Shahid Beheshti University

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

Bachelor's Thesis

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Abstract

Contents

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 **V2X!** (**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 **ITS!** (**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. **V2V!** (**V2V!**) communication allows direct data exchange between vehicles, enabling applications such as collision avoidance and coordinated lane changes. **V2I!** (**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, **V2P!** (**V2P!**) communication ensures vehicles are aware of nearby pedestrians, even in scenarios with poor visibility. Finally, **V2C!** (**V2C!**) links vehicles to cloud servers for updates on navigation, weather, or software improvements [4].

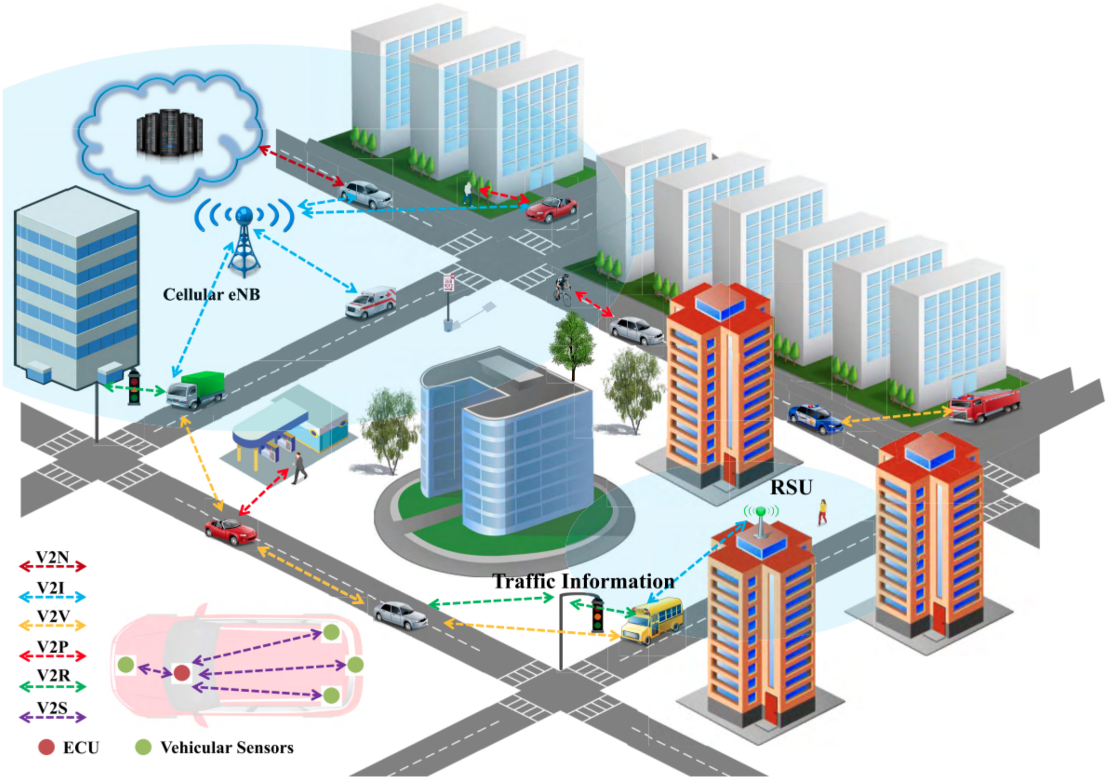

Figure 1: An overview of V2X scenario

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: **V2N!** (**V2N!**) connects vehicles to cloud-based systems via the Cellular **eNB!** (**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 **RSUs!** (**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. **DSRC!** (**DSRC!**), a Wi-Fi-based protocol, is optimized for low-latency, reliable communication, making it suitable for safety-critical applications like emergency braking. **C-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].

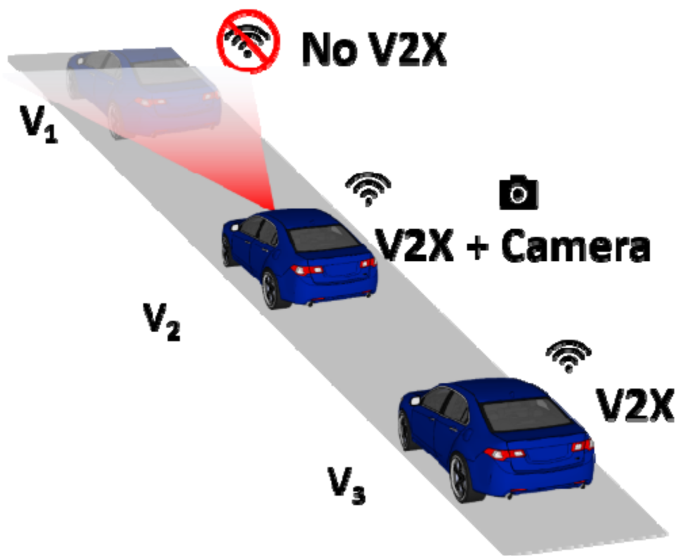

Figure 2: Illustration of the collaborative perception concept

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 **VANET!** (**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. **ADAS!** (**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 **GTSRB!** (**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 **CNNs!** (**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].

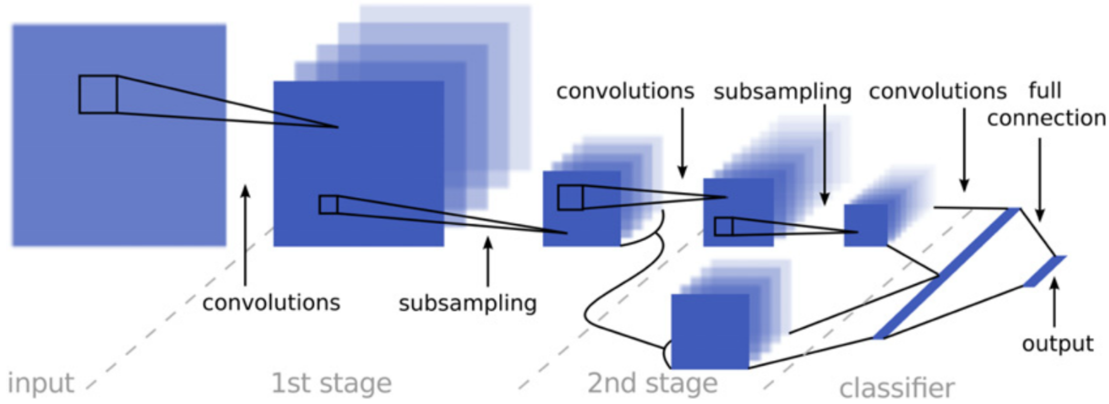

Figure 4: Example of a CNN architecture used for TSR

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

In this study, a deep learning model was developed for traffic sign recognition using the pretrained MobileNetV2 architecture. The application of transfer learning allowed the model to be fine-tuned effectively for the classification of German traffic signs, which significantly enhanced both training efficiency and performance on the target dataset. Transfer learning is particularly beneficial in scenarios where computational resources are limited, as it leverages existing knowledge from pretrained models to improve learning outcomes in specific tasks [24]. The MobileNetV2 architecture, known for its efficiency and low computational complexity, is well-suited for real-time applications in traffic sign recognition [25].

Following the training and optimization of the model, a Vehicular Ad Hoc Network (VANET) system was simulated to evaluate the model's real-world applicability in dynamic vehicular environments. VANETs are characterized by their ability to facilitate communication between vehicles, which is crucial for applications such as traffic sign recognition and real-time traffic management [26]. The dynamic nature of VANETs, due to the movement of vehicles, presents unique challenges for traffic prediction and management, making the integration of deep learning models essential for enhancing the accuracy and reliability of traffic sign recognition systems [27].

Finally, the model's accuracy was rigorously tested under various conditions, both within and outside the simulated VANET system, to assess its robustness and reliability across diverse contexts. The evaluation of traffic sign recognition systems in varying environmental conditions, such as different lighting and weather scenarios, is critical for ensuring their effectiveness in real-world applications [28]. The results from these tests provide valuable insights into the model's performance and its potential for deployment in intelligent transportation systems [29].

2.1 Deep Learning Model Training

A pretrained MobileNetV2 model was selected and fine-tuned by modifying its classifier layer to adapt it for traffic sign recognition. The model was subsequently trained on the prepared dataset to optimize its performance for accurate classification.

2.1.1 MobileNetV2

MobileNetV2 is a state-of-the-art CNN architecture specifically designed for mobile and edge devices, emphasizing computational efficiency and performance. It builds upon its predecessor, MobileNetV1, by introducing several enhancements that address the limitations of earlier models, particularly in terms of non-linearities and bottlenecks in narrow layers [30, 31]. The architecture is characterized by its use of depthwise separable convolutions and an inverted residual structure, which significantly reduces the number of parameters and computational cost while maintaining high accuracy in image classification tasks [31, 32].

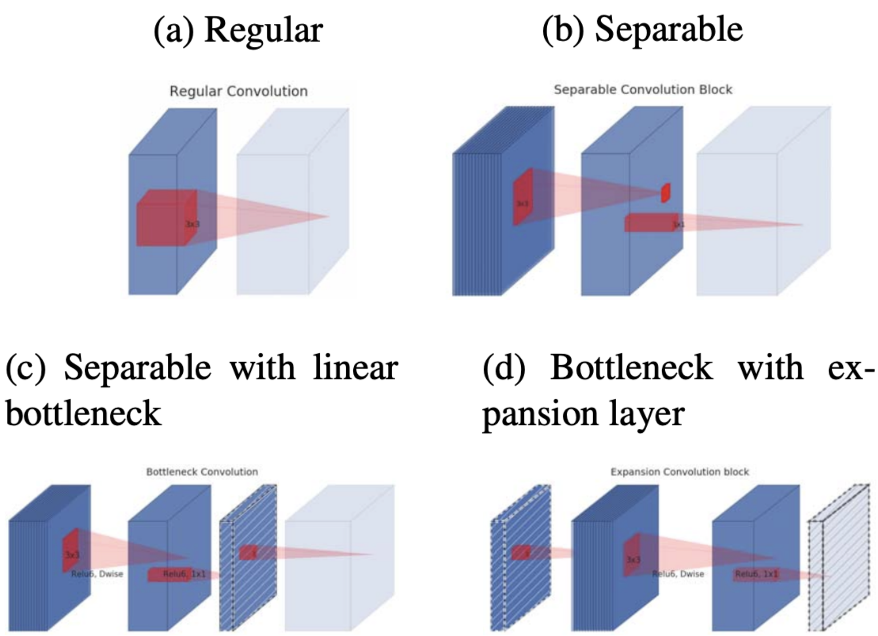

Figure 1: The difference between residual block and inverted residual.

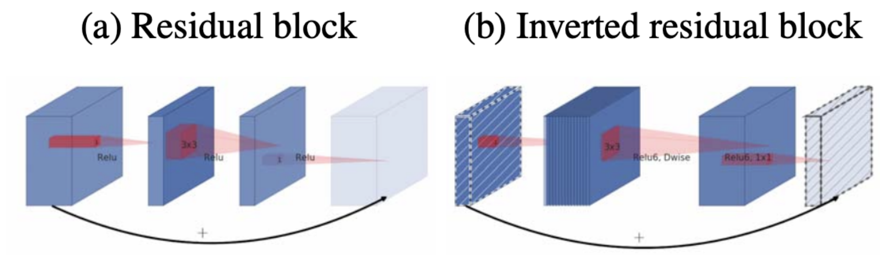

Figure 2: Evolution of separable convolution blocks

The structure of MobileNetV2 consists of 53 layers organized into 17 blocks, with a total of approximately 2.25 million parameters [33, 34]. Each block employs a linear bottleneck design, which allows for the reduction of channels before applying depthwise convolutions and subsequently expanding them again through pointwise convolutions. This design minimizes the introduction of non-linearities that could hinder performance, thus enhancing the model's ability to learn complex features while remaining lightweight [32, 35]. The architecture also incorporates global average pooling at the end, converting the spatial input into a fixed-size vector suitable for classification tasks [31, 35].

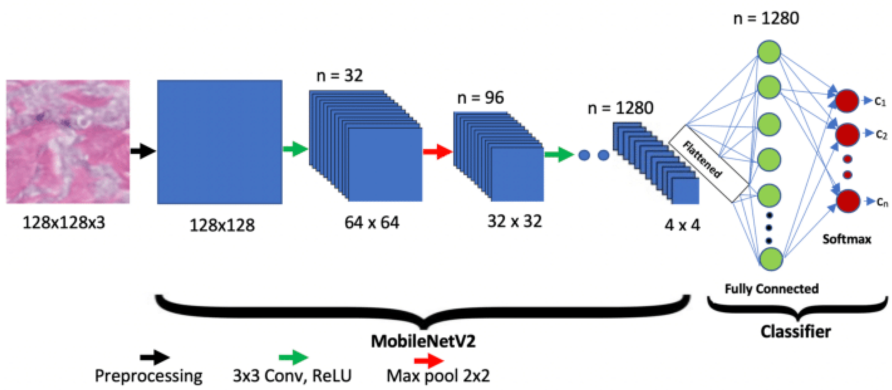

Figure 3: MobileNetV2 network architecture [33].

MobileNetV2 has demonstrated remarkable versatility across various applications, including image classification, feature extraction, and real-time inference on devices with limited computational resources [36, 37]. Its efficient design principles make it particularly well-suited for deployment in mobile applications, where speed and accuracy are critical [37, 38]. Furthermore, the architecture supports transfer learning, allowing it to leverage pre-trained weights for improved performance in specific tasks, even with smaller datasets [33, 37, 39].

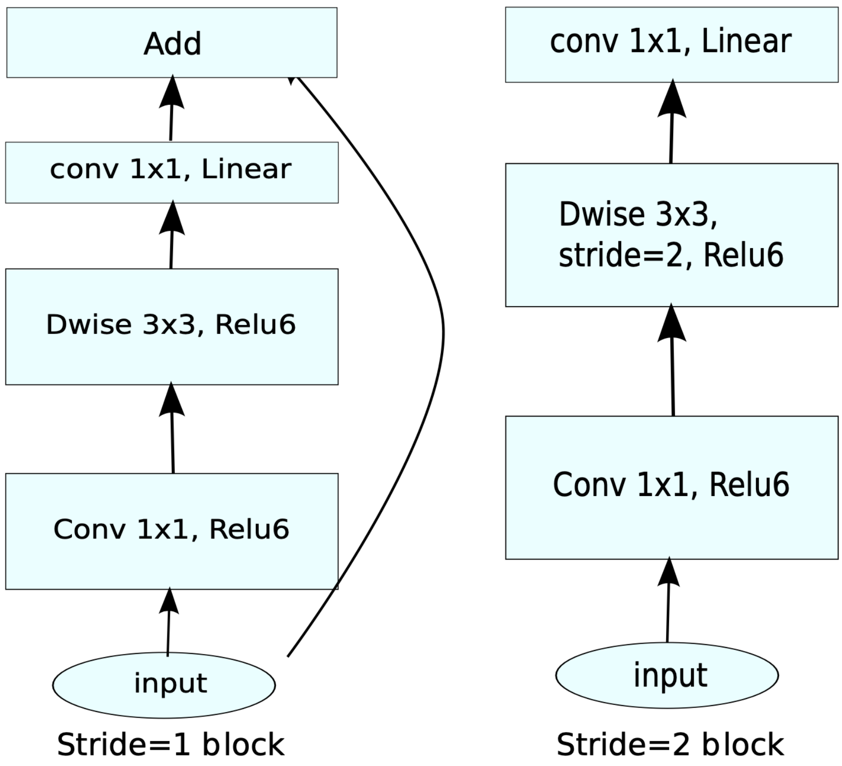

Figure 4: MobileNetV2 layers.

2.1.2 Pretrained Model Selection

The MobileNetV2 architecture was selected as the foundational model for traffic sign recognition due to its lightweight design and computational efficiency. MobileNetV2 is characterized by its use of depthwise separable convolutions and inverted residual structures, which significantly reduce the number of parameters and computational cost compared to standard convolutional networks [31]. This architectural choice is particularly advantageous for mobile and edge devices, where computational resources are limited, allowing for efficient processing without sacrificing performance [37]. The lightweight nature of MobileNetV2 makes it highly optimized for real-time applications, which is crucial for deployment in vehicular environments where low-latency processing is essential [37].

Moreover, initializing the model with pretrained weights on the ImageNet dataset allows MobileNetV2 to leverage rich feature representations, thereby expediting the convergence process during training [40]. This practice is supported by evidence that pretrained models can achieve better performance in various tasks, including image classification, by utilizing learned features from large datasets [40, 41]. The effectiveness of this approach is further underscored by studies demonstrating that pretrained networks can enhance model robustness and generalization capabilities, particularly in scenarios with limited labeled data [42].

In summary, the selection of MobileNetV2 for traffic sign recognition is justified by its efficient architecture, suitability for real-time applications, and the benefits derived from transfer learning through pretrained weights on the ImageNet dataset.

2.1.3 Dataset Partitioning

The German Traffic Sign Recognition Benchmark (GTSRB) dataset was partitioned to facilitate effective training, validation, and testing. The training dataset was split using an 80/20 ratio, where 80% of the data was allocated for training and 20% for validation. This stratified partitioning ensures that the model generalizes well by validating its performance on unseen data during training. The test dataset was kept entirely separate to provide an unbiased assessment of the model's final performance.

2.1.4 Image Preprocessing and Data Augmentation

Robust image preprocessing and data augmentation techniques were applied to enhance the model's generalization capabilities. Training images underwent a series of transformations, including resizing to 224x224 pixels, random horizontal flipping, random rotations up to 15 degrees, and color jittering to simulate variations in lighting conditions. These transformations artificially increased the diversity of the dataset, mitigating overfitting. All images were subsequently converted to tensors and normalized using the ImageNet mean and standard deviation values to standardize the input distribution. Testing images were subjected to resizing and normalization only, ensuring consistent evaluation conditions.

2.1.5 Fine-Tuning Strategy

To adapt MobileNetV2 for traffic sign recognition, the final classification layer was replaced with a fully connected layer comprising 43 output nodes, corresponding to the number of traffic sign classes in the GTSRB dataset. All preceding convolutional layers were frozen to preserve the pretrained feature extraction capabilities, while the new classifier layer was fine-tuned to specialize in distinguishing between traffic sign categories. This selective fine-tuning strategy balances computational efficiency with task-specific learning.

2.1.6 Training Configuration

The model was trained over 10 epochs with a batch size of 16, utilizing the Adam optimizer with a learning rate of 0.001. Cross-entropy loss was employed as the objective function to handle the multi-class classification task. A validation split of 20% within the training set enabled continuous performance monitoring and adjustment during training. These hyperparameters were chosen to provide an optimal trade-off between model convergence speed and generalization performance, ensuring efficient and stable learning across the dataset.

2.2 simulation system

2.3 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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