IMAGE-BASED ROADWAY HAZARD DETECTION AND RISK RATING USING ARTIFICIAL INTELLIGENCE

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ABSTRACT

Road safety is affected not only by road geometry, but also by the visibility and condition of roadside safety features such as warning signs, pavement markings, and guardrails. This paper presents an image-based framework for roadway hazard detection and risk rating using artificial intelligence. Three YOLOv8-based models were trained to detect right-turn and left-turn warning signs, double road lines, and guardrails from road scene images. In parallel, 148 horizontal curves along the Colombo-Hatton Road (A7) were identified in QGIS and described using radius, direction, and curve class. Roadside drop-off was assessed using a digital elevation model. The detection outputs, curve geometry, roadside drop values, and guardrail condition were then combined through a weighted likelihood–impact matrix. Likelihood was calculated using curve radius, warning sign condition, and road marking condition, while impact was calculated using roadside drop and guardrail condition. The weighted values were converted into matrix levels and multiplied to classify the selected curves as low, medium, or high risk. The results show strong performance for warning sign and double line detection, while guardrail detection is more difficult because of occlusion, roadside clutter, and background similarity. High-risk curves were mainly associated with sharp curvature, significant roadside drop-off, and inadequate roadside protection. The framework therefore provides a practical screening method for identifying hazardous curves and optimum locations for guardrail installation.

Keywords: road safety, computer vision, YOLOv8, horizontal curves, risk assessment

1. INTRODUCTION

Road safety depends on both the geometric design of the road and the guidance provided to drivers through visible roadside features. On horizontal curves, warning signs, pavement markings, and guardrails are particularly important because they help drivers recognize the curve, maintain lane position, and reduce the consequences of roadside departures. Conventional inspection of these features is usually manual and can be slow, labour-intensive, and inconsistent across long corridors. This work develops a modular image-based framework to detect key roadside safety features from road images and combines those outputs with curve radius and roadside drop-off height to support rule-based risk rating along the A7 corridor in Sri Lanka.

2. LITERATURE REVIEW

Horizontal curves are commonly treated as crash-prone road segments because drivers must reduce speed and maintain lateral control within a short distance. Curve radius is one of the most useful geometric indicators, with smaller radii linked to greater driving risk on sharp curves (Ma et al., 2023). Visible features such as lane markings, warning signs, and guardrails also affect driver perception and the likely severity of a road departure (Ben-Bassat & Shinar, 2011).Automated lane-marking studies show that deep learning models can identify missing, worn, or classified road markings from road images, making them useful for maintenance and safety inspection(Azmi et al., 2022). Recent deep learning and segmentation-based approaches also support roadway asset detection and inventorying (Zhang et al., 2025), while active-learning methods have been applied to rural roadside safety features such as guardrails(Yi et al.,

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2021). However, much of the existing work reports detection or inventory results without converting them into clear hazard indicators. The present work addresses this gap by combining image-based detections with curve geometry and roadside drop-off conditions for curve-level risk rating.

3. METHOD

3.1. Roadside Feature Detection

Three fine-tuned YOLOv8 models were developed independently. The road sign model detects two selected curve warning sign classes and an additional other-sign class. In this study, DWS-01 denotes the right-turn-ahead warning sign, while DWS-02 denotes the left-turn-ahead warning sign. The double line model detects double white road markings from a custom Roboflow dataset. Guardrail detection was implemented as an instance segmentation task using KITTI and Google Street View images so that the visible extent of roadside barriers could be captured more accurately.

3.2. Curve Identification and Roadside Drop Assessment

The A7 road centreline was analysed in QGIS. Deflection angles between consecutive vertices were computed, and curves were grouped using a 15-degree threshold with a minimum of six consecutive points. Roadside drop was measured using an ALOS AW3D digital elevation model by comparing centreline elevation against offset points 15 meters from the road edge.

3.3. Risk Rating Framework

A rule-based likelihood–impact risk rating framework was developed to classify selected curve locations into low, medium, or high-risk levels. The framework combines five inputs: curve radius, warning sign condition, road marking condition, roadside drop condition, and guardrail condition. Curve radius, warning sign condition, and road marking condition were used to represent the likelihood of a hazardous situation, while roadside drop and guardrail condition were used to represent the potential impact of a run-off-road event.

The weighted likelihood score was calculated as:

$$Lw = 0.40R + 0.30S + 0.30M$$

where R is the curve radius score, S is the warning sign score, and M is the road marking score. The weighted impact score was calculated as:

$$Iw = 0.60D + 0.40G$$

where D is the roadside drop score and G is the guardrail score. The weighted scores were then converted into integer matrix levels from one to three. The final risk score was calculated by multiplying the likelihood level and impact level. Risk scores of one to two were classified as low risk, scores of three to four as medium risk, and scores of six to nine as high risk. This method makes the final risk rating traceable because each curve risk level can be linked back to its geometric condition, roadside exposure, and detected safety features.

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4. RESULTS AND DISCUSSION

4.1. Detection Performance

The road sign model achieved approximately 98% accuracy for DWS-01, the right-turn-ahead warning sign, and 87% for DWS-02, the left-turn-ahead warning sign. The double line model achieved a normalized class value of 0.94. Guardrail detection achieved 0.74, with missed detections mainly occurring in cluttered or occluded scenes. Figure 1 presents sample detection outputs, and Figure 2 shows the corresponding normalized confusion matrices for all three modules.

4.2. Curve Identification and Drop Assessment

Figure 7. Detection results: road sign DWS-01 (left), guardrail on A7 (centre), double white line (right)

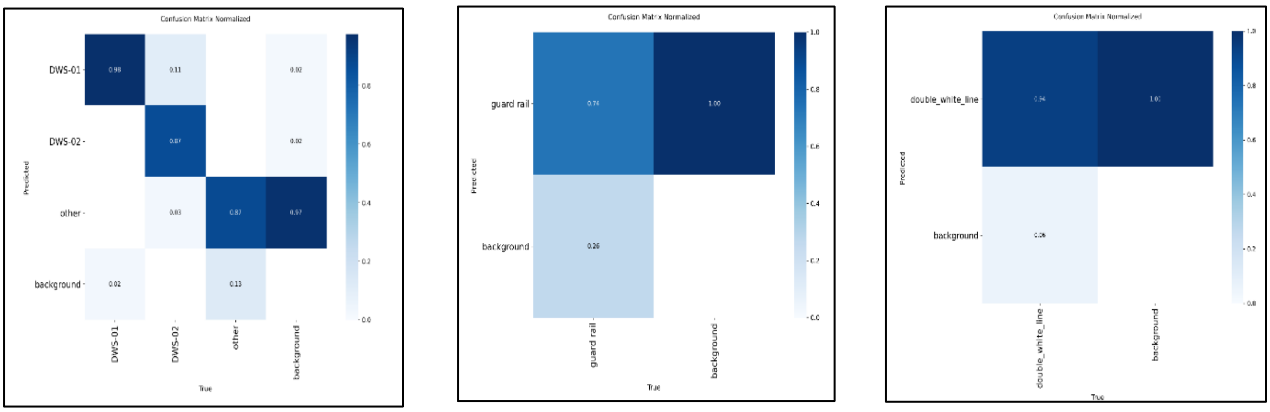

Figure 6. Normalized confusion matrices: road signs (left), guardrail (centre), double lines (right)

A total of 148 curves were identified along the A7 corridor. Radii ranged from 17.95 m to 22,865.03 m, with a median of 100.40 m. Eight curves were extremely sharp, 24 were sharp, 51 were moderate, 30 were gentle, and 35 were very gentle. Twenty-three curves exhibited critical roadside drop-off conditions exceeding three meters, concentrated mainly in the Avissawella-Hatton hilly section. Table 1 summarizes the classification results.

Table 4. Curve Classification and Roadside Conditions

Curve Class	Radius (m)	Count	Roadside Drop Condition	Risk Priority
Extremely Sharp	< 30	8	High	Very High
Sharp	30–60	24	Moderate	High
Moderate	60–115	51	Variable	Medium

Gentle	115–230	30	Low	Low–Medium
Very Gentle	> 230	35	Low	Low

4.3. Risk Rating and Guardrail Placement

The likelihood–impact matrix was applied to selected representative curves using five inputs: curve radius, warning sign condition, road marking condition, roadside drop, and guardrail condition. The results were classified as low, medium, or high risk. High-risk locations were generally associated with sharp curves, significant roadside drop-off, weak visual guidance, and absence of guardrail protection. These locations were considered candidate priority locations for field verification and possible guardrail installation. For sharp curves with low roadside drop, other treatments such as warning signs, chevrons, improved markings, vegetation clearing, or speed control may be more suitable than guardrail installation.

5. CONCLUSION

This work developed a modular image-based framework for roadway hazard detection and risk rating. YOLOv8 models were used to detect warning signs, double road lines, and guardrails, while GIS and DEM analysis were used to assess curve geometry and roadside drop along the A7 corridor. The results showed strong performance for warning sign and double line detection, while guardrail detection was more affected by occlusion and roadside clutter.

A weighted likelihood–impact matrix was used to combine curve radius, warning sign condition, road marking condition, roadside drop, and guardrail condition into low, medium, and high-risk levels. The framework supports preliminary identification of hazardous curves and candidate priority locations for field verification and safety improvements. Future work should improve local dataset quality, validate the risk ratings through field observations, and test the method on other road corridors.

6. REFERENCES

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