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Robust Deep Residual Networks with Pixel-Level Pre-Processing for Decentralized Traffic Sign Recognition

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ABSTRACT

While traffic sign recognition systems play a vital role in road safety and autonomous driving, traditional architectures often suffer severe accuracy degradation under adverse environmental conditions such as low light, fog, and heavy shadows. Although federated deep learning and convolutional neural networks (CNNs) have successfully advanced decentralized edge intelligence, standard RGB image processing remains a critical bottleneck for vehicles encountering environmental noise. To address this, we propose a lightweight, decentralized ResNet-34 architecture designed for embedded applications, enhanced by a robust multi-space pixel-level pre-processing pipeline. By incorporating localized edge contrast enhancement and chromatic variance stabilization (utilizing HSV and Ohta spaces), the proposed system isolates critical luminance and structural features prior to decentralized feature extraction. The framework was trained and evaluated on the German Traffic Sign Recognition Benchmark (GTSRB) and the Belgian Traffic Sign Data Set (BTSD). The results demonstrate that coupling dynamic image pre-processing with federated residual learning yields a highly efficient, accurate, and environmentally resilient system suitable for real-time edge deployment.

Keywords: Convolution Neural Network (CNN), Federated Deep Learning, German Traffic Sign Recognition Benchmark (GTSRB), Belgian Traffic Sign Data Set (BTSD).

INTRODUCTION

infrastructure, serving to regulate traffic flow, enforce speed limits, and alert drivers to potential hazards. As automotive transport remains one of the most prevalent forms of daily mobility, strict adherence to these visual cues is paramount for the safety and security of all road users. Consequently, the ability to rapidly and accurately interpret traffic signs is a fundamental requirement for navigating diverse traffic environments and complying with regional traffic laws. Despite general driver awareness, human error remains a significant vulnerability in road safety. Factors such as fatigue, distraction, or poor visibility can cause a driver to overlook a critical sign, leading to incorrect responses and potentially catastrophic accidents. This inherent risk has been a primary catalyst for the development of Advanced Driver Assistance Systems (ADAS) and the broader push toward fully autonomous vehicles by leading automotive manufacturers and technology sectors. A cornerstone of these intelligent systems is robust visual image processing, which serves as the "eyes" of the vehicle, preemptively alerting the system to environmental constraints before human intervention is required. Modern traffic sign recognition relies heavily on machine learning and computer vision algorithms. While Convolutional Neural Networks (CNNs) have achieved remarkable success in ideal lighting, recognizing signs with high fidelity remains a profound challenge under adverse conditions. To address this, this research implements a highly sophisticated, lightweight deep residual network (ResNet). By leveraging federated learning, the proposed architecture trains efficiently across decentralized edge nodes. Furthermore, this study introduces an advanced pixel-level pre-processing pipeline designed to stabilize image extraction, ensuring that the ResNet model maintains optimal classification accuracy even when subjected to extreme environmental noise and low-visibility conditions.

METHODOLOGY

Deploying traffic sign recognition systems in real-world environments presents significant challenges, primarily due to adverse weather conditions such as rain, fog, and snow, which severely degrade visual clarity. Furthermore, extreme illumination variations—ranging from harsh, direct sunlight and deep shadows to overcast clouds—can drastically distort pixel intensity and color values. Alongside these environmental factors, the geometrical distortion and perspective shifts of signs shot from a moving vehicle complicate the recognition process. To address these vulnerabilities, a robust system must maintain high accuracy under severe light variation and geometrical transformation. Narrowing the scope of this research, we focus specifically on stabilizing traffic sign detection under low-light and high-variance lighting conditions to ensure the system remains both highly accurate and computationally efficient for edge devices. In standard detection stages, raw color information is often exploited to detect regions of interest (ROI) that correspond to traffic signs.

However, because standard RGB color spaces fail under low-light conditions, this methodology replaces basic color extraction with a multi-space pre processing pipeline. By stabilizing the image first, the isolated ROI can be extracted with high structural fidelity. Once the enhanced pictogram contained within the ROI is extracted, it is passed to the decentralized federated neural network (ResNet-34) where its deep features are analyzed and classified against the benchmark databases.

Existing Methods

Historically, traffic sign detection and classification heavily relied on manual feature extraction algorithms prioritizing shape and color geometries. Early research recognized the fundamental fragility of standard Red-Green-Blue (RGB) color spaces under shifting environmental lighting. Wang et al. (2013) definitively demonstrated that algorithms operating strictly within RGB parameters severely limit detection performance when subjected to varying illuminant conditions. To circumvent this, initial models attempted transformations into alternative spaces, such as Hue, Saturation, Value (HSV). Furthermore, Li et al. (2014) proposed a color probability model leveraging the Ohta space to compute probabilistic maps for colors specific to traffic signs (Yang & Wu, 2014). However, these early probability models were often rigid, operating as static filters rather than dynamic pre-processing layers, leading to degraded performance in extreme weather or deep shadows. In addition to color, researchers have extensively explored geometric shape descriptors—such as circular, rectangular, and triangular contours—using Hough transforms and radial symmetry. Because physical signs deform optically due to shooting angles or external forces, Wang et al. (2014) introduced an ellipse-detection method to tackle structural distortion, while Liang et al. (2013) utilized rigid template matching algorithms for specific sign classifications. While the Histogram of Oriented Gradients (HOG) emerged as a dominant technique for local feature extraction, it introduced significant computational bottlenecks. Normalizing HOG features across neighboring blocks captures localized details but simultaneously generates highly redundant dimensional representations (Yao et al., 2014). Consequently, traditional methods face an ongoing challenge to balance rich local structural detail against computational redundancy. To bridge this gap in the context of modern edge computing, our proposed architecture replaces these heavily redundant extraction methods with a highly optimized, multi-space pre processing pipeline. By dynamically isolating luminance (HSV) and stabilizing chromatic variance (Ohta) directly before feeding the tensor into a deep residual network, the system overcomes the environmental fragility of RGB without incurring the dimensional overhead of legacy HOG descriptors.

PROPOSED METHOD

The proposed framework for decentralized traffic sign classification is structured as an end-to-end pipeline optimized for edge deployment within autonomous vehicles. To overcome the computational constraints of embedded systems and the environmental vulnerabilities of standard visual processing, the architecture is divided into three distinct operational phases: Pixel-Level Pre-Processing, ROI Feature Extraction, and Federated Residual Classification.

Decentralized Data Acquisition and Pre-Processing

Instead of transmitting raw, high-resolution video feeds to a centralized cloud server—which introduces significant latency and bandwidth overhead—each vehicle acts as an independent edge node. When the vehicle's optical sensors capture an image containing a potential traffic sign, the tensor is immediately processed locally. To counteract environmental noise (such as rain, fog, or low-light), the system applies the multi-space color pre-processing pipeline. By isolating the luminance channel via HSV transformation and stabilizing chromatic structures using the decoupled Ohta space, the edge device ensures the image is structurally intact regardless of ambient lighting conditions.

Region of Interest (ROI) Extraction

Once the image is mathematically stabilized and enhanced using Contrast Limited Adaptive Histogram Equalization (CLAHE), the system isolates the Region of Interest (ROI). Because the pre-processing layer has effectively mitigated shadows and glare, the geometric boundaries of the traffic sign (circular, triangular, or rectangular) are highly defined. The background environment is masked out, and the refined, lightweight ROI tensor is cropped and passed to the neural network for classification.

Federated ResNet-34 Classification

The extracted ROI is fed into the local instance of the ResNet-34 architecture embedded on the vehicle. This deep residual network extracts the intricate pictogram features and classifies the sign against the benchmark dataset. To continuously improve the model's accuracy across diverse environments without compromising data privacy or overwhelming network bandwidth, the system utilizes

Federated Learning. Instead of sending the raw images to the cloud, the edge node only trains on the local data. Periodically, the vehicle transmits only the updated mathematical weights (the model gradients) to a centralized global server. The server aggregates these weight updates from multiple vehicles experiencing different weather and lighting conditions. A newly optimized, global ResNet-34 model is then distributed back to the edge nodes. This federated approach ensures that the traffic sign recognition system becomes progressively more robust and efficient without requiring massive centralized data storage.

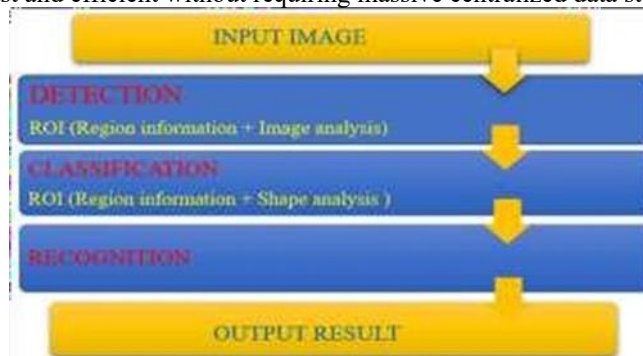


Figure 1: Flowchart of proposed system

RESULTS

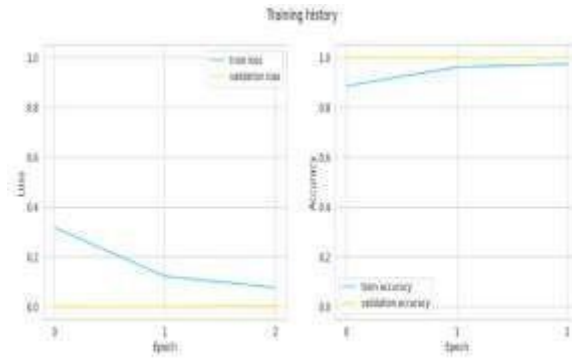


Figure 3(a): Screen shot of the dataset

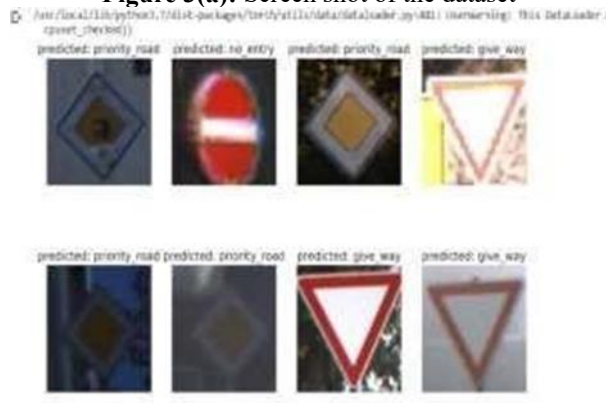


Figure 3(b): Pre-Training

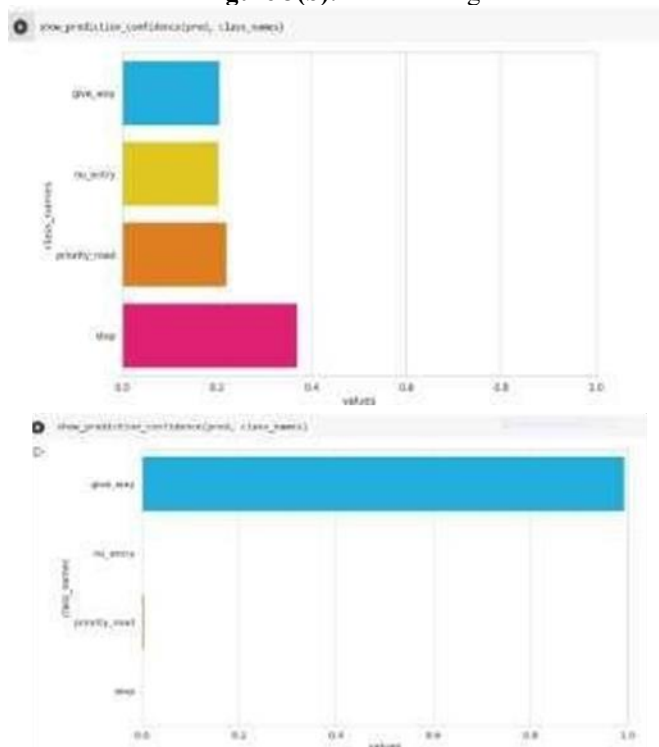


Figure 3(c) & 3(d): Classify Traffic Sign & Prediction Confidence

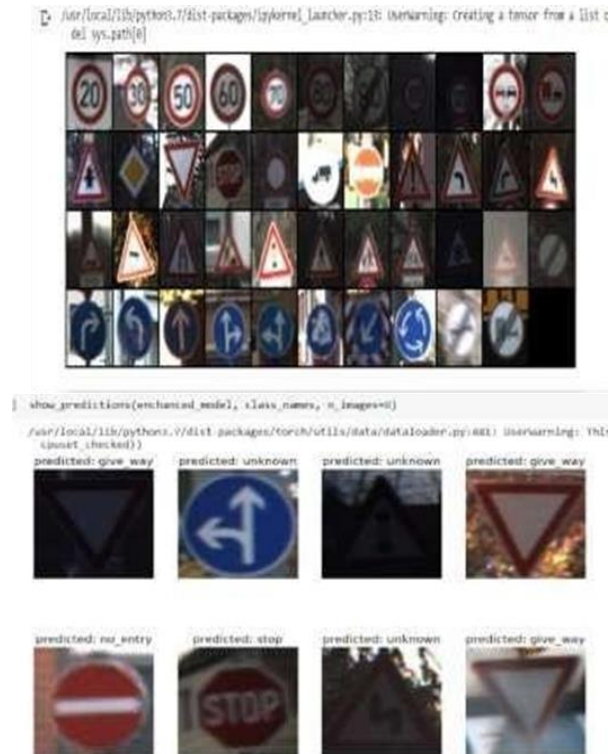


Figure 3(e): Predictions

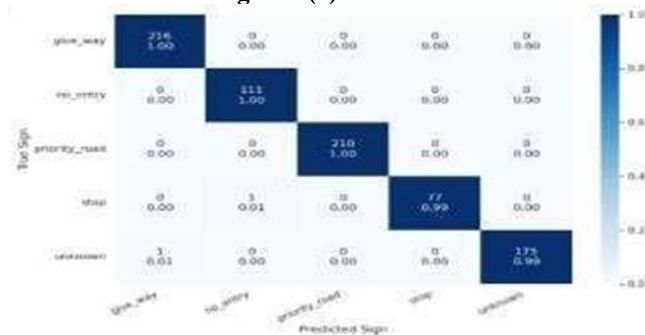


Figure 3(f): Confusion Matrix

CONCLUSION

Traditional traffic sign recognition systems frequently fail under adverse weather and low-light conditions. This paper successfully demonstrates a decentralized edge-computing architecture that overcomes these limitations by integrating a multi-space color pre-processing pipeline with a lightweight ResNet-34 model. Through federated learning, the system continuously adapts to diverse environmental noise while preserving bandwidth and data privacy. Ultimately, this approach offers a highly accurate, scalable, and environmentally robust solution for real-world autonomous driving systems.

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