US Road Sign Detection and Visibility Estimation using Artificial Intelligence Techniques

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***Abstract*—This paper presents a fully-automated system for detecting road signs in the United States and assess their visibility during daytime from the perspective of the driver using images captured by an in-vehicle camera. The system deploys YOLOv8 to build a multi-label detection model and then, calculates various readability and detectability factors, including the simplicity of the surroundings, potential obstructions, and the angle at which the road sign is positioned, to determine the overall visibility of the sign. This proposed system can be integrated into Driver Assistance Systems (DAS) to manage the information delivered to drivers, as an excess of information could potentially distract them. Road signs are categorized based on their visibility levels, allowing Driver Assistance Systems to caution drivers about signs that may have lower visibility but are of significant importance. The system comprises four main stages: 1) identifying road signs using YOLOv8; 2) segmenting the surrounding areas; 3) measuring visibility parameters; and 4) determining visibility levels through fuzzy logic inference system. This paper introduces a visibility estimation system for road signs specifically tailored to the United States. Experimental results showcase the system's effectiveness. The visibility levels generated by the proposed system were subjectively compared to decisions made by human experts, revealing a substantial agreement between the two approaches.**

***Keywords*—Road sign detection; YOLOv8; driver assistance system; fuzzy logic; detectability; visibility estimation**

I. Introduction

In recent times, there has been a notable rise in the adoption of Driver Assistance Systems (DAS), primarily driven by the expanding complexity of road networks [1]. These systems are integrated into vehicles to simplify the driving experience and enhance overall driver safety. Road signs serve as a vital source of information for both drivers and these advanced systems, yet their visibility and detectability (the driver's capacity to spot a road sign within a complex or cluttered environment, essentially measuring how effectively the sign stands out) can be compromised in various scenarios. These scenarios can be categorized as either temporary, influenced by factors like lighting and adverse weather conditions, or permanent, resulting from vandalism or improper sign placement [2].

Reduced visibility of road signs significantly diminishes the effectiveness of communication between drivers and these signs. Consequently, DASs can play a crucial role in notifying drivers about warnings in such situations. Road sign detection is a basic step that every DAS system should have. It is noteworthy that an effective Driver Assistance System (DAS) should achieve a balance, avoiding the inundation of drivers with excessive road information. Overloading drivers with information may pose a risk of distraction, as discussed in [3].

Employing computer vision techniques in Driver Assistance Systems (DASs) enables the detection and estimation of road sign visibility. This information can then be used to alert drivers about crucial warnings regarding less visible signs. The implementation of these techniques contributes to enhanced driver safety.

In this work, we propose a fully-automated computer vision system for detecting and assessing the visibility of road signs in the United States in terms of their detectability and readability. Detectability is defined as the driver's capacity to identify and acknowledge the presence of specific road signs within complex or cluttered environments while readability represents the clearness degree of the foreground text on the sign. This proposed system can be integrated into Driver Assistance Systems (DAS) to streamline the information presented to drivers. Furthermore, transportation agencies could leverage this system to assess the placement of road signs across their road networks. The proposed system deploys YOLOv8 in the detection of road signs and estimates their visibility using fuzzy logic after measuring five different visibility parameters.

The proposed system aims to: 1) implement a fully-automated multi-label detection model of United States road signs using YOLOv8 which is the latest YOLOs' detection algorithm; 2) measuring five novel visibility parameters of road signs that describe both sign readability and detectability; 3) evaluate visibility level of road signs to low, medium and high using fuzzy inference system that connects the suggested visibility parameters to the visibility output.

The rest of the article is prepared as follows: Section II provides a background of road sign detection and visibility estimation systems. Section III demonstrates the proposed visibility estimation system. Section IV evaluates the system performance experimentally based on certain metrics. Lastly, Section V elaborates the conclusions.

II. Related Work

Automated estimation systems for assessing the visibility of road signs should integrate Road Sign Detection (RSD) systems. The primary objective of RSD is to pinpoint the location of road sign objects within a scene or within images captured from inside a vehicle. RSD systems can be primarily categorized into two groups: those reliant on color and those based on shape. In the realm of color-based detection, some researchers have utilized RGB color thresholding to segment road sign images, as demonstrated in [4, 5], while others have proposed the use of HSI color space for the same purpose, as indicated in [6].

Conversely, shape-based approaches have also been put forth by various researchers. In study [4], for instance, a Support Vector Machine (SVM) was trained using four vectors representing distances from the border to the bounding box to recognize road sign shapes. Researchers in [7] employed a Distance to Border (DtB) vector to identify the shape of road signs. For detecting Regions of Interest (ROI), a boosted detector cascade was trained using dissociated dipoles, while the recognition of triangular or circular road sign shapes was achieved through the utilization of the Hough transform and radial symmetry, as described in [8]. In study [9], a genetic algorithm was employed, and Haar-like features were deployed in study [6] to detect road sign shapes. Researchers in study [10] employed a set of cascaded geometric detectors, capitalizing on the inherent symmetry of road sign shapes for detection and recognition. In study [11], a speed recognition system has been proposed based on independent component analysis. In research [12], geometric features were deployed in the recognition of speed signs in the United States.

Recently, Convolutional Neural Network (CNN) was deployed with different architectures in detection tasks [13, 14] including road sign detection and recognition. In research [15], mask R-CNN was deployed to detect 200 traffic-sign categories with automatic end-to-end learning. In study [16], the authors analyzed seven architectures for detecting the road signs: YOLO, YOLOv2, YOLOv3, PP-YOLO model and R-CNN, Fast R-CNN, Faster R-CNN. This study implies that YOLOv3 and Faster R-CNN perform comparatively better for road sign detection. In [17], authors proposed a detection model to detect and identify traffic signs based on YOLOv7 and Convolutional Block Attention Module. In study [1], authors proposed a road sign detection and recognition system based onYOLOv5s object detection algorithm.

Several researchers have also proposed methods for estimating road sign visibility from digital images. Researchers in [18] introduced a novel technique for measuring road sign retro-reflectivity using two varied illumination images. In study [3], traffic signals' detectability and discriminability were quantified using in-vehicle images. Researchers in [19] utilized five image features to gauge the visibility of certain sign. For visibility estimation in foggy conditions, authors of study [20] introduced a method utilizing in-vehicle images. Researchers in [21] extracted both local and global features to evaluate a human driver's ability to detect and recognize road sign objects. Lastly, researchers in [22] showcased a novel approach based on SVM learning to estimate road sign saliency. In study [23], tilt angle of road sign was used to assess its condition. In study [24], various detectability features of road signs were measured to estimate the visibility level in cluttered environments.

In research [25], a three-dimensional approach for visibility assessment of highway signs has been proposed. The proposed approach measures sign's visibility, legibility, and readability based on its placement, height, and traffic flow. In [26], a system for classifying horizontal road signs as correct or with poor visibility is proposed. This system deploys YOLOv4-Tiny neural network model for classification and the contrast difference for visibility estimation. In [27], a study authors proposed a camera-based visibility estimation method for a traffic sign. The proposed method integrates both the local features and global features in a driving environment. These features measure sign's positional relationships and the contrast between a traffic sign and its surroundings. In research [28], author proposed an imaging-based system to estimate road sign visibility in a cluttered environment from the driver's perspective in daytime using in-vehicle camera images. The proposed system deploys a geometric sign detector and suggests two visibility parameters which are color difference and environment complexity. In study [29], authors proposed a method that can automatically detect the occlusion and continuously quantitative estimate the visibility of traffic sign. The proposed method deploys road sign orientation and occlusion in evaluating its visibility. In study [30], authors proposed a quantitative visual recognizability evaluation method for traffic signs in large-scale traffic environment. The proposed method evaluates the geometric, occlusion and sight line deviation factors of traffic signs.

In conclusion, the literature demonstrates that the implementation of automated vision-based road signs detection and recognition systems represents a significant advancement in modern transportation networks. In addition, visibility of these road signs is a major concern for both drivers and transportation agencies. The literature shows a lot of shortcomings of current road sign visibility estimation systems which can be concluded as the lack of automation in both the detection and visibility estimation, the deficiency of road sign detection models under different illumination and occlusion conditions, the failure to measure all visibility parameters that represent the road sign readability and detectability, and the need to estimate the road sign visibility to various levels either by a rule-based or machine learning techniques. As artificial intelligence techniques continue to evolve towards greater efficiency, these systems could be improved and automated completely for better safety over transportation networks. Additionally, current road sign visibility estimation systems should deploy powerful detection models that have the capability

III. The Proposed System

The proposed system based on road sign imaging, depicted in Fig. 1, comprises four distinct modules:

1) Multi-label road sign detection: In this initial module, the system builds a detection model using YOLOv8 algorithm based on the in-vehicle images to detect and identify three categories of road sign objects (regulatory, warning and stop signs).

2) Cropping of surrounding regions: In this module, the system geometrically extracts four adjacent regions around the road sign object. These regions would be used in the next module to calculate some visibility parameters.

3) Measurement of visibility parameters: During this module, the system establishes and computes five visibility parameters which are: 1) readability of sign foreground; 2) color difference between the sign and its four surrounding regions; 3) complexity of surroundings; 4) occlusion; and 5) tilting. These parameters characterize both the readability and detectability of each road sign.

4) Determination of visibility levels: In this module, the system assesses and categorizes the visibility level of each road sign as low, medium, or high using fuzzy logic inference system.

B. Multi-Label Road Sign Detection

In this module, YOLOv8 algorithm is used to detect three different types of US road signs: 1) Regulatory Signs (White Rectangular-shape signs); 2) Warning Signs (Yellow Diamond-shape signs); and 3) Stop Sign (Red Octagonal-shape signs. The multi-label detection model was trained on Google Colab notebook after building an annotated road sign dataset of 664 images. Once the model was trained, it was tested on a separate set of validation images to evaluate its performance.

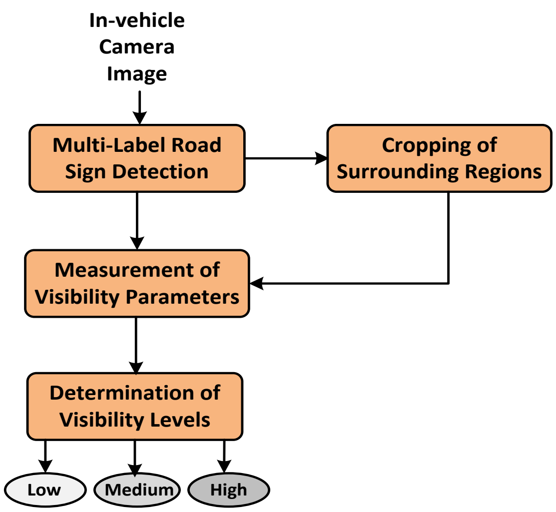

Fig. 1. Flow diagram of the proposed system.

1) Dataset preparation: Originally, 664 images in which one US road sign is existed, was collected and uploaded to Roboflow. Data analysis operations were achieved such as: pre-processing, resizing, annotation, augmentation and health check. All images were resized to 640x640. The following augmentations were done on these images: Rotation (between -21° and +21°), Saturation (between -20% and +20%), Brightness (between -20% and +20%), Blur (up to 1px), Noise (up to 3% of pixels). A set of 1519 images was achieved splitted as: 1332 for training, 116 for validation, and 71 for testing.

2) Model training and evaluation: The model was trained using YOLOv8. It was evaluated for detecting three classes: Stop signs, Warning signs and Regulatory signs. The number of Epochs used to train the model was 150. The model detection performance was evaluated using mean average precision (mAP), recall and precision.

The output of this module is road sign surrounded by a bounding box as shown in Fig. 2. This detected road sign would be used in the next modules to estimate its visibility.

Fig. 2. Examples of detected road signs.

C. Cropping of Surrounding Regions

In the module of the proposed system, road sign visibility is characterized by the driver's capacity to distinguish the sign's location from the surrounding background in a real-life scenario. Various elements in the background might divert the driver's attention away from identifying the road sign's location. To gauge visibility, we assess the road sign's location in relation to its surroundings. For Stop, Warning, and Regulatory signs, we have extracted four adjacent regions from the input image, as illustrated in Fig. 3. This process has been accomplished by mirroring the bounding box in the four directions. For Warning signs, the four regions were obtained after rotating the sign. Each region possesses a symmetrical shape and double the area of the sign region. These four surrounding regions are denoted as R1, R2, R3, and R4, while the sign region is designated as S, as shown in Fig. 3.

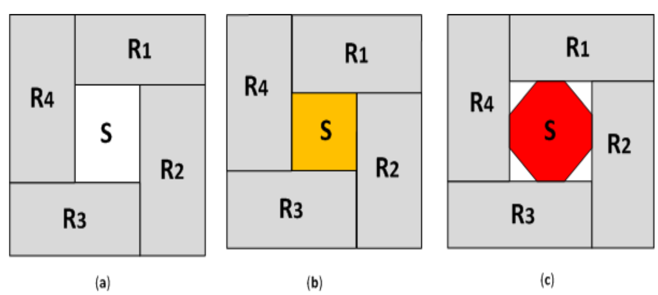

Fig. 3. The four surrounding regions for: a) Regulatory sign; b) Warning sign; c) Stop sign.

D. Measurement of Visibility Parameters

Different detectability and readability parameters of road sign region and surrounding regions are used to determine the visibility level of the road sign. Five parameters are proposed to describe the visibility of road signs: 1) readability of sign foreground; 2) color difference between the sign and the four surrounding regions; 3) complexity of surroundings; 4) sign occlusion; and 5) sign tilting.

Fig. 4 shows some road signs exhibiting poor visibility based on these parameters. Each parameter is designed as low or high based on ranges that were determined by a human expert.

1) Readability of sign foreground: This parameter measures the clearness degree of the foreground text on the sign. The greater the difference between the foreground and background is better considering the different colors in the three sign classes. This parameter, denoted by R, has been computed on the gray images of the detected signs by subtracting the average gray levels of both foreground and background as:

$$R = G_F - G_B \tag{1}$$

where, G_F is the gray level of the sign foreground (white on Stop signs and black on Warning and Regulatory signs), G_B is the gray level of the sign background (red on Stop signs, yellow on Warning signs and white on Regulatory signs).

A lower color difference between the sign foreground and background (0 - 120) diminishes a driver's ability to read and recognize road signs, whereas a higher color difference (120 - 255) enhances readability probabilities. Therefore, a significant color difference between the sign foreground and background leads to improved road sign visibility.

Fig. 4. Examples of low visibility road signs due to: a) Color difference between sign and surroundings, b) Occlusion, c) Complexity of surrounding regions, d) Readability of sign foreground, e) Tilting.

2) Color difference: This parameter measures the clearness degree of the sign with respect to its surrounding regions. The process involves computing the average color of the RGB values for both the road sign and its four surrounding regions. The color disparity between the sign region and each of its four surrounding regions is then quantified as follows:

$$D1 = \sqrt{(\overline{R}_S - \overline{R}_{R1})^2 + (\overline{G}_S - \overline{G}_{R1})^2 + (\overline{B}_S - \overline{B}_{R1})^2} \tag{2}$$

$$D2 = \sqrt{(\overline{R}_S - \overline{R}_{R2})^2 + (\overline{G}_S - \overline{G}_{R2})^2 + (\overline{B}_S - \overline{B}_{R2})^2} \tag{3}$$

$$D3 = \sqrt{(\overline{R}_S - \overline{R}_{R3})^2 + (\overline{G}_S - \overline{G}_{R3})^2 + (\overline{B}_S - \overline{B}_{R3})^2} \tag{4}$$

$$D4 = \sqrt{(\overline{R}_S - \overline{R}_{R4})^2 + (\overline{G}_S - \overline{G}_{R4})^2 + (\overline{B}_S - \overline{B}_{R4})^2} \tag{5}$$

where, ($\overline{R}_S, \overline{G}_S, \overline{B}_S$) are the average RGB colors of the sign region and ($\overline{R}_{Ri}, \overline{G}_{Ri}$, $\overline{B}_{Ri}$) are the average RGB colors of each surrounding region Ri.

Subsequently, these four disparity values are averaged to derive the overall color difference value, denoted as D. A lower color difference (0 - 120) diminishes a driver's ability to detect road signs, whereas a higher color difference (120 - 255) enhances detection probabilities. Therefore, a significant color difference between the sign region and its adjacent regions leads to improved road sign visibility.

3) Surrounding complexity: This parameter computes the amount of details that exist in the sign surroundings. It involves extracting the edges from all the surrounding areas and calculating the total number of edge pixels. The ratio between the number of edge pixels and the total number of pixels in these surrounding regions is employed to ascertain the shape complexity (C) of the road sign's surroundings, as follows:

$$C = \frac{N_E}{N_T} \tag{6}$$

where, N_E is the number of edge pixels in the surrounding regions and N_T is the total number of pixels in these regions.

A complex environment around the road sign will result in a high complexity parameter value, leading to a reduced level of visibility. The overall complexity level of the surrounding regions of the sign will vary between high (0.2 - 1) and low (0 – 0.2) based on the value of the complexity parameter

4) Occlusion: This parameter quantifies the extent to which the road sign is partially obscured by objects like trees or leaves. It takes into account partial occlusion occurring on the top and right sides of the road sign region while disregarding occlusion on the left and bottom sides. The occlusion parameter (O) is formulated as follows:

$$O = 1 - \frac{A_O}{A_T} \tag{7}$$

where, A_O is the filled area of the apparent sign blob computed as the number of pixels and A_T is the estimated area of road sign region computed as the bounding box area.

The level of occlusion can vary, being classified as either low (0 - 0.15) or high (0.15 - 1) based on the occlusion parameter value. Increased occlusion in the sign region would lead to reduced detectability and visibility of the road sign

5) Tilting: This parameter measures the tilting degree of road sign. The tilting parameter (T) is computed using the regionprops function on Python.

The degree of tilting can be categorized as either low (0 - 15^o) or high (15^o - 90^o), contingent upon the tilting angle value. A pronounced tilt of the road sign would result in reduced detectability and consequently, a low visibility level.

E. Determination of Visibility Levels

Road signs are classified in this module using fuzzy logic in terms of visibility levels to: low, medium, or high. A Fuzzy Inference System (FIS) connecting parameters to the visibility level operates through a series of defined steps to determine the appropriate visibility label based on the input parameters. Considering the parameters calculated in the previous module (Readability, Color Difference, Surrounding Complexity, Occlusion, and Tilting) and their fuzzy sets mapped to visibility levels (Low, Medium, High), here's how the FIS functions:

1) Input variables and membership functions

- Parameters like Readability, Color Difference, Surrounding Complexity, Occlusion, and Tilting serve as input variables.
- Each parameter has fuzzy membership functions (e.g., low, high) that describe how input values correspond to these linguistic terms. These membership functions have defined ranges and shapes, such as triangular or Gaussian that assign degrees of membership to each linguistic term based on the input's value within its range. Table I shows the membership functions of the input parameters.

2) Fuzzy rules

- Based on expert knowledge or empirical data, fuzzy rules are established to connect the input parameters to the output visibility levels.
- For example, rules might state:
- "If Readability is High AND Occlusion is Low AND Color Difference is Low, THEN Visibility Level is High."

TABLE I. THE MEMBERSHIP FUNCTIONS OF THE FIVE VISIBILITY PARAMETERS

Fuzzy Parameter	Membership Function Type	Parameter Range for Low	Membership Parameters for Low	Parameter Range for High	Membership Parameters for High
Readability	Triangular	0 to 120	a=0, b=60, c=120	120 to 255	a=120, b=180, c=255
Color difference	Triangular	0 to 120	a=0, b=60, c=120	120 to 255	a=120, b=180, c=255
Surrounding complexity	Triangular	0 to 0.2	a=0, b=0.1, c=0.2	0.2 to 1	a=0.2, b=0.4, c=0.6
Occlusion	Gaussian	0 to .15	Mean = 0.075 Standard Deviation = 0.0375	0.15 to 1	Mean = 0.575 Standard Deviation = 0.2125
Tilting	Trapezoidal	0 to 15	a=0, b=5, c=10, d=15	15 to 90	a=15, b=20, c=85, d=90

3) Inference engine

- The inference engine evaluates the fuzzy rules based on the current input values.
- It calculates the degree to which each rule contributes to different visibility levels using fuzzy logic operations like AND, OR, and NOT.

- Aggregation methods, such as the Mamdani, combine the rules to determine the degree of support for each visibility level based on the input parameter values.

4) Defuzzification

- Once the inference engine processes the rules and combines their outputs, the defuzzification process aggregates the fuzzy output sets to derive a crisp, actionable output.
- This process converts the fuzzy output into a specific visibility level, such as Low, Medium, or High, based on methods like centroid, mean of maximum (MOM), or weighted average.

5) Output - determining visibility level

- The final step yields a specific visibility level determined by the FIS after processing the input parameters through the defined membership functions and rules.
- This output provides a clear and actionable visibility level based on the linguistic description or numerical range that best fits the input parameter combinations. Table II shows the membership functions of the output variable which is the visibility level.

The Fuzzy Inference System connects the input parameters related to visibility to the appropriate visibility level using fuzzy logic, allowing for a more understanding and decision-making process in scenarios where traditional binary or crisp logic might be insufficient.

The relationship between parameters and visibility levels is determined according to the following fuzzy rules:

1) If Readability is Low AND Occlusion is not high THEN Visibility Level is Low

2) If Occlusion is High THEN Visibility Level is Low

3) If Readability is High AND Occlusion is Low AND Color Difference is Low AND Surrounding Complexity is High AND Tilting is High THEN Visibility Level is Low

4) If Readability is High AND Occlusion is Low AND Color Difference is Low AND Surrounding Complexity is Low AND Tilting is High THEN Visibility Level is Medium

5) If Readability is High AND Occlusion is Low AND Color Difference is Low AND Surrounding Complexity is Low AND Tilting is Low THEN Visibility Level is High

6) If Readability is High AND Occlusion is Low AND Color Difference is Low AND Surrounding Complexity is Low AND Tilting is Low THEN Visibility Level is High

7) If Readability is High AND Occlusion is Low AND Color Difference is High AND Surrounding Complexity is Low AND Tilting is Low THEN Visibility Level is High

8) If Readability is High AND Occlusion is Low AND Color Difference is High AND Surrounding Complexity is High AND Tilting is Low THEN Visibility Level is High

9) If Readability is High AND Occlusion is Low AND Color Difference is High AND Surrounding Complexity is Low AND Tilting is High THEN Visibility Level is High

10)If Readability is High AND Occlusion is Low AND Color Difference is High AND Surrounding Complexity is High AND Tilting is High THEN Visibility Level is Medium

The rules connecting parameters to visibility levels in this fuzzy inference system have varying weights, indicating their significance in determining the visibility level. The lowest weight, at 0.2, is assigned to Rule 1, while Rule 2 holds a weight of 0.7, emphasizing the role of Occlusion in determining visibility. Rules 3 and 4, with weights of 0.8 and 0.9 respectively, highlight the combined impact of Readability, Occlusion, Color Difference, and Surrounding Complexity. Finally, Rules 5 to 10, each with a weight of 1.0, underscore the comprehensive consideration of Readability, Occlusion, Color Difference, Surrounding Complexity, and Tilting in determining the visibility level, demonstrating their paramount importance in decision-making.

TABLE II. THE MEMBERSHIP FUNCTIONS OF THE OUTPUT VARIABLE WHICH IS THE VISIBILITY LEVEL

Visibility Level Fuzzy Output	Membership Function Type	Parameter Range for Low	Membership Parameters for Low	Parameter Range for Medium	Membership Parameters for Medium	Parameter Range for High	Membership Parameters for High
Low	Triangular	0 to 0.33	a=0, b=0.17, c=0.33	0.17 to 0.67	a=0.17, b=0.42, c=0.67	0.33 to 1	a=0.33, b=0.67, c=1
Medium	Triangular	0.17 to 0.67	a=0.17, b=0.42, c=0.67	0.33 to 0.83	a=0.33, b=0.58, c=0.83	0.67 to 0.83	a=0.67, b=0.83, c=0.83
High	Triangular	0.33 to 1	a=0.33, b=0.67, c=1	0.67 to 1	a=0.67, b=0.83, c=1	0.67 to 1	a=0.67, b=0.83, c=1

IV. EXPERIMENTAL RESULTS

The visibility estimation system was tested on images of road signs taken by an in-vehicle camera in the United States. These in-vehicle images were obtained using a SAMSUNG ST65 camera, along with images from the VISAT^{TM} Mobile Mapping System. All images were resized to 640x640 pixels. In this section, we will demonstrate the results of both the detection model and the visibility estimation model.

A. Road Sign Detection Results

In this subsection, we evaluate the performance of the YOLOv8 detection model, which plays a crucial role in automatically identifying the road sign. The evaluation focuses on key metrics such as Accuracy, Precision, and mAP@0.5, providing insights into the model's accuracy and proficiency in object detection. The detection model underwent training for 150 epochs.

Fig. 5 presents a snapshot of quantitative metrics used to gauge the detection model's performance during training, including precision, recall, and mean average precision (mAP@0.5). These metrics shed light on the model's effectiveness in identifying road signs in in-vehicle images. Additionally, it is observed that box loss and class loss are converging.

The detailed breakdown of the model's performance is illustrated in the confusion matrix presented in Fig. 6, outlining true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) for each object class (e.g., Warning sign, Regulatory sign, Stop sign, and background).

Precision measures the accuracy of true predictions made by the model. It is a crucial metric for object detection, as it assesses the model's ability to correctly identify objects without generating too many false positives. Recall assesses the model's ability to detect all relevant objects, reducing false negatives and ensuring no objects of interest are overlooked. mAP@0.5, a comprehensive metric, combines precision and recall, providing an aggregate evaluation of the model's performance across different object classes and considering precision-recall trade-offs.

The detection model has achieved remarkable results of the three performance metrics where mAP@0.5= 91.5%, Precision= 86.1%, and Recall= 90.5%. It is noticed that the model achieved better results of both Stop and Warning signs while missing some Regulatory signs. This happens because of the high effect of illumination on white signs especially when they are facing the sun.

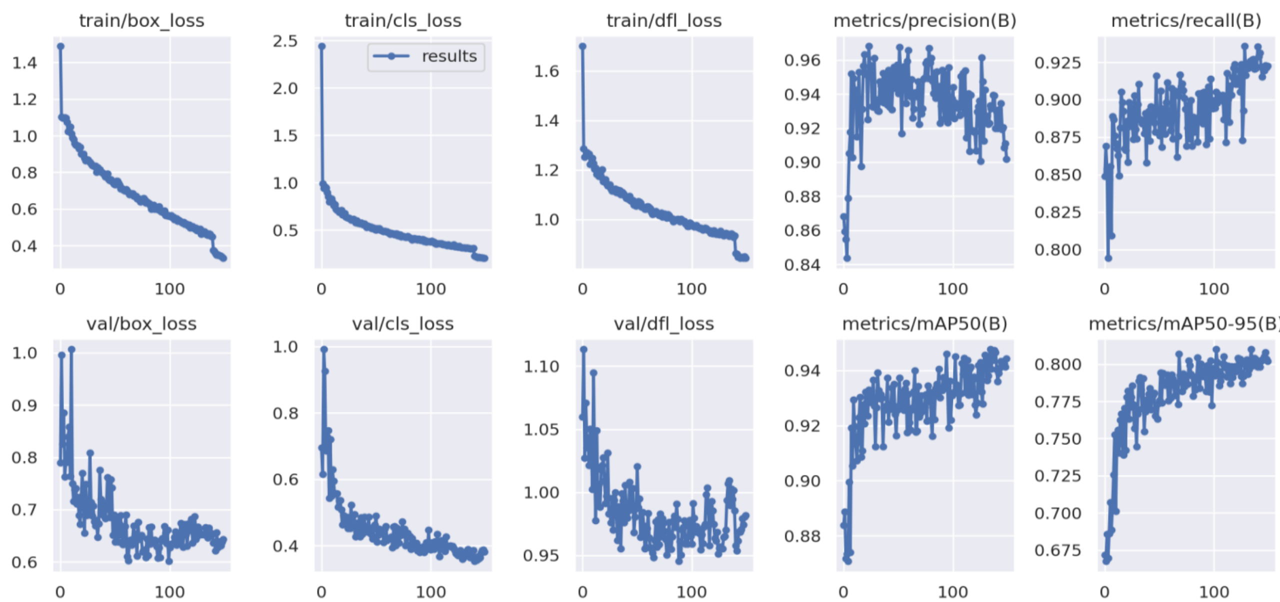

Fig. 5. Performance metrics of the detection model throughout the training process for 150 epochs.

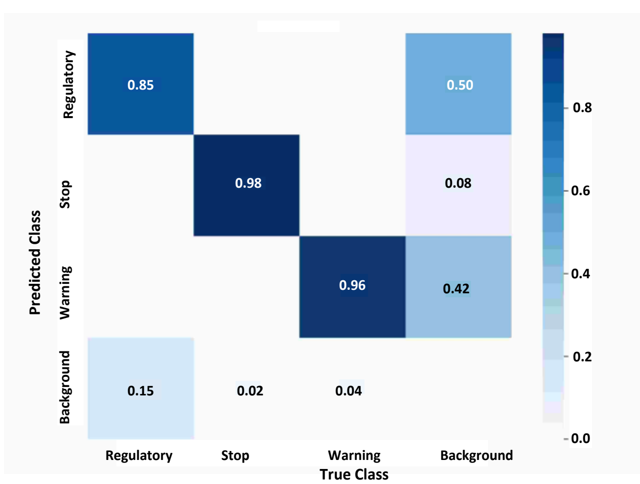

Fig. 6. Confusion matrix of the detection model.

B. *Visibility Estimation Results*

Testing the fuzzy inference system (FIS) designed for road sign visibility demands a comprehensive procedure, especially when assessing its efficacy with a set of images. The initial step involves sourcing a diverse dataset of road sign images captured in various conditions, encompassing differing lighting, weather scenarios, angles, and distances. This dataset must cover a wide spectrum of potential real-world scenarios to ensure the FIS is tested under varying conditions. Upon gathering the images, preprocessing becomes pivotal. Standardizing the dataset involves resizing images to a uniform dimension, normalizing lighting conditions, and potentially applying filters or enhancements to accentuate visibility features present within the signs. Feature extraction follows, where specific visual features linked to the parameters considered in the FIS - such as readability, color difference, occlusion, surrounding complexity, and tilting - are identified and extracted from the images. This process is crucial to align the image data with the FIS parameters for subsequent analysis.

Integrating the FIS into the testing process involves applying the system to the extracted features from each image. This step aims to predict the visibility level for each sign based on the rules and weights defined within the system. Simultaneously, ground truth labeling becomes essential (assigning visibility labels to the images based on either human judgment or known visibility conditions captured during image acquisition). This establishes a benchmark against which the FIS's predictions can be evaluated. Post-prediction, an evaluation phase ensues where the predicted visibility levels are compared with the ground truth labels using various metrics, such as accuracy, precision and recall. Any discrepancies or misclassifications are carefully analyzed to understand potential shortcomings within the FIS. The procedure allows for iterative refinement. Any observed inconsistencies or errors guide adjustments to the FIS, such as tweaking membership functions, rules, or weights, aiming to enhance its accuracy and reliability.

1) Evaluating the Effectiveness of the Proposed Fuzzy Inference System: In evaluating the effectiveness of the proposed fuzzy inference system for visibility estimation, a distinct approach has been taken. Through a training phase involving 45 in-vehicle images, thresholds for detectability parameters were determined, crucial for classification into high, medium, or low visibility levels. This training set, comprising various road signs and diverse visibility scenarios, was instrumental in setting suitable threshold values, guided by expert decisions. These thresholds, rooted in the training phase, were then applied to a test set consisting of 50 in-vehicle images, including rectangular regulatory, diamond warning and stop signs, mirroring real-world diversity in visibility conditions.

The comparison between the decisions rendered by the proposed system and those of human experts unveils promising results. Out of 50 road signs tested, there was concurrence between the proposed system and expert judgments for 4 signs, representing an impressive 92% accuracy. Notably, even within the 4 instances of discordance, the disagreement usually amounted to merely one visibility level, showcasing a remarkable alignment between the proposed system's estimations and the human expert decisions. Fig. 7 shows examples of the proposed visibility estimation output along with the five visibility parameters and expert decision.

Further analysis revealed a nuanced performance difference in handling yellow and red versus white road signs. The system exhibited a higher proficiency with yellow and red signs owing to the impact of illumination on white color, affecting the accuracy of the color difference detectability parameter.

2) Parametric influence on fuzzy inference system: shaping accuracy and decision dynamics: The effectiveness and accuracy of the outcomes are profoundly influenced by the parameters incorporated within the system. These parameters, such as membership functions, threshold values, and rule weights, play a pivotal role in shaping the decisions and predictions made by the system. Membership functions, serving as the backbone of fuzzy logic, define the degree of membership of an input to a specific linguistic term (like 'low,' or 'high'). Their design profoundly impacts the system's ability to interpret and categorize input data, significantly influencing the resulting output. Threshold values, especially in the context of detectability parameters for road sign visibility estimation, dictate the boundary between different visibility levels. Setting these thresholds involves a delicate balance; they need to be robust enough to delineate distinct visibility categories while remaining adaptable to varying environmental conditions.

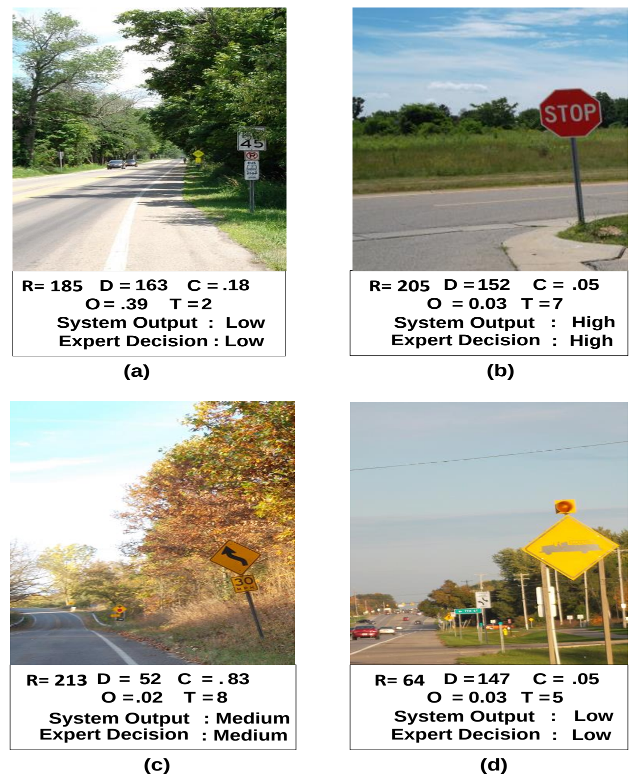

Fig. 7. Visibility estimation outputs of the proposed system for road signs with expert decision: a) Low, b) High, c) Medium, d) Low.

Rule weights hold significance in the determination of the overall decision-making process within the fuzzy system. They assign importance or precedence to different rules, emphasizing the relative significance of specific parameters in contributing to the final output. Properly calibrated weights ensure that more critical parameters exert a more considerable influence on the system's decision. The effect of these parameters on the system's output is intricate and interconnected. Subtle adjustments or alterations in membership function shapes, threshold values, or rule weights can significantly impact the system's performance. Well-tuned parameters often lead to more accurate, reliable, and adaptable outcomes, enhancing the system's robustness across diverse datasets and real-world conditions.

Understanding the influence of these parameters allows for iterative refinement, facilitating continuous improvement in the system's accuracy and adaptability. Through careful calibration and fine-tuning of these parameters, a fuzzy inference system can be optimized to yield more precise and dependable results, making it a valuable tool in addressing complex decision-making tasks where traditional binary logic falls short.

V. Conclusions

In this work, we proposed a fully-automated system to detect road signs in the United States and estimate their visibility from images captured by an in-vehicle camera. Sign visibility is defined as the drivers' capability to perceive road signs on roadways, encompassing both the ability to detect the signs (Detectability) and the ability to read and recognize their contents (Readability).

The proposed system can be deployed in Driver Assistance Systems (DAS) or by transportation agencies. The proposed system has deployed YOLOv8 to build a detection model of three different road sign categories. Then, it measured five visibility parameters which are: readability of sign foreground, color difference between the sign and its surroundings, complexity of surroundings, sign occlusion, and sign tilting. The proposed system classifies road signs to three visibility levels: high, medium, and low. A Fuzzy Inference System (FIS) connecting these parameters to the visibility level operates through a series of defined steps to determine the appropriate visibility label based on the input parameters. The proposed system has achieved outstanding efficiency results with mAP@0.5= 91.5% for the detection model and an accuracy= 92% for the visibility estimation module. The accuracy of the proposed visibility estimation system has been compared with human expert pre-determined decisions.

The proposed system is distinguished by its being fully-automated, the efficiency of detecting road signs under various illumination and occlusion conditions, the ability to classify road signs visibility to multiple levels and the inclusion of both readability and detectability parameters of road signs from the perspective of driver.

In the future, we are planning to include more road sign categories in the visibility estimation system. Additionally, the size of dataset can be increased to improve the precision of the detection model. Hardware implementation can also be implemented based on the proposed computer vision system.

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