Robust Traffic Sign Recognition Through Collaborative Perception in VANETs Under Adverse Conditions

Bachelor's Thesis

Handed in by:	Mohammad Karbalaee Shabani
Matriculation number:	99222085
Supervisor:	Prof. Ziba Eslami
Faculty:	Mathematical Sciences
Department:	Computer Science

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Abstract

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List of Abbreviations

V2X	Vehicle-to-Everything
ITS	intelligent transportation systems
V2V	Vehicle-to-Vehicle
V2I	Vehicle-to-Infrastructure
V2P	Vehicle-to-Pedestrian
V2C	Vehicle-to-Cloud
DSRC	Dedicated Short-Range Communication
C-V2X	Cellular V2X
V2N	Vehicle-to-Network
eNB	evolved Node B
RSUs	Roadside Units
VANET	Vehicular Ad-Hoc Network
TSR	Traffic Sign Recognition
ADAS	Advanced Driver Assistance Systems
GTSRB	German Traffic Sign Recognition Benchmark
CNNs	convolutional neural networks

Introduction

Traffic sign recognition plays a pivotal role in autonomous driving systems by enabling vehicles to interpret and respond to road signs in real-time. Accurate recognition is essential for ensuring the safety and efficiency of these systems. However, real-world scenarios introduce significant challenges. Environmental conditions such as poor lighting, rain, or fog, physical obstructions like overgrown trees or dirt-covered signs, and damaged or unclear signage can all hinder reliable recognition. These challenges emphasize the need for innovative solutions that address the limitations of traditional standalone recognition models [1].

Integrating traffic sign recognition with Vehicle-to-Everything (V2X) communication presents a promising avenue for overcoming these challenges. V2X communication fosters a connected environment where vehicles and infrastructure exchange data in real-time, enabling collaborative decision-making [2]. By leveraging V2X, vehicles can validate their recognition results through shared observations, reducing the risks associated with isolated errors and enhancing overall system reliability. This synergy holds the potential to improve traffic sign recognition by combining the strengths of machine learning techniques and connected vehicular ecosystems.

1 Problem Statement

Despite advancements in traffic sign recognition technology, existing systems often struggle in real-world conditions due to environmental factors, damaged signage, and obstructions. These limitations pose a risk to road safety, as errors in recognizing critical traffic signs can lead to incorrect or delayed responses.[3] Standalone recognition systems further exacerbate the problem by lacking a mechanism to cross-verify observations, leaving room for inaccuracies that may compromise autonomous driving systems' reliability.

While V2X communication offers a potential solution by facilitating real-time data sharing among vehicles, its implementation presents several challenges. These include ensuring data security, minimizing latency, and developing efficient mechanisms for aggregating shared data to derive consensus. Furthermore, research in this area remains limited, particularly in the context of applying V2X communication to enhance traffic sign recognition. Addressing these gaps is crucial for the safe and effective deployment of autonomous vehicles in complex, real-world scenarios.

2 Objectives

This thesis seeks to improve the reliability and accuracy of traffic sign recognition systems through the integration of V2X communication. The specific objectives of the research are as follows:

- **Develop a robust traffic sign recognition model:** Create a system capable of operating effectively under real-world conditions, accounting for challenges like environmental variability and occlusions.
- **Design a reliable consensus mechanism:** Develop an efficient method to aggregate recognition data from multiple vehicles, improving decision-making accuracy.
- **Simulate real-world scenarios:** Evaluate the performance of the integrated system in terms of recognition reliability, security, and efficiency within simulated environments.

3 Scope of the Study

This study contributes to the advancement of intelligent transportation systems by addressing critical challenges in traffic sign recognition and vehicular communication. Its findings are expected to enhance the safety, reliability, and efficiency of autonomous driving systems. By bridging the gap between recognition accuracy and collaborative data sharing through V2X, this research underscores the importance of secure and reliable vehicular communication in building public trust in autonomous technologies.

1 Background

This section provides an overview of the foundational concepts and technologies relevant to this research. It discusses V2X communication, its enabling technologies, applications, and associated challenges, as well as TSR as a critical component of intelligent transportation systems. Additionally, it introduces the dataset used for this study, highlighting its significance in training and evaluating machine learning models for traffic sign recognition.

1.1 Vehicle-to-Everything (V2X) Communication

Vehicle-to-Everything (V2X) communication is a groundbreaking technology that enables vehicles to exchange data with their surroundings, including other vehicles, infrastructure, pedestrians, and cloud-based systems. This interconnected framework is a cornerstone of modern intelligent transportation systems (ITS), designed to enhance road safety, improve traffic flow, and facilitate autonomous driving.

1.1.1 Types of V2X Communication

V2X encompasses several key components. Vehicle-to-Vehicle (V2V) communication allows direct data exchange between vehicles, enabling applications such as collision avoidance and coordinated lane changes. Vehicle-to-Infrastructure (V2I) extends this interaction to roadside elements like traffic lights and road sensors, which provide vehicles with vital updates about traffic conditions or hazards. Additionally, Vehicle-to-Pedestrian (V2P) communication ensures vehicles are aware of nearby pedestrians, even in scenarios with poor visibility. Finally, Vehicle-to-Cloud (V2C) links vehicles to cloud servers for updates on navigation, weather, or software improvements [4].

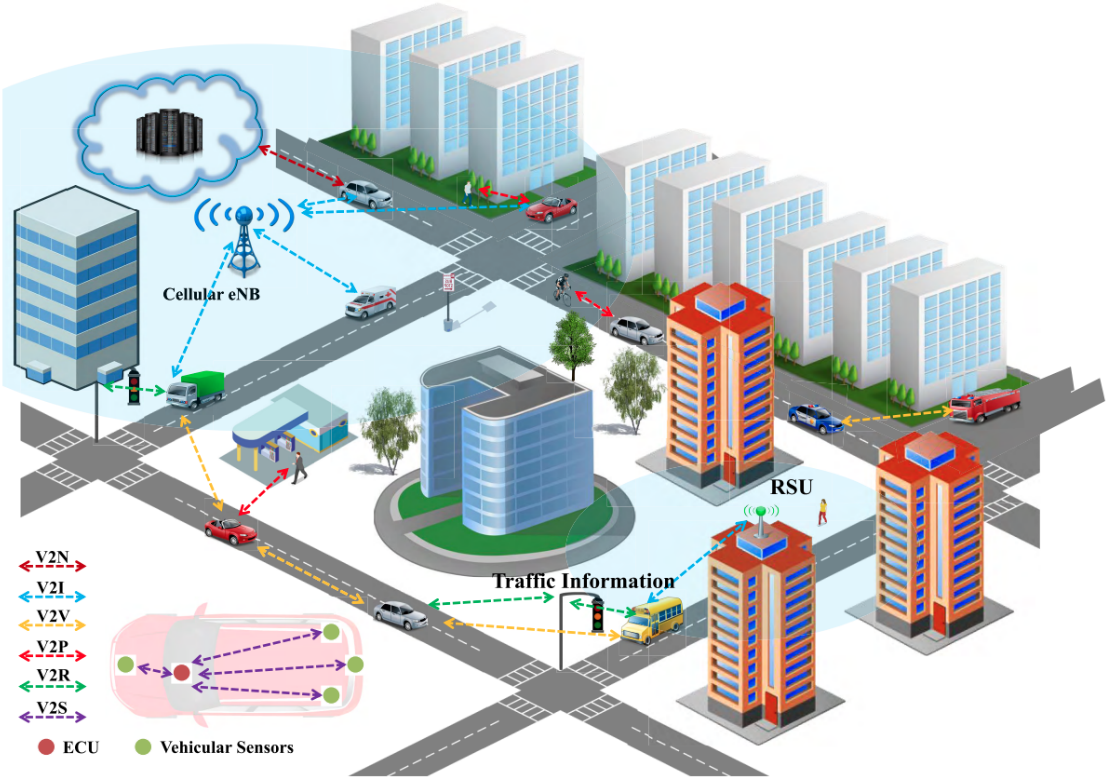

Figure 1: An overview of V2X scenario

Figure 1 illustrates a V2X communication network in a smart city environment, showcasing the interactions between vehicles, infrastructure, pedestrians, and networks. Various types of V2X communication are represented: Vehicle-to-Network (V2N) connects vehicles to cloud-based systems via the Cellular evolved Node B (eNB), which serves as the backbone of the cellular communication infrastructure. The Cellular eNB provides real-time updates and broad connectivity by leveraging 4G LTE and 5G technologies, enabling vehicles to access services such as navigation, traffic information, and emergency alerts [5].

Vehicle-to-Infrastructure (V2I) is enabled through Roadside Units (RSUs), which are positioned near roadways and intersections. RSUs act as intermediaries between vehicles and the infrastructure, collecting and disseminating localized traffic information such as signal timings, road hazards, or construction updates. These units enhance traffic management and safety by maintaining a continuous flow of communication with nearby vehicles and infrastructure elements like traffic lights and road signs [6].

1.1.2 Technologies Enabling V2X Communication

The technology behind V2X is built on two major standards. Dedicated Short-Range Communication (DSRC), a Wi-Fi-based protocol, is optimized for low-latency, reliable communication, making it suitable for safety-critical applications like emergency braking. Cellular V2X (C-V2X), on the other hand, leverages 4G LTE and 5G networks to support broader connectivity, enabling advanced functionalities such as real-time updates and large-scale data sharing [7].

1.1.3 Applications of V2X Communication

Applications of V2X are vast and transformative. In addition to enhancing safety through collision prevention, V2X optimizes traffic management by reducing congestion and enabling efficient vehicle platooning. For autonomous vehicles, V2X complements onboard sensors like cameras and LiDAR, providing an additional layer of environmental awareness [8, 9].

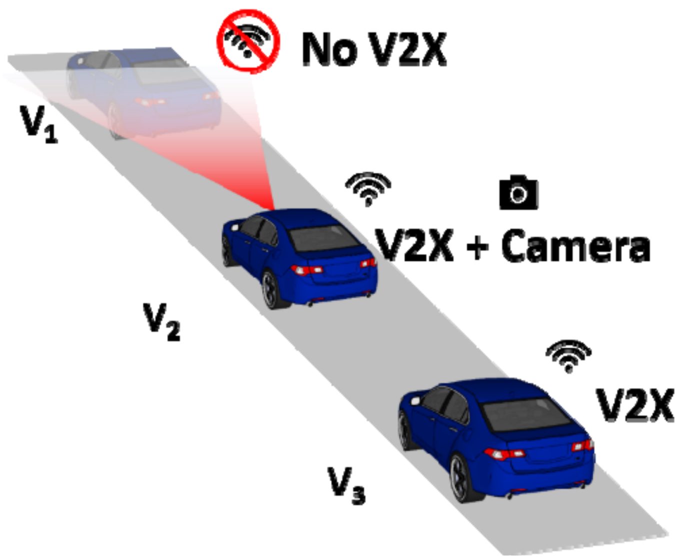

Figure 2: Illustration of the collaborative perception concept

1.1.4 Security Challenges in V2X Communication

Despite its potential, V2X faces several challenges. Security and privacy concerns arise from the constant exchange of real-time data, while ensuring seamless interoperability across manufacturers remains a significant hurdle [10].

A critical subset of V2X communication is the Vehicular Ad-Hoc Network (VANET), which enables vehicles to form dynamic, self-organized communication networks without relying on fixed infrastructure. In VANETs, vehicles act as both transmitters and receivers, exchanging information with other vehicles (V2V) and infrastructure (V2I). The decentralized nature of VANET allows for real-time communication, making it essential for time-sensitive applications. However, this decentralized architecture also introduces unique security and privacy challenges.

The challenges of VANET stem primarily from the misuse of information provided by vehicles. Clearly, the use of incorrect messages can lead to accidents and the adoption of erroneous strategies by traffic control centers. Therefore, the completeness and authenticity of messages must be verified before use [10].

Additionally, one of the essential security requirements of VANET is conditional privacy preservation. Conditional privacy means that while others are unable to identify vehicles based on their transmitted messages, it should still be possible to trace vehicles if necessary. Furthermore, given the coverage limitations of RSUs and the traffic volume within these areas, data compression becomes a critical issue that must be addressed in VANET systems to maintain efficient communication [10].

1.2 Traffic Sign Recognition (TSR)

Traffic Sign Recognition (TSR) is a critical component of intelligent transportation systems (ITS) and autonomous vehicle technology. Its primary goal is to identify and interpret traffic signs to aid driver decision-making or to enable autonomous vehicles to navigate roads safely and efficiently. By accurately recognizing signs such as speed limits, stop signs, and warnings, TSR systems enhance road safety and contribute to the seamless integration of automated driving technologies [11].

The importance of TSR extends beyond autonomous vehicles. Advanced Driver Assistance Systems (ADAS) also rely heavily on TSR to provide real-time feedback to human drivers, reducing accidents caused by missed or misinterpreted traffic signs. For instance, TSR systems can alert drivers about an upcoming speed limit change or detect stop signs even in adverse weather conditions [12].

Developing robust TSR systems poses unique challenges, given the vast diversity of traffic signs worldwide, as well as the influence of environmental factors such as poor lighting, occlusion, and weather-related impairments. As a result, TSR has become a prominent research area in computer vision and machine learning, driving advancements in algorithms and models that strive to match human-level accuracy and reliability [13].

1.2.1 Datasets for TSR: The GTSRB Dataset

The German Traffic Sign Recognition Benchmark (GTSRB) dataset has been selected as the primary dataset for this study. Widely recognized in the field of traffic sign recognition, GTSRB serves as a standard benchmark for developing and evaluating machine learning models. Its comprehensive collection of real-world traffic sign images provides the foundation for building robust TSR systems [14].

The German Traffic Sign Recognition Benchmark (GTSRB) dataset is a pivotal resource in the field of computer vision, particularly for traffic sign detection and recognition tasks. Introduced during the International Joint Conference on Neural Networks (IJCNN) in 2011, the GTSRB dataset was designed to facilitate research and development in traffic sign recognition systems, which are crucial for intelligent transportation systems and autonomous vehicles [15]. The dataset encompasses a diverse collection of over 50,000 images, categorized into 43 distinct classes of traffic signs, including various speed limits, warning signs, and informational signs [16].

Figure 3: Representatives of the 43 traffic sign classes in the GTSRB dataset.

This extensive classification allows for comprehensive training and evaluation of machine learning models, particularly convolutional neural networks (CNNs), which have demonstrated significant efficacy in recognizing traffic signs [17].

The GTSRB dataset is particularly notable for its real-world applicability, as it includes images captured under varying conditions, such as different lighting and weather scenarios, which enhances the robustness of the models trained on it [18]. The dataset's structure supports both supervised learning and evaluation methodologies , making it an ideal benchmark for comparing the performance of various algorithms and architectures [19]. For instance, researchers have utilized GTSRB to validate innovative approaches, such as multi-column deep neural networks and attention mechanisms, which have shown promising results in improving classification accuracy [16, 20].

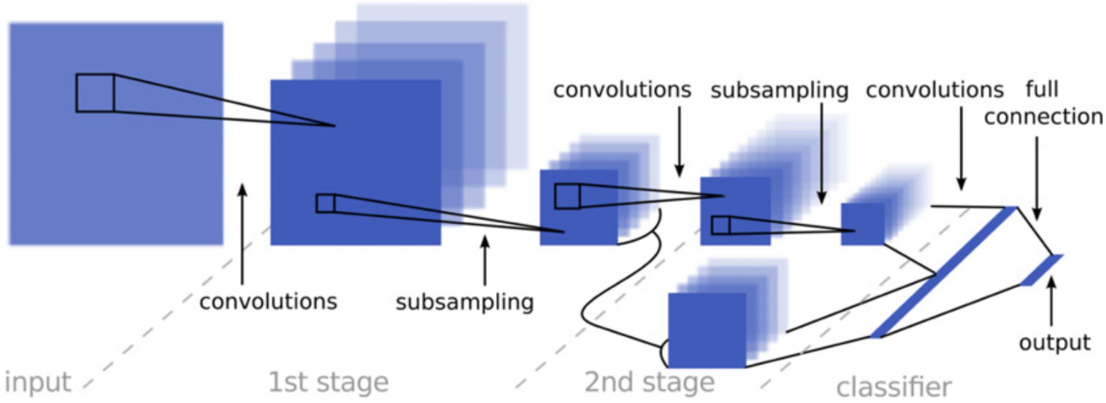

Figure 4: Example of a CNN architecture used for TSR

Moreover, the GTSRB dataset has been instrumental in advancing the understanding of adversarial attacks and model robustness in traffic sign recognition systems. Studies have employed GTSRB to evaluate the resilience of CNNs against various forms of adversarial perturbations, highlighting the importance of security in autonomous driving applications [21, 22]. The dataset's widespread use in the academic community underscores its significance as a benchmark for both foundational and cutting-edge research in traffic sign recognition [23].

In summary, the GTSRB dataset serves as a critical benchmark in the domain of traffic sign recognition, providing a rich resource for training and evaluating machine learning models. Its comprehensive collection of images, diverse classes, and real-world applicability make it an invaluable tool for researchers aiming to enhance the accuracy and reliability of traffic sign recognition systems.

2 Methodology

2.1 General intro

2.2 model

2.3 simulation system

2.4 conducted tests

3 Results

3.1 generally what results

list generally what you achieved

3.2 pure test

without any change in data what was the result and why

3.3 brightness test

what did you do and why didn't it make a big difference?

3.4 motion blur

what did you do and it made a little difference.

3.5 angles

it had a significant impact

4 Discussion

say that based on what you achieved in some scenarios the system works better than single recognition

draw some charts some tables how they differ.

5 Conclusions

using v2x doesn't have negative impact, but it has lots of positive impact.

the results vary from little non to lots.

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