

Retinex-Based Traffic Sign Recognition for Robust Performance Under Low-Visibility Conditions

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Abstract—With the advancement of autonomous vehicles and Advanced Driver Assistance Systems (ADAS), Traffic Sign Recognition (TSR) systems have become increasingly important. However, adverse weather conditions such as fog, rain, and low illumination significantly degrade model performance, leading to missed detections and false positives. To address this challenge, we propose an enhanced TSR model built upon RetinaNet and augmented with a Retinex-based image enhancement algorithm. The model adopts a decoupled detection-classification architecture to improve both accuracy and efficiency. Experiments on the German Traffic Sign Detection Benchmark (GTSDb) and German Traffic Sign Recognition Benchmark (GTSRB) demonstrate that the proposed method partially mitigates detection errors occurring under challenging visibility conditions. For challenging test cases satisfying the Retinex application criterion, the Auto MSR-augmented training configuration improved recall and mAP by approximately four percentage points compared with the original-only baseline. This study highlights the potential of Retinex-based enhancement for improving TSR robustness and contributes to the advancement of intelligent transportation systems.

Keywords—RetinaNet; retinex; traffic sign recognition; adverse weather conditions; german traffic sign benchmark

I. INTRODUCTION

Autonomous driving technology has emerged as a foundational technology in the modern automotive industry for maximizing safety and convenience. In particular, Advanced Driver Assistance Systems (ADAS) play a critical role in enhancing the driving experience and improving vehicle safety. Among these, Traffic Sign Recognition (TSR) is an essential technology that enables autonomous vehicles to accurately and rapidly perceive road conditions. Traffic signs convey information such as speed limits, lane changes, and caution zones, making them indispensable for vehicles to make appropriate decisions.

Early TSR research predominantly employed a two-stage approach. This involved first using a high-precision detector such as Faster R-CNN to localize signs, and subsequently passing the detected regions to a high-performance classifier. Such a design allowed each task to be optimized independently, providing a foundation for maximizing overall system accuracy. Empirically, separating detection and classification reduces the complexity of each module and yields consistent improvements in end-to-end system accuracy [1].

More recent studies have also explored semi-supervised frameworks that combine CNN-based feature extraction with

multiscale Transformer representations for traffic sign detection and recognition [2].

Most existing studies have focused on European and Chinese datasets, such as the German Traffic Sign Detection Benchmark (GTSDb) [3], the Tsinghua-Tencent 100K benchmark, and the Swiss Traffic Sign Detection Benchmark (STDB) [4]. Among these, GTSDb is commonly used to achieve broader generalizability, and the number of studies combining multiple datasets for model validation is also increasing.

Nevertheless, significant limitations remain under adverse conditions such as illumination and weather variation, motion blur, and small sign sizes. For instance, the difference in lighting between daytime and nighttime, as well as weather factors such as rain and fog, can substantially reduce recognition rates. In real-world driving environments, rain, fog, and low illumination degrade image quality and impose constraints on the performance of recognition systems. To mitigate these issues, super-resolution techniques such as SRGAN have been actively studied to restore image quality prior to feeding images into recognition models, and this has been regarded as a key strategy for improving system robustness.

Specific adverse weather conditions, particularly fog, distort the color and boundaries of signs, causing severe performance degradation. Accordingly, integrating dehazing algorithms such as Dark Channel Prior and AOD-Net into preprocessing pipelines—to provide cleaner inputs to recognition models and thereby ensure reliability under adverse weather—has become an increasingly important research direction [5].

Furthermore, poor and non-uniform illumination environments, such as nighttime scenes or tunnels, impose significant constraints on recognition performance. To address this, Retinex theory-based image enhancement—which separates and suppresses the illumination component—has emerged as a major research direction. Among Retinex variants, MSRCR preserves color information while improving the visibility of signs under low illumination, providing a foundation for subsequent deep learning models to recognize traffic signs more reliably [6].

Current approaches primarily address this problem through preprocessing of training data. Commonly used techniques in recent TSR research include dataset augmentation, contrast adjustment, brightness correction, Gaussian blur, and color space conversion from RGB to HSV. However, these approaches also have inherent limitations [7].

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As an alternative, this study adopts Retinex-based image enhancement. Retinex is a classical model for image quality improvement and has been applied not only to general image enhancement but also to traffic sign images. Noting that the basic Retinex algorithm has received relatively limited attention, this study evaluates both the basic and extended variants to assess their potential performance gains.

Regarding the application of the Retinex algorithm, this study references prior work that incorporates an illumination enhancement stage prior to detection for traffic sign detection and recognition under low-illumination conditions. That study demonstrates the importance of condition-aware preprocessing for TSR in scenes with degraded visual quality, supporting the methodology proposed in this work [8]. Building on this approach, we investigate strategies to minimize image distortion caused by indiscriminate enhancement or additional computational costs.

For detection and classification, this study employs RetinaNet as the detection model and a CNN with asymmetric convolutional kernels for traffic sign classification. RetinaNet demonstrated competitive performance compared to representative CNN-based detectors such as Faster R-CNN and YOLOv3, particularly in small-object detection, while offering high throughput as a single-stage solution. The asymmetric kernel CNN classifier provides real-time processing capability and competitive performance compared to conventional CNN classifiers [9].

The objective of this study is to detect and subsequently classify traffic signs under low-illumination and adverse weather conditions. For detection, various Retinex algorithms—including SSR, MSR, MSRCR, MSRCRCP, and Auto MSR—are selectively applied to a subset of training data satisfying predefined adverse-condition criteria to improve detection performance. For classification, an asymmetric kernel CNN classifier proven effective in prior research is adopted. Through this pipeline, we aim to improve detection robustness under weather and illumination variation while retaining a computationally efficient classification stage.

The main contributions of this study are as follows. First, we systematically compare five Retinex-based enhancement algorithms for traffic sign detection under low-visibility conditions. Second, we construct a decoupled TSR pipeline that integrates RetinaNet-based detection with a previously validated asymmetric-kernel CNN classifier. Third, we validate a condition-aware selective image-enhancement strategy during model development, applying Retinex only to training and validation images satisfying predefined luminance-distribution criteria.

II. DATA AND ALGORITHMS

A. Datasets

1) *German Traffic Sign Detection Benchmark (GTSDDB)*: The German Traffic Sign Detection Benchmark (GTSDDB) [3] was used to train the detection model. GTSDDB consists of 900 images with a resolution of 1360×800 pixels. The number of traffic signs per image ranges from 0 to 6, and sign sizes vary from 16×16 to 128×128 pixels. Images are provided in PPM format for cross-platform compatibility, and sign locations are

provided as coordinates in a separate text file. In this study, the dataset was split into 600 training images, 150 validation images, and 150 test images. Fig. 1 shows examples from the GTSDDB dataset.



Fig. 1. Examples from the GTSDDB dataset.

2) *German Traffic Sign Recognition Benchmark (GTSRB)*: The German Traffic Sign Recognition Benchmark (GTSRB) [10] was used to train the classification model. GTSRB contains more than 50,000 images across more than 40 classes, with image sizes ranging from 15×15 to 250×250 pixels. This dataset is also provided in PPM format for cross-platform use, and sign location information per image is provided in text files. Images are provided as cropped regions extracted from full road scene images. Since the number of samples per class varies considerably, appropriate preprocessing and data balancing strategies are required for effective model training. Accordingly, five data augmentation techniques adopted in prior work were applied in this study [9]. Fig. 2 shows examples from the GTSRB dataset.



Fig. 2. GTSRB dataset examples.

B. Algorithms

1) *Retinex algorithm*: In computer vision for autonomous driving, image quality degradation due to illumination variation is a significant concern. Real-world road scenes often contain mixed light sources such as sunlight, fluorescent lighting, and tungsten illumination, and under low-illumination or adverse weather conditions, image color and luminance can be severely distorted. Such degradation hinders the accurate detection and recognition of essential objects, including traffic signs. The Retinex algorithm addresses this problem by simultaneously achieving dynamic range compression and color constancy, generating images that more closely resemble human visual perception.

In this study, Retinex-based image enhancement is applied to improve traffic sign detection performance. Retinex

adjusts the brightness and color of images in a manner consistent with human visual perception—exploiting relative luminance differences between adjacent pixels to suppress illumination-induced artifacts and restore intrinsic reflectance and perceived brightness. In particular, Retinex adopts a spatial center-surround configuration that models local context using a Gaussian surround, attenuating the effects of non-uniform illumination and emphasizing the reflectance component to enhance visual clarity [11].

The mathematical representation of the Retinex algorithm is as follows:

$$R_i(x, y) = \log[I_i(x, y)] - \log[F(x, y) * I_i(x, y)] \quad (1)$$

where, $R_i(x, y)$ denotes the Retinex-processed output (reflectance estimate) in the i -th channel, $I_i(x, y)$ is the i -th channel of the input image, and $F(x, y)$ is the surround function, typically instantiated as a Gaussian kernel. The symbol $*$ denotes convolution, and $\log$ denotes the natural logarithm.

While the Retinex algorithm demonstrates excellent performance in enhancing image quality under varying illumination conditions, a variety of extensions have been developed—grounded in the original principles—to address practical issues encountered in real applications. In this study, we employ five algorithms, including Single-Scale Retinex (SSR) and Multi-Scale Retinex (MSR), to enhance images captured under low-light and adverse weather conditions.

Single-Scale Retinex (SSR) uses a single Gaussian scale to compress dynamic range or to improve the rendering of color and luminance. In this setting, the surround function $F(x, y)$ is defined as a Gaussian: small scales provide strong dynamic-range compression but may introduce halo artifacts, whereas large scales yield more natural color rendition but offer limited dynamic-range compression. Because SSR relies on a single scale, it exhibits inherent limitations; to overcome these, MSR was proposed by applying multiple scales simultaneously [12].

Multi-Scale Retinex (MSR) addresses the limitations of SSR by combining several different scales; its mathematical expression is given as follows.

$$R_{MSR,i}(x, y) = \sum_{n=1}^N w_n [\log I_i(x, y) - \log(F_n(x, y) * I_i(x, y))] \quad (2)$$

Here, N denotes the number of Gaussian scales, and w_n represents the weight assigned to the n -th scale. Typically, three surround scales are employed—small (15), medium (80), and large (250)—with $N = 3$ and $w_n = 1/3$ for each scale. Because multiple scales are combined, detail in dark regions is enhanced and artifacts caused by excessive contrast are reduced. However, MSR can induce a gray-out of image colors; to prevent this, MSRCR introduces a color restoration component [13].

Multi-Scale Retinex with Color Restoration (MSRCR) is designed to prevent the gray-out observed in MSR and to

restore the original color appearance; its mathematical formulation is given as follows.

$$R_{MSRCR,i}(x, y) = G[C_i(x, y)R_{MSR,i}(x, y) + b] \quad (3)$$

The function $C_i(x, y)$ is defined as the Color Restoration Function (CRF) as follows:

$$C_i(x, y) = \beta \log[\alpha I'_i(x, y)] \quad (4)$$

where, $I'_i(x, y)$ denotes the normalized intensity of the (i)-th color channel, defined as

$$I'_i(x, y) = \frac{I_i(x, y)}{\sum_{j=1}^S I_j(x, y)} \quad (5)$$

Here, $I_j(x, y)$ represents the intensity of the (j)-th RGB channel, and $S = 3$ denotes the number of color channels. The commonly adopted constants are $\alpha = 125$, $\beta = 46$, $G = 192$, $b = -30$. Although MSRCR provides strong color-restoration performance, MSRCP—by preserving chromaticity—was developed to mitigate the computational complexity of the color-restoration stage and to more precisely correct color distortions.

Multi-Scale Retinex with Chromaticity Preservation (MSRCP) enhances contrast while retaining the original image's color appearance: it computes an intensity channel from RGB, applies MSR to the intensity, and then recombines the enhanced intensity with the original chromatic components to reconstruct the image. Despite its merits, manual parameter tuning can be cumbersome; accordingly, an Automated Multi-Scale Retinex (Auto MSR) algorithm has been proposed to automate parameter selection [14].

Auto MSR automatically sets the parameters in MSRCR, improving ease of use and consistency. It determines clipping points from the image histogram and adjusts contrast automatically, thereby delivering strong performance and making the method suitable for real-time processing [15].

In this study, we employ five Retinex algorithms to improve image quality under low-light and adverse weather conditions and, in turn, to enhance traffic sign detection performance.

2) *RetinaNet*: Fig. 3 illustrates the overall architecture of the RetinaNet detector. RetinaNet is a single-stage object detection network that simultaneously achieves high accuracy and speed, and is known to effectively handle small object detection and class imbalance. The architecture uses ResNet-50 or MobileNet as a backbone. It generates multi-scale feature maps through a Feature Pyramid Network (FPN). At each location, the network predicts both object presence for classification and bounding box coordinates for localization. A key component is focal loss, which alleviates foreground-background sample imbalance and improves training stability and overall accuracy.

Reflecting these characteristics, this study employs RetinaNet as the traffic sign detection model.

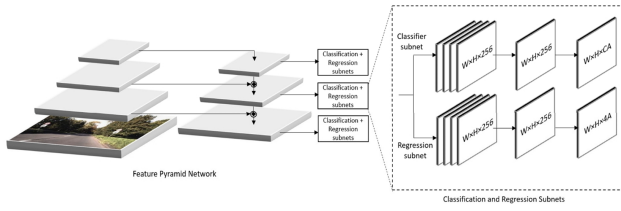


Fig. 3. RetinaNet detector architecture [16].

3) *CNN with asymmetric kernels*: A convolutional neural network with asymmetric kernels substantially reduces computational cost compared to conventional symmetric kernel architectures. Specifically, it decomposes an $n \times n$ convolution into a $1 \times n$ convolution followed by an $n \times 1$ convolution, significantly reducing the number of operations. This architecture not only achieves model compactness but also effectively captures diverse spatial information to ensure high classification accuracy.

The design incorporates Inception modules that merge feature maps generated from kernels of different sizes and integrate them along the channel dimension, enabling efficient learning of complex spatial representations. Experiments demonstrated that the proposed architecture achieves higher accuracy with fewer operations compared to a baseline using symmetric kernels. Furthermore, experiments on the GTSRB dataset confirmed that inference time is suitable for real-time applications [9].

Therefore, this study adopts the asymmetric-kernel CNN architecture proposed by Li and Wang [9] as the classification model without architectural modifications. The network employs asymmetric convolutional kernels and an Inception module to efficiently extract and integrate spatial features. The detailed layer configuration is presented in Table III of [9].

Since the classifier architecture was adopted directly from prior work [9], the classification model itself is not the primary subject of performance evaluation in this study. Instead, the experimental analysis focuses on the effect of Retinex-based preprocessing on traffic sign detection performance under low-visibility conditions.

III. METHODOLOGY

A. Selection Criteria for Retinex Application

To improve the performance of the detection model, this study selectively enhanced the image quality of a subset of GTSDB images rather than applying Retinex uniformly to all images. Uniform application would increase computational cost and could cause image distortion; therefore, enhancement was limited to images meeting predefined criteria.

The luminance distribution of each image was assessed through histogram analysis. Retinex was applied only when the proportion of pixels falling within the mid-tone brightness range of 30–225 was $\leq 60\%$. This empirically derived criterion effectively identifies low-illumination and low-contrast images with significant quality degradation, providing a practical filter for selective enhancement. Fig. 4 shows example images requiring Retinex and their corresponding histograms.

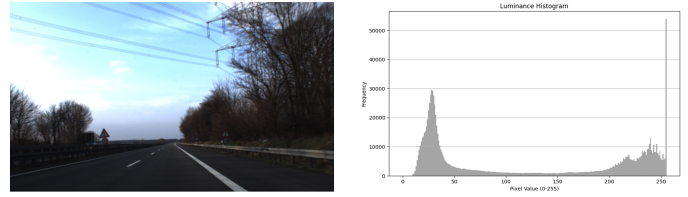


Fig. 4. Example images and luminance histogram for images with a mid-tone brightness ratio of 60% or below.

B. Traffic Sign Detection and Classification Experiments

In this study, detection and classification models are constructed separately to improve accuracy and computational efficiency. For model training, the experimental configuration was set as follows: batch size = 4, epochs = 64, optimizer = Adam, learning rate = 1×10^{-5} , $\alpha_{\text{focal}} = 0.25$, $\gamma = 2$, $\lambda = 1$, and random seed = 42. Experiments were conducted using an NVIDIA RTX 4090.

1) *Detection model*: In this study, a RetinaNet-based detection model was trained using the GTSDB dataset comprising 900 images. The dataset was split into 600 training, 150 validation, and 150 test images in a 4:1:1 ratio.

Based on the predefined selection criteria for selective image enhancement, 271 out of 600 training images were identified as candidates for Retinex application, and six training configurations were designed accordingly. In the validation set, 77 out of 150 images satisfied the same criterion. To ensure distributional alignment with the deployment environment and to avoid preprocessing-induced bias in evaluation, the 150 test images were retained in their original, unenhanced form. Table I summarizes the dataset configurations used for each model.

TABLE I. GTSDB DATASET CONFIGURATIONS

	Train	Validation	Test
(a) Original	600	150	150
(b) Original + SSR(80)	871(600+271*)	227(150+77*)	150
(c) Original + MSR	871(600+271*)	227(150+77*)	150
(d) Original + MSRCR	871(600+271*)	227(150+77*)	150
(e) Original + MSRCP	871(600+271*)	227(150+77*)	150
(f) Original + Auto MSR	871(600+271*)	227(150+77*)	150

2) *Classification model*: To improve training performance on the GTSRB dataset and strengthen the model's generalization ability, we applied five data augmentation techniques adopted from prior work: (1) horizontal flip; (2) random rotation in the range -10° to 10° ; (3) scaling by a factor of 0.8 to 1.2; (4) horizontal and vertical translation of -4 to 4 pixels; and (5) random shear in the range 0 to 0.1 radians.

These augmentation strategies artificially increase the diversity of training data, reducing overfitting, narrowing the performance gap between classes, and improving robustness to various visual conditions.

The classifier was trained using the preprocessing and augmentation procedures described above and integrated into the overall TSR pipeline. Because the classifier architecture was adopted from the previously validated model in [9]

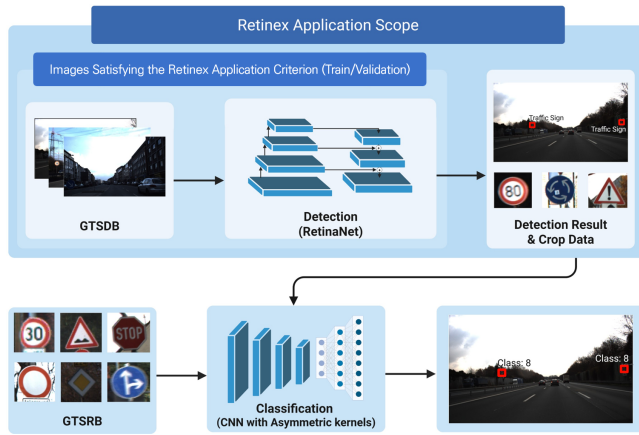


Fig. 5. Overall pipeline of the proposed method.

without architectural modification, this study does not perform a separate comparative analysis of classification performance. The experimental evaluation therefore focuses on the detection stage, where the proposed Retinex-based preprocessing strategy is applied. Fig. 5 illustrates the overall pipeline of the proposed approach.

C. Evaluation Metrics

The detection model is evaluated using precision, recall, and mean average precision (mAP). Precision represents the proportion of detected signs that are actual traffic signs, while recall represents the proportion of ground-truth signs that the model correctly detected. mAP integrates the precision-recall relationship to comprehensively assess overall detection performance.

For localization accuracy, the Intersection over Union (IoU) threshold was set to 0.5; a prediction was considered correct only when the IoU between the predicted bounding box and the ground-truth box was 0.5 or greater. This protocol provides a standard for evaluating detection performance objectively and consistently.

IV. EXPERIMENTAL RESULTS

A. Overall Experimental Results

Table II reports the detection performance obtained under selective Retinex application. In this study, Retinex was applied only to the training and validation sets according to predefined criteria, while the 150 test images were retained in their original, unenhanced form. Therefore, all evaluations were conducted on a single fixed test distribution, enabling a controlled comparison across the six training configurations. The performance differences among the Retinex-based configurations were relatively small. Fig. 6 visualizes representative test results obtained from the six training configurations.

Overall, selective Retinex application did not produce a substantial improvement in overall performance compared with training on the original dataset alone. However, a separate analysis of the 82 test images that satisfied the predefined Retinex application criterion identified 10 challenging cases with frequent missed detections and false positives. For these

TABLE II. DETECTION METRICS ACROSS SIX TRAINING CONFIGURATIONS

Train data	Precision	Recall	mAP
(a) Original	79.17%	96.07%	95.02%
(b) Original + SSR(80)	80.48%	94.94%	94.30%
(c) Original + MSR	81.73%	95.51%	94.84%
(d) Original + MSRCR	80.86%	94.94%	94.39%
(e) Original + MSRCP	77.52%	94.94%	94.05%
(f) Original + Auto MSR	80.10%	94.94%	94.28%

cases, both quantitative metrics and visual results were compared across the six training configurations.



Fig. 6. Detection results across six configurations for a single test image (00682.ppm).

B. Limitations of the Original Dataset and Proposed Solutions

From the 150 test images, 82 images satisfying the predefined Retinex application criterion were identified. Among these, 10 images exhibiting frequent missed detections and false positives were selected for an in-depth case-based analysis. A baseline model was first trained and validated using only original data, and its results were compared against the other five training configurations. Table III summarizes the dataset configurations used in this analysis.

1) *Original-only configuration*: To evaluate performance gains attributable to Retinex, a baseline was first established by training, validating, and testing using only original data. Table IV reports the corresponding results.

The experimental results showed a relatively low precision of 62.86% and a relatively high recall of 91.67%. To enhance

TABLE III. DATASET CONFIGURATIONS FOR DETAILED ANALYSIS

	Train	Validation	Test
(a) Original	600	150	10
(b) Original + SSR(80)	871(600+271*)	227(150+77*)	10
(c) Original + MSR	871(600+271*)	227(150+77*)	10
(d) Original + MSRCR	871(600+271*)	227(150+77*)	10
(e) Original + MSRCP	871(600+271*)	227(150+77*)	10
(f) Original + Auto MSR	871(600+271*)	227(150+77*)	10

TABLE IV. PERFORMANCE RESULTS WITH ORIGINAL-ONLY TRAINING
(10 TEST IMAGES)

Train	Precision	Recall	mAP
Original	62.86%	91.67%	87.56%

the interpretability of these metrics, a case-based visual error analysis was performed on the 10 test images. Fig. 7 presents example visualizations of missed detections and false positives.

Visual analysis of the 10 test images revealed 5 missed traffic sign detections across 5 images, and 6 false positive bounding boxes across 5 images. Cases were also observed in which signs were difficult to perceive even for human observers due to illumination-induced visibility degradation, and cases in which signs in the distance appeared too small for reliable detection. These situations resulted in missed detections or incorrect detection of non-sign objects. This distribution supports the interpretation that the overall metric pattern of low precision and high recall was substantially influenced by a small number of images generating a disproportionately large number of false positives.

2) *Analysis of 10 test images using retinex-augmented trained models:* Using the original-only training model as a baseline, the same 10 test images were re-evaluated and the results were compared against five Retinex-augmented training configurations (SSR, MSR, MSRCR, MSRCP, Auto MSR) on the same original, unenhanced test inputs. Table V reports the evaluation metrics for the baseline and the Retinex-augmented models.

Compared to the original-only baseline, SSR, MSR, MSRCR, and MSRCP showed generally lower precision, with recall maintained or decreased. In contrast, the model augmented with Auto MSR achieved higher recall, which led to improved mAP. These results demonstrate that training with Retinex-processed data does not consistently improve performance, but can selectively mitigate specific failure patterns—particularly when parameters are automatically configured, as in Auto MSR.

Beyond aggregate metrics, visual analysis of the 10 images confirmed qualitative improvements. Across multiple cases, unnecessary bounding boxes—i.e., false positives—were eliminated, and signs that were previously undetected were successfully detected by Retinex-augmented models.

Taken together, the metric trends and visualization results support the potential of integrating Retinex-processed training data to address missed detections and false positives in specific challenging conditions. Fig. 8 illustrates a representative example in which Retinex-augmented training delivers visibly improved detections over the original-only baseline.



Fig. 7. Visualization of detection results using original data (upper row: missed detections in 00610.ppm and 00740.ppm; lower row: false positives in 00775.ppm and 00776.ppm).

TABLE V. PERFORMANCE RESULTS WITH 10 TEST IMAGES

Train data	Precision	Recall	mAP
(a) Original	62.86%	91.67%	87.56%
(b) Original + SSR(80)	52.50%	87.50%	84.80%
(c) Original + MSR	41.51%	91.67%	85.75%
(d) Original + MSRCR	43.75%	87.50%	83.78%
(e) Original + MSRCP	52.38%	91.67%	85.57%
(f) Original + Auto MSR	52.27%	95.83%	91.85%

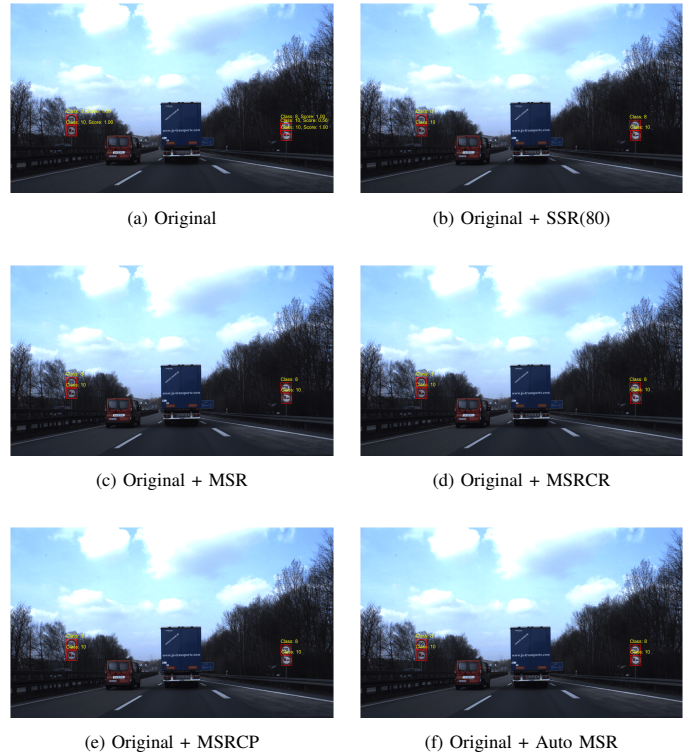


Fig. 8. Detection results across six configurations for a single test image (00746.ppm).

V. CONCLUSION

To improve TSR performance under low-illumination and non-uniform lighting conditions, this study selectively applied

Retinex-based image enhancement during training and validation. The test set was maintained in its original, unenhanced distribution to enable a controlled comparison across the six training configurations.

On the full test set, most Retinex-augmented configurations improved precision while showing slightly reduced recall. However, for the selected challenging cases, Auto MSR improved recall and mAP at the expense of precision. In other words, selective enhancement tends to suppress false positives and induce more conservative predictions, but may increase the risk of missed detections under certain scene characteristics or excessive enhancement conditions. Therefore, a practical strategy is to retain the original data as the baseline to preserve distributional alignment, and to selectively incorporate Retinex-enhanced low-visibility and low-contrast samples during model development—thereby improving precision while managing potential recall loss.

Additionally, 82 test images satisfying the predefined Retinex application criterion were further examined, and an in-depth analysis was conducted on 10 challenging cases. Common characteristics were observed in these cases where Retinex contributed to reducing missed detections and false positives. Based on these observations, it is proposed to quantify a selection criterion combining histogram-based luminance and contrast measurements with an exposure imbalance index. This would enable 1) automatic selection of samples for Retinex application during training, and 2) threshold-based and post-processing calibration to adjust the precision-recall trade-off in alignment with operational objectives.

In summary, the results of this study support a strategy of using original data as the default while selectively incorporating Retinex-processed data particularly Auto MSR to improve performance on challenging cases. Future work will formalize the selection criteria based on the 10 analyzed cases and refine the empirically set Retinex application threshold. The goal is to minimize recall loss while maintaining precision gains through targeted model fine-tuning.

DECLARATIONS

Availability of Data and Materials

The data analyzed in this study are publicly available in the German Traffic Sign Detection Benchmark (GTSDb) [3] and the German Traffic Sign Recognition Benchmark (GT-SRB) [10] datasets.

Competing Interests

The authors declare that they have no competing interests.

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DECLARATION ON GENERATIVE AI

Generative AI tools were used solely for language refinement and improvement of English expressions during manuscript preparation. All AI-assisted text was critically reviewed and edited by the authors, who take full responsibility for the accuracy, originality, and integrity of the manuscript.

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