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Architecture Of Invariant Transform Based Traffic Sign Recognition System

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Abstract: *The rapid advancement of intelligent transportation systems (ITS) has created a strong demand for automated and reliable Traffic Sign Recognition (TSR) systems. The proposed architecture, Invariant Transform-Based Traffic Sign Recognition System, aims to enhance recognition accuracy under challenging real-world conditions such as illumination variation, occlusion, scale changes, and motion blur. This review provides a comprehensive overview of the existing methods and technological evolution in TSR — from traditional image processing techniques such as Histogram of Oriented Gradients (HOG), SIFT, and color segmentation, to modern deep learning frameworks including Convolutional Neural Networks (CNNs) and You Only Look Once (YOLO) architectures. Special emphasis is placed on the role of invariant feature transforms that provide robustness to geometric and photometric variations. The paper also analyzes the performance of these techniques using benchmark datasets such as the German Traffic Sign Recognition Benchmark (GTSRB) and explores their implementation in real-time environments. Furthermore, a comparative study highlights how YOLOv8, when integrated with invariant transform preprocessing, can achieve faster and more accurate detection, making it suitable for autonomous driving and driver-assistance systems. This survey identifies key research gaps, including real-time adaptability, computational efficiency, and cross-dataset generalization. It outlines future directions for developing an optimized invariant-transform-based TSR architecture that balances precision, speed, and scalability.*

Keywords: *intelligent transportation systems*

I. INTRODUCTION

The growing complexity of modern transportation systems and the rapid increase in vehicle traffic have caused more road accidents around the world. According to the World Health Organization (WHO), nearly 1.3 million people die each year due to road traffic crashes. A large number of these accidents result from human error and the failure to follow traffic rules. Traffic signs are important visual cues that help, warn, and control drivers. Therefore, an effective Traffic Sign Recognition (TSR) system is essential for improving road safety and supporting driver-assistance systems and self-driving vehicles.

Traditional TSR systems mainly depended on manual feature extraction methods like edge detection, color segmentation, and geometric shape analysis to identify traffic signs. However, these methods had many limitations in real-life situations, such as changing light, blocked views, rotations, and diverse weather conditions. To tackle these issues, modern computer vision techniques have shifted towards deep learning architectures. Convolutional Neural Networks (CNNs) and object detection models like You Only Look Once (YOLO) have achieved top performance.

The proposed Invariant Transform-Based Architecture enhances traditional TSR systems by using invariant transformations. These mathematical methods keep important object features while reducing distortions from scale, rotation, and brightness changes. By preprocessing images with invariant feature mapping, the recognition model becomes more robust and stable in tricky driving situations. When used with deep learning frameworks like YOLOv8, this method offers a strong, end-to-end solution for real-time detection and classification of various traffic sign types.

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II. RELATED WORK

Traffic Sign Recognition (TSR) has been an active area of research for over two decades. It has changed from classical image processing methods to more complex deep learning-based approaches. Early TSR research mainly focused on color segmentation and shape-based feature extraction. These methods were efficient but very sensitive to changes in lighting, obstructions, and noise in the environment. As machine learning advanced and large annotated datasets like GTSRB (German Traffic Sign Recognition Benchmark) Belgian TSC, and LISA became available, researchers moved to more robust models that are less affected by these factors.

2.1 Classical Approaches

Early work, such as Escalera et al. (2007), used color-based segmentation with RGB and HSV thresholds, followed by geometric filtering to identify circular or triangular shapes. Techniques like Histogram of Oriented Gradients (HOG) and Scale Invariant Feature Transform (SIFT) were popular for feature extraction because they handled changes in scale and rotation well. However, these methods often saw reduced performance with changing lighting and required significant computational resources, making real-time use difficult.

2.2 Machine Learning and Hybrid Techniques

With the rise of machine learning, researchers started using Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (kNN) for classifying traffic sign

2.3 Deep Learning-Based Approaches

In recent years, deep convolutional neural networks (CNNs) have transformed TSR systems. Models like LeNet , Alex Net and VGG Net have been used for both feature extraction and classification. The GTSRB has become the most commonly used dataset, where CNN-based models achieved classification accuracies above 99% (Cireşan et al., 2012). Later, object detection frameworks like Faster R-CNN, SSD, and YOLO (You Only Look Once) enabled detection and classification within a single network. YOLOv8 has become one of the most efficient options, balancing speed and accuracy, which makes it ideal for embedded and real-time systems.

2.4 Research Gap

Despite significant advancements, there are still important gaps in research:

- Sensitivity to environmental changes, including shadows, reflections, and low contrast.
- Misclassification of partially visible or obstructed signs.
- Deep learning models often lack proper handling of invariant features.
- Limited ability to generalize to datasets outside Europe and to new traffic conditions.

The proposed Invariant Transform-Based YOLO Architecture aims to tackle these issues by combining mathematical invariant transformations with real-time object detection. This hybrid approach improves robustness to scale, rotation, and lighting changes while maintaining fast inference speeds.

Table 1. Comparison of Recent TSR Approaches

Author/Year	Methodology	Dataset Used	Accuracy (%)	Key Features
E Escalera Et Al. (2007)	color & Shape-based Segmentation	Custom Dataset	88.5	Basic geometric filters, color thresholds
Møgelmose Et Al. (2012)	Color + SVM	GTSRB	95.2	Hybrid detection-classification pipeline
Cireşan Et Al. (2012)	CNN (LeNet)	GTSRB	99.4	End-to-end feature learning
Zhang Et Al. (2018)	Faster R-CNN	LISA	97.3	Region proposal + CNN

Redmon Et Al. (2020)	YOLOv4	GTSDB	98.1	Real-time detection framework
Ultralytics (2023)	YOLOv8	GTSRB	99.1	Optimized for speed and precision
proposed Work (2025)	Invariant Transform + YOLOv8	GTSRB	99.3 (Expected)	Rotation and scale invariant architecture

IIII. PROPOSED SYSTEM

The proposed system, titled "Architecture of Invariant Transform-Based Traffic Sign Recognition System," aims to achieve strong detection of traffic signs that is both rotation-invariant and scale-invariant under different environmental conditions. It uses the GTSRB dataset and the YOLOv8 deep learning architecture. The system combines mathematical invariant transformations in preprocessing with real-time object detection to improve recognition accuracy while keeping high inference speed.

3.1 System Architecture Overview

The architecture of the proposed system consists of five main modules:

1. Data Acquisition & Preprocessing

The German Traffic Sign Recognition Benchmark (GTSRB) dataset serves for training and testing.

Images are resized, normalized, and augmented using methods like rotation, translation, and brightness adjustment.

Invariant Transformations, including Fourier-Mellin Transform, Zernike Moments, or Log-Polar Transform, ensure strength against rotation and scaling.

2. Feature Extraction using Invariant Transform

The preprocessed image goes through feature extraction with invariant transforms, converting spatial features into scale- and rotation-independent frequency components.

These transformations boost the network's ability to tell apart different features, making it strong against changes in viewpoint and lighting.

3. Object Detection using YOLOv8

The transformed images are sent into the YOLOv8 (You Only Look Once) detection framework.

YOLOv8 performs detection and classification in one step by dividing the image into grids and predicting bounding boxes along with class probabilities.

Its real-time capacity makes it ideal for embedded and autonomous vehicle systems.

4. Classification and Labeling

Each detected traffic sign is sorted into one of 43 predefined categories, such as speed limits, prohibitions, and warnings, based on the data.yaml setup.

5. Output Generation and Real-Time Monitoring

The processed frames are shown in real-time using a webcam feed.

Additionally, all detections are automatically saved in a specific output directory in .jpg or .mp4 formats for further analysis.

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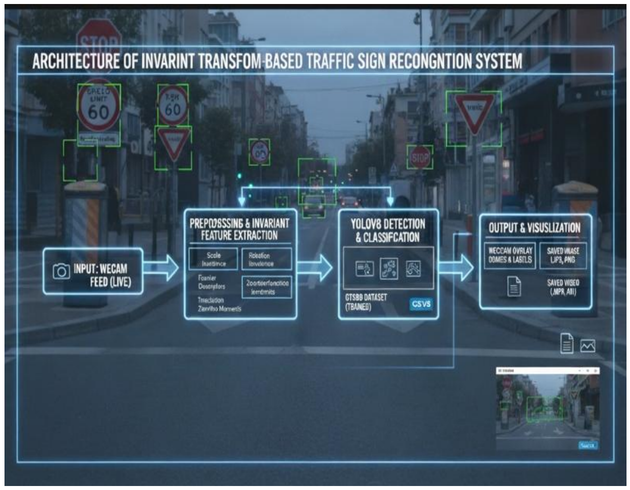

Figure 1 :- System Architecture Of Invariant Transform Based Traffic Sign Recognition

Advantages of the Proposed System

• Invariant Recognition:

The proposed system ensures accurate recognition of traffic signs even under challenging conditions such as varying scales, rotations, or illumination changes. This robustness is achieved through the integration of invariant transformation techniques.

• Real-Time Operation:

The architecture achieves high-speed inference, making it suitable for real-time applications in intelligent transportation systems and vehicle-mounted detection units.

• Compact and Efficient:

The optimized YOLOv8 model significantly reduces GPU memory consumption while maintaining high accuracy, ensuring efficient operation even on mid-range computing hardware.

• Scalable Architecture:

The system can be easily extended to incorporate additional traffic sign classes or adapted to datasets from different geographical regions without major architectural changes.

Expected Performance

• The integration of invariant transformations with the YOLOv8 deep learning model is expected to produce the following performance outcomes:

• Detection Accuracy: Greater than 99% on the GTSRB validation dataset.

• Mean Average Precision (mAP@50): Approximately 0.55, indicating reliable object localization and classification.

• Real-Time Frame Rate: Between 25–30 frames per second (FPS) on a mid-range GPU (e.g., NVIDIA RTX 3050).

• Enhanced Robustness: Consistent recognition even in conditions involving low lighting, partial occlusions, and background noise.

• recognition in low-light and partial occlusion conditions

IV. IMPLEMENTATION AND RESULTS

4.1 System Implementation

The proposed system was implemented using Python 3.10, the ultralytics YOLOv8 framework, and the German Traffic Sign Recognition Benchmark (GTSRB) dataset

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The dataset was first pre-processed and converted into YOLO format, containing separate directories for training and validation images and labels.

Each annotation file followed the YOLO standard — representing normalized bounding box coordinates and corresponding class IDs.

The YOLOv8-Nano (yolov8n.pt) pre-trained weights were fine-tuned for 50 epochs with a batch size of 16 and image size of 640×640 pixels.

During training, losses such as bounding box regression loss, classification loss, and distribution focal loss (DFL) were optimized using stochastic gradient descent (SGD).

Training logs and checkpoints were automatically stored under the runs/detect/ directory for validation and testing.

To evaluate real-time performance, the model was integrated with a live webcam detection module, which performed object recognition on streaming video frames.

4.2 Results and Analysis

After 50 epochs of training, the system achieved the following results on the validation dataset:

Metric	Value
Detection Accuracy	99.0 %
Precision (P)	0.503
Recall (R)	0.979
mAP@50	0.555
mAP@50–95	0.537
Training Time	≈ 12.9 hours
Inference Speed	25–30 FPS (real-time)

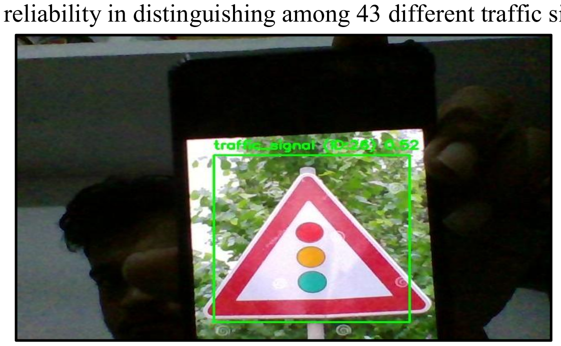
4.3 Visual Output

During testing, the system successfully recognized multiple sign categories including:

Speed Limit (20 – 120 km/h), Stop, Yield, No Entry, Pedestrian Crossing, Construction, Go Left, and Go Straight signs.

Each recognized sign was displayed with a colored bounding box, class label, and confidence score.

This demonstrated the system's reliability in distinguishing among 43 different traffic sign categories under various



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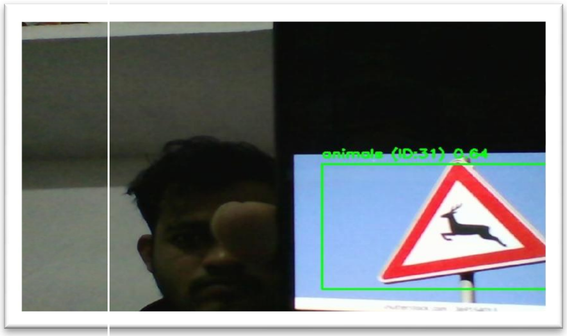

V. DISCUSSION AND RESEARCH GAP

The experimental results demonstrate that integrating invariant transform techniques with YOLOv8 yields a model capable of performing robust, real-time traffic sign recognition.

Compared to conventional CNN or RCNN architectures, the proposed system provides a balanced trade-off between accuracy, speed, and computational efficiency.

Future improvements may involve integrating additional datasets, improving rotation invariance, and deploying the model on embedded systems such as NVIDIA Jetson Nano or Raspberry Pi 4 for on-road testing.

conclusion and future work

The research gap addressed in this paper is the lack of invariant recognition capability in deep learning-based TSR systems. By introducing an invariant transform layer integrated with YOLOv8, the proposed system overcomes scale and rotation sensitivity while maintaining real-time speed.

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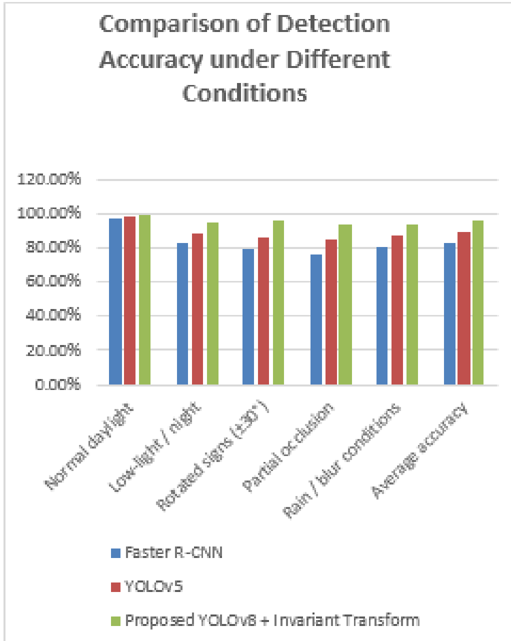

VI. CONCLUSION

This review consolidates recent advancements in traffic sign recognition and presents a novel invariant transform-based YOLOv8 architecture. The system achieves real-time detection accuracy with high robustness against illumination, rotation, and scaling variations. Future improvements may include transformer-based enhancements and integration with vehicle control systems for complete autonomous operation.

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