signs. The initial step involves pre-processing to improve the quality of signs, addressing challenges like resolution and size variations, noise, and fluctuations in lighting. To remove noise, Gaussian filters are employed as shown in Figure (1), while Histogram equalizers are utilized to address variations in lighting. The detection of road signs involves a three-stage process:

1-colour segmentation: Road signs exhibit two distinct regions, one with the chromatic colour and the other with the achromatic colour for white signs, as depicted in Figure (2). The RGB colour space should be converted to The HSV model as shown in Figure (3) because The RGB faces some problems such as weather conditions, various lighting, and moving cameras, which lead to damage signs partially, as their colors may fade. The HSV is employed to determine these colors, where the Hue value signifies the chromatic color type, and the Saturation value represents the achromatic color. For instance, chromatic colors can be identified as red (if $H \leq 0.027$ or $H \geq 0.0833$), blue (if $H \leq 0.625$ and $H \geq 0.527$), and yellow (if $H \leq 0.166$ and $H \geq 0.055$ and $S \geq 0.35$). The achromatic color can be white if $S \leq 0.200$. Figure (4) shows the color segmentation for different colors.

2- Shape classification: the shape of road signs can be from the following shapes Diamond, Hexagonal, circular, and square/rectangular. We can distinguish between them through the value of Extent.

$$\text{Extent} = \frac{Total\ Pixel\ of\ ROI}{Total\ Pixel\ of\ Bounding\ Box}$$

In Figure (2), The boundary of the box is indicated by the red line, while the shape's boundary is denoted by the green line. The shape is Diamond if 0.46≤ Extent ≥0.55, the shape is Circular if 0.73≤ Extent ≥0.77 , The shape is Hexagonal if 0.78≤ Extent ≥0.83, and the shape is Square or Rectangular if 0.95≤ Extent ≥1.00.

3- Symbol recognition: This is achieved through a comparison of the area and perimeter ratios of the symbol region with reference ratios derived from standard images. The Area Ratio is computed as the division of the symbol region's area by that of the reference standard image, while the Perimeter Ratio is determined by dividing the perimeter of the symbol region by the perimeter of the reference standard image.

$$\text{Area Ratio} = \frac{\textit{Area of symbol region}}{\textit{Area of reference standard image}}$$

$$\text{Perimeter Ratio} = \frac{\textit{perimeter of symbol region}}{\textit{Perimeter of the reference standard image}}$$

To enhance the recognition process, all signs are categorized into three distinct groups: Prohibitory signs, characterized by a red background; Warning signs, distinguished by a yellow background; and Mandatory signs, identified by a blue background as shown in Figure (6). After we detect the colors and the shape of the sign, we can recognize the sign completely by applying the Joint Transform Correlator (JTC) technique by taking the Fourier transform to the target image and reference image as shown in Figure (7), the cross-correlation peak occurs if the target image and reference image are the same.

Figure (1)

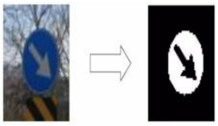

Figure (2)

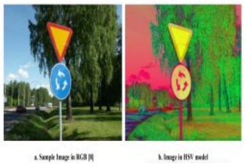

Figure (3)

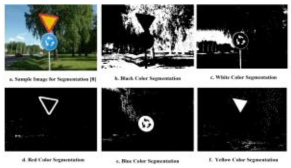

Figure (4)

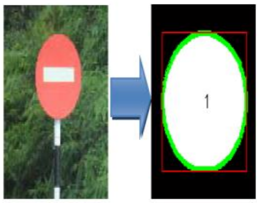

Figure (5)

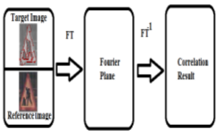

Figure (6)

Figure (7)

Random Forest is an ensemble learning algorithm:

Random Forest is an ensemble learning algorithm widely employed for both classification and regression tasks. It belongs to the family of decision tree-based methods, which have garnered significant attention in the field of machine learning. The fundamental concept underlying Random Forest is to construct a multitude of decision trees during the training phase and derive the mode (classification) or mean prediction (regression) of the individual trees for each input. These decision trees, as depicted in the accompanying figure, serve as the building blocks of the Random Forest algorithm. The functioning of Random Forest can be outlined as follows:

1. Bootstrapped Sampling (Bagging): Random Forest generates multiple decision trees by employing a technique known as bootstrapped sampling. This process involves creating several random subsets of the training data through sampling with replacement. Each of these subsets is then utilized to train a distinct decision tree. By training on different subsets, Random Forest introduces diversity into the ensemble, which helps mitigate overfitting issues.

2. Random Feature Selection: In the construction of each decision tree within the forest, Random Forest incorporates

an additional layer of randomness by considering only a random subset of features when making decisions at each node. This selective feature consideration, as opposed to evaluating all features, imparts further diversity among the trees and enhances the robustness of the ensemble.

3. Voting or Averaging: During the prediction phase, Random Forest employs a voting or averaging mechanism to determine the final prediction. In classification tasks, the mode (most frequent prediction) among the individual tree predictions is selected as the ensemble's prediction. In regression tasks, the final prediction is computed as the meaning of the predictions made by each tree.

The Random Forest algorithm offers several advantages, which contribute to its widespread adoption and empirical success:

1. Reduced Overfitting: The combination of bootstrapped sampling and random feature selection aids in reducing overfitting. By training each decision tree on a slightly different subset of the data, Random Forest mitigates the risk of over-reliance on specific patterns or noise in the training set.
2. High Accuracy: Random Forest often yields accurate predictions and exhibit lower susceptibility to overfitting compared to individual decision trees. The ensemble's ability to combine the predictions of multiple trees helps capture complex relationships in the data.
3. Versatility: Random Forest is highly versatile and can effectively handle both classification and regression problems. It is particularly well-suited for high-dimensional datasets with a substantial number of features, where it can uncover intricate patterns and relationships.
4. Implicit Feature Importance: Random Forest provides a measure of feature importance, allowing for the identification of influential features. By assessing the impact of different features on the ensemble's predictions, researchers and practitioners can gain insights into the underlying factors driving the predictive accuracy of the model.
5. Tree Correlation: While each tree within a Random Forest is trained independently, there is typically a degree of correlation between them. The introduction of randomness in both data sampling and feature selection helps to decorrelate the trees, thereby enhancing the ensemble's robustness and generalization capabilities.

In conclusion, Random Forest is a powerful ensemble learning algorithm that leverages the collective wisdom of multiple decision trees to achieve accurate predictions. Its utilization of bootstrapped sampling, random feature selection, and voting or averaging mechanisms contributes to its effectiveness in reducing overfitting, handling diverse problem domains, and implicitly assessing feature importance. With its wide-ranging applications and robustness, Random Forest continues to be a valuable tool in the field of machine learning and data analysis.

III. Results

In this section, we will explore the results of the random forest classifiers like ROC, AUC, Precision, and some images that the model identified. The model has been tested multiple times and given good results with the detection of signs like speed limit, no overtaking, stop sign, etc... The model has used 16000 images in training with 11800 as training data and 4800 as testing data. The data set was much bigger than 52000 images, but the reduction of the image size was due to computation time and complexity. The algorithm used 700 decision trees to provide a more accurate model and more accurate predictions.

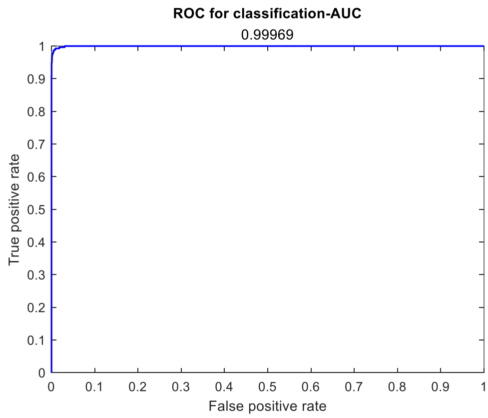

Figure 8- the model has a good ROC with an AUC approaching 99%.

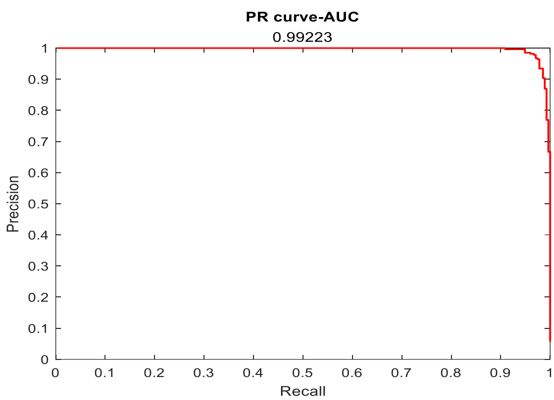

Figure 9- the model has a good PRC approach of 99%.

The model has gotten ROC and AUC as illustrated in Figure 8 99% and PRC 99 % as in Figure 9. The model has got F1-Score of around 97% which is an indication of good trade between total recall and Precision. Here are Random pictures from testing the machine-learning model.

Figure 10- The model has identified the road narrows sign

Figure 11- The model has identified no overtaking sign.

Figure 12- The model has identified the danger of snow sign.

Even if the model has good precision, tasting with new unseen data gives some wrong answers which need further investigation, but the first conclusion is the model is overfitted.

V.Conclusion

Traffic Sign Detection and Recognition using machine learning and masks in MATLAB offers a promising approach for enhancing road safety, traffic management, and the development of autonomous vehicles. The outcomes of this project contribute to the ongoing efforts in intelligent transportation systems, and we anticipate that further advancements in this field will lead to safer and more efficient roadways in the future.

VI.Reference

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