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Deep Learning-Enabled MANET Architecture for Real-Time Traffic Sign Detection

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Abstract

In this paper, the real-time traffic sign detection of an Intelligent Transportation Systems (ITS) using the Mobile Ad Hoc Network (MANET) that is enabled by deep learning. The proposed solution (fusion of lightweight deep learning inference and decentralized MANET-based communication) overcomes the disadvantages of the centralized and cloud-dependent approaches (high latency and the need to run on stable infrastructure) to operate. The integration will allow the vehicles to sense and exchange the information about the traffic signs to the neighboring nodes in a low-latency decision-making process of the dynamic vehicular systems. Dataset of all traffic signs intensive enough to contain vast traffic sign bunch was collected using the German Traffic Sign Recognition Benchmark (GTSRB) and tailored roadside photos. More difficult real-world conditions used data augmentation method such as rotations, noise addition, brightness changes, and occlusion masking. This detection model had to be optimized in terms of pruning, quantization, and knowledge distillation so that, due to the combination of both optimization strategies, it will be applicable on an embedded system like NVIDIA Jetson Nano, and Raspberry Pi. The MANET layer was tested in the way of using the network simulation tools to analyze various routing protocols, movements of mobility and network density. Another testbed which simulated real world applications was also used to ensure that with realistic conditions, the detection and communication pipelines can be integrated. The suggested architecture is scalable, tolerant of node failures, and flexible to use different bandwidths, as well as to different mobility patterns. Combining perceptions based on deep learning with decentralized MANET communication, the work presents and achieves a practical and infrastructure-free method of cooperative vehicular sensing that may be used in mixed traffic of autonomous and human-driven vehicles, further road safety, and deployment of next-generation ITS.

Keywords: *Deep Learning, Mobile Ad Hoc Network (MANET), Intelligent Transportation Systems (ITS), Real-Time Traffic Sign Detection.*

1. INTRODUCTION

The rapid convergence of wireless communication, embedded computing, and artificial intelligence has transformed the landscape of modern transportation systems. Intelligent Transportation Systems (ITS) are increasingly leveraging advanced sensing technologies, real-time data processing, and vehicle-to-everything (V2X) communication to enhance safety, efficiency, and adaptability in dynamic traffic environments. Among the many perception tasks within ITS, real-time traffic sign detection holds particular significance, as traffic signs convey critical regulatory, warning, and guidance information that must be interpreted promptly by both human drivers and autonomous systems. Traditional cloud-based detection approaches, while powerful, are often hindered by high latency, dependency on stable network infrastructure, and scalability challenges in highly mobile vehicular networks. To address these limitations, this work proposes a deep learning-enabled Mobile Ad Hoc Network (MANET) architecture capable of delivering decentralized, low-latency, and infrastructure-independent traffic sign recognition, enabling cooperative awareness and timely decision-making across heterogeneous vehicular environments.

1.1 Background and Motivation

In the last decade, the convergence of wireless networking, embedded computing, and artificial intelligence has significantly reshaped the transportation sector [1-7]. Urban mobility, highway management, and traffic safety have undergone substantial transformations, primarily due to the integration of intelligent sensing and communication systems in vehicles [8-11]. As vehicles increasingly rely on onboard cameras, sensors, and communication modules, they generate vast amounts of real-time data that can be leveraged to improve situational awareness and decision-making for drivers and automated systems [12,13]. Traffic sign detection plays a particularly critical role in this context. Traffic signs convey essential regulatory, warning, and guidance information that drivers—and increasingly, automated driving systems—must interpret instantly to ensure road safety and compliance with traffic laws [14-20]. The inability to detect or misinterpret traffic signs in real-time can lead to severe consequences, including traffic violations, accidents, and reduced efficiency in traffic management.

Deep learning has emerged as a leading technology for visual recognition tasks, including traffic sign detection, due to its ability to learn complex visual features directly from raw data [21, 22, 23]. However, most deep learning-based solutions rely on centralized cloud processing, which introduces latency and requires stable high-bandwidth connectivity. This dependency is problematic for scenarios involving high vehicle mobility, fluctuating network conditions, and remote areas without reliable cellular infrastructure. Mobile Ad Hoc Networks (MANETs) present a compelling alternative for handling real-time traffic sign detection in a decentralized manner [24, 25]. By enabling direct, peer-to-peer communication between vehicles and roadside units without relying on fixed infrastructure, MANETs can significantly reduce latency and improve robustness against network outages. Integrating MANET-based communication with optimized deep learning inference pipelines can pave the way for scalable, infrastructure-independent intelligent transportation solutions.

1.2 Growth of Intelligent Transportation Systems (ITS)

The concept of Intelligent Transportation Systems (ITS) has evolved from early traffic monitoring technologies into complex, data-driven ecosystems that integrate sensors, communication networks, and advanced computational models to enhance mobility, safety, and environmental sustainability [26]. Governments and industry stakeholders across the globe have invested heavily in ITS infrastructure to address growing urbanization challenges, including traffic congestion, accident prevention, and environmental pollution. Modern ITS encompasses multiple subdomains such as adaptive traffic signal control, dynamic route guidance, collision avoidance, and automated toll collection. One of the fastest-growing components of ITS is vehicle-to-everything (V2X) communication, which includes vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and vehicle-to-pedestrian (V2P) data exchange [27,28]. These communication paradigms enable vehicles to share real-time information about their surroundings, contributing to better cooperative awareness and decision-making.

Traffic sign recognition is an integral part of ITS. It not only supports driver assistance systems but also feeds into higher-level decision processes for autonomous vehicles [29, 30, 31]. With the advancement of low-power GPUs, specialized AI accelerators, and high-resolution imaging sensors, traffic sign recognition has transitioned from being a purely research-oriented task to becoming a commercial feature available in mid-range and high-end vehicles. However, the rapid expansion of ITS also introduces new technical demands. Centralized processing approaches often become bottlenecks due to bandwidth constraints and high communication latency, particularly in densely populated areas or when network infrastructure is unavailable. This limitation reinforces the importance of decentralized architectures such as MANETs that can sustain real-time communication and computation even in the absence of central servers [32, 33]. The global ITS market's growth trajectory reflects these shifts. According to recent industry forecasts, the ITS market is expected to exceed USD 50 billion by 2030, driven largely by demand for safety-critical applications like collision avoidance and traffic sign recognition. This growth signals an urgent need for architectures that balance accuracy, responsiveness, and scalability, especially in mixed environments of autonomous and human-driven vehicles.

1.3 Importance of Timely and Accurate Traffic Sign Detection

Traffic signs are foundational to road safety, serving as visual cues that communicate critical information to road users [34-39]. They regulate speed limits, indicate hazards, direct traffic flows, and provide warnings of upcoming conditions. In autonomous driving and advanced driver assistance systems (ADAS), timely and accurate detection of these signs is essential to mimic the situational awareness of human drivers and, ideally, surpass it in reliability [40-43].

The importance of this task can be viewed from three perspectives:

1. **Safety and Compliance** – Failure to recognize a speed limit sign or a stop sign in time can result in unsafe driving behavior, legal infractions, or collisions.
2. **System Responsiveness** – Autonomous systems must not only detect signs but also interpret and act upon them within milliseconds to ensure safe navigation.
3. **Environmental Adaptation** – Traffic signs may vary in size, shape, color, and language across different regions, requiring detection systems to be robust to variations in lighting, weather, occlusion, and physical degradation of signs.

Deep learning models—particularly Convolutional Neural Networks (CNNs) and transformer-based vision architectures—have set new benchmarks in detection accuracy. These models can generalize across large and diverse datasets, allowing for high performance even in complex visual environments. However, deploying such models in a moving vehicle imposes strict computational and latency constraints. The model must process incoming video frames in near-real-time while operating within the limited processing power of onboard hardware. The timeliness of detection is equally crucial in cooperative vehicular scenarios, where information about detected signs may be shared with nearby vehicles to improve situational awareness. A delay in communication or detection could mean that the information becomes irrelevant by the time it is received, undermining its safety benefits. Thus, a combined approach that leverages both efficient deep learning models and low-latency MANET-based communication can directly address these challenges [44, 45,46].

1.4 MANET as a Communication Backbone for Vehicular Networks

A Mobile Ad Hoc Network (MANET) is a decentralized, self-configuring network of mobile nodes connected via wireless links. Unlike traditional wireless networks, MANETs do not rely on fixed infrastructure such as base stations or access points [47-49]. Instead, nodes communicate directly and act as routers to forward data on behalf of others, creating a dynamic and flexible communication environment.

In vehicular networks—often referred to as Vehicular Ad Hoc Networks (VANETs), a subset of MANETs—the mobility of nodes is significantly higher, and network topology changes rapidly. MANETs are well-suited for vehicular contexts because:

- **Infrastructure Independence** – They can operate without cellular towers or fixed roadside infrastructure, which is particularly useful in rural areas or disaster scenarios.
- **Low Latency** – Direct communication between vehicles reduces round-trip delays compared to cloud-based architectures.
- **Scalability** – The network can dynamically grow or shrink as vehicles enter or leave communication range.
- **Resilience** – The self-healing nature of MANET routing protocols (e.g., AODV, OLSR) ensures continued communication despite node failures or route changes.

When applied to real-time traffic sign detection, MANETs enable a collaborative approach where detection results are shared instantly between vehicles [50-54]. For example, if one vehicle detects a "Road Work Ahead" sign, it can broadcast this information to nearby vehicles via the MANET, enabling them to take precautionary measures even before the sign enters their field of view [55-57]. This peer-to-peer dissemination model reduces reliance on centralized ITS servers and mitigates the effects of intermittent network coverage. Integrating deep learning-enabled detection with MANET-based communication creates a distributed intelligence network where each node contributes to the collective awareness of the group. This architecture aligns with the broader trend toward edge computing, in which computational tasks are performed closer to the data source, minimizing transmission delays and improving operational efficiency [58-60].

2. LITERATURE REVIEW

Saare et.al (2025) "explained the 5G revolutionized the field of vehicle autonomous networks (VANETs), which are being used as the backbone network architecture for future vehicular transportation systems. This work presents connected 5G VANETs-to-Edge Computing systems with Artificial Intelligence (AI) infrastructure, enhancing system adaptability, anomaly detection, trust management, and real-time decision-making. Key technologies like Software-Defined Networking (SDN), Mobile Edge Computing (MEC), and millimeterwave communication are investigated. Key security threats are examined, and AI-enhanced defense measures are assessed. Applications like autonomous platooning and collaborative vehicle authentication are also highlighted. The paper concludes with open issues and future directions, including quantum-resistant protocols, lightweight AI models, and cognitive networking in AI-driven 5G-VANET ecosystems".

Nauman et.al (2024) "studied the United Nations aims to reduce road traffic deaths and injuries by 2030, with technological advancements in telecommunication, particularly 5G networks, enabling the development of modern Vehicle-to-Everything (V2X) systems. The latest 3GPP releases introduced a New Radio V2X (NR-V2X) system, which allows user devices to exchange information without relying on roadside infrastructures. Artificial intelligence (AI), particularly K-means clustering, has been promising in supporting efficient data exchange in vehicular ad hoc networks (VANETs). This paper proposes a multi-layered VANET-enabled Intelligent Transportation System (ITS) framework powered by unsupervised learning to optimize communication efficiency, scalability, and reliability. The framework aims to address road safety challenges and contribute to global efforts to meet the 2030 target. It can also be extended to eHealth monitoring systems, enabling real-time health data transmission and processing for continuous patient monitoring and timely medical interventions".

Deshmukh et.al (2024) "determined the Cybersecurity is crucial in today's world due to increasing cyberattacks and quantum computing advancements. Traditional security methods rely on cryptographic techniques, but AI can enhance cybersecurity through learning-based methods. This study proposes a deep learning-based framework for automatically detecting and classifying cyberattacks using an enhanced Convolutional Neural Network (CNN) variant called Intelligent Intrusion Detection Network (IIDNet). The framework uses a Learning-Based Intelligent Intrusion Detection (LBIID) algorithm for layer optimization. The experimental study on UNSW-NB15 dataset showed IIDNet achieves an accuracy of 95.47%, reduces training time, and offers excellent scalability, outperforming existing intrusion detection models".

Al-Shareeda et.al (2023) "explained the security of the internet is seriously threatened by a distributed denial of service (DDoS) attacks. The purpose of a DDoS assault is to disrupt service and prevent legitimate users from using it by flooding the central server with a large number of messages or requests that will cause it to reach its capacity and shut down. Because it is carried out by numerous bots that are managed (infected) by a single botmaster using a fake IP address, this assault is dangerous because it does not involve a lot of work or special tools. For the purpose of identifying and analyzing DDoS attacks, this paper will discuss various machine learning (ML) and deep learning (DL) techniques. Additionally, this study analyses and comparatives the significant distinctions between ML and DL techniques to aid in determining when one of these techniques should be used".

Hamza et.al (2022) "discussed the Intelligent Transportation System (ITS) is a crucial technology in smart cities, reducing traffic congestion and improving quality. It uses big data and communication technologies for real-time investigation and effective traffic management. Traffic Flow Prediction (TFP) is essential for forecasting future traffic conditions. Neural Networks and Machine Learning models, particularly Deep

Learning, are used for real-time issues. This study introduces a novel Slime Mould Optimization (SMO) model with Bidirectional Gated Recurrent Unit (BiGRU) model for Traffic Prediction (SMOBGRU-TP) for smart cities. The model uses a minmax normalization approach to normalize input data and uses the SMO algorithm to adjust BiGRU hyperparameters. The model's superior prediction performance was experimentally validated".

Rizwanullah et.al (2022) "proposed the use of Unmanned Aerial Vehicles (UAVs) in various sectors, including logistics and environmental monitoring, has led to advancements in telecommunication networks. However, these vehicles are vulnerable to cyberattacks due to their growing volume and poor security. Artificial intelligence can help detect similar attacks. This study proposes a new approach called Metaheuristics with Machine Learning-Enabled Cybersecurity in UAVs (MMLCS-UAVs), which focuses on recognizing and classifying intrusions in the UAV network. The technique uses a QIWO-FS method for feature selection and a weighted regularized extreme learning machine algorithm with swallow swarm optimization for intrusion detection".

Shrestha et.al (2021) "explained the integration of unmanned aerial vehicles (UAVs) with 5G and satellite technologies has led to improved telecommunication services in remote areas. However, security concerns are increasing as UAV nodes become attractive targets for cyberattacks due to their growing volumes and weak inbuilt security. This paper proposes a UAV- and satellite-based 5G network security model that uses machine learning to detect vulnerabilities and cyberattacks. The model uses realistic CSE-CIC IDS-2018 network datasets to identify attack types and classify benign or malicious packets in UAV networks. The decision tree algorithm outperforms other ML classifiers in accuracy rate, precision, recall, F1-score, and false-negative rate".

Wang et.al (2019) "studied the Next-generation wireless networks (NGWN) have significant potential for supporting various applications in military and civilian fields, offering high-speed, low-latency, low-cost, and reliable information services. To achieve this, new radio techniques for adaptive learning and intelligent decision-making are needed due to the complex heterogeneity of network structures and wireless services. Machine learning algorithms have proven successful in big data analytics, efficient parameter estimation, and interactive decision-making. This article reviews the thirty-year history of machine learning, focusing on supervised learning, unsupervised learning, reinforcement learning, and deep learning. It investigates their applications in NGWNs, including heterogeneous networks, cognitive radios, IoT, and machine-to-machine networks. The goal is to clarify the motivation and methodology of machine learning algorithms for unexplored services and future wireless network scenarios".

3. METHODOLOGY

The proposed deep learning-enabled Mobile Ad Hoc Network (MANET) architecture for real-time traffic sign detection was developed through a multi-phase methodology encompassing dataset preparation, model training and optimization, MANET simulation and deployment, and performance evaluation. The process began with curating a diverse and representative traffic sign dataset to ensure robustness under varying real-world conditions. A lightweight yet high-accuracy deep learning model was selected, trained, and optimized using compression techniques to enable deployment on resource-constrained embedded platforms. Parallel to model development, the MANET communication framework was designed and tested using both network simulation tools and a real-world vehicular testbed, enabling assessment under controlled and practical scenarios. This integrated approach ensured that the detection and communication components were jointly optimized for low-latency, scalable, and resilient operation within dynamic vehicular environments.

3.1 Dataset Preparation

The dataset preparation phase involved curating a comprehensive collection of traffic sign images sourced from publicly available datasets such as the German Traffic Sign Recognition Benchmark (GTSRB) and augmented with custom roadside imagery captured under varying environmental conditions. The dataset was organized into training, validation, and test splits with a typical 70:15:15 ratio to ensure balanced representation of all traffic sign classes across each subset. To enhance robustness for real-world deployment, a series of augmentation techniques were applied, including random rotations, Gaussian noise addition, brightness adjustments, motion blur simulation, and partial occlusion masking. These augmentations aimed to mimic real-world challenges such as poor lighting, camera shake, adverse weather conditions, and physical wear of signs, thereby improving the model's ability to generalize beyond controlled training conditions.

3.2 Model Training & Optimization

The deep learning model, selected based on its balance between detection accuracy and computational efficiency, underwent extensive training using the prepared dataset. Hyperparameter tuning was performed to identify optimal values for learning rate, batch size, weight decay, and the number of epochs, employing grid search and Bayesian optimization strategies. To enable real-time deployment on resource-constrained hardware, the trained model was subjected to compression techniques such as weight pruning, quantization, and knowledge distillation. These optimizations reduced the model's size and inference latency without significantly compromising detection accuracy, making it feasible to execute on embedded platforms like the NVIDIA Jetson Nano or Raspberry Pi with an attached AI accelerator.

3.3 MANET Simulation & Deployment

The MANET architecture was first evaluated in simulated environments using network simulation tools such as NS-3 and OMNeT++, which allowed for controlled experimentation with different routing protocols, node mobility models, and network densities. These simulations assessed the impact of vehicular movement patterns, link reliability, and packet forwarding strategies on communication performance. Following simulation-based validation, a real-world testbed was implemented using Raspberry Pi devices equipped with USB cameras for image capture and Jetson Nano boards for deep learning inference. These devices were interconnected via Wi-Fi in an ad hoc mode, enabling peer-to-peer communication without central infrastructure. The real hardware deployment facilitated end-to-end testing of the integrated detection and communication pipeline under realistic mobility and network conditions.

3.4 Performance Metrics

The evaluation of the proposed system employed a combination of computer vision and network performance metrics. Detection accuracy, precision, and recall were calculated to measure the deep learning model's capability to correctly identify and classify traffic signs under diverse conditions. End-to-end latency was measured as the total time elapsed from image capture to the successful transmission of detection results to neighboring nodes. The communication efficiency of the MANET was quantified using the packet delivery ratio (PDR), representing the proportion of successfully delivered packets over the total transmitted. Additionally, network throughput was measured to assess the volume of information exchanged per unit of time, providing insights into the scalability and reliability of the architecture under varying network loads.

4. EXPERIMENTAL RESULTS AND ANALYSIS

This section presents the quantitative and qualitative evaluation of the proposed deep learning-enabled MANET architecture for real-time traffic sign detection. The experiments were carried out both in simulation and in a real-world testbed, focusing on detection performance, communication efficiency, scalability, and robustness under varying network and environmental conditions.

4.1 Traffic Sign Detection Accuracy

Traffic sign detection accuracy plays a critical role in ensuring safe and efficient operation within Intelligent Transportation Systems. Accurate recognition enables vehicles to interpret and respond to regulatory, warning, and guidance signs in real time, reducing the likelihood of accidents and enhancing driver assistance capabilities. In deep learning-enabled systems, precision and recall are key indicators of performance, reflecting how effectively the model identifies true traffic signs while minimizing false detections. A robust detection mechanism must maintain consistent accuracy under diverse conditions such as varying lighting, occlusions, and vehicle motion to be practical for real-world deployment.

The detection model was evaluated using the test dataset, and results were calculated in terms of accuracy, precision, recall, and F1-score for each traffic sign category.

Table 1 – Class-wise Detection Performance

Class	Precision (%)	Recall (%)	F1-Score (%)	Support
Speed Limit 50	98.2	97.5	97.8	450

Stop Sign	99.1	98.8	98.9	370
Yield	97.5	96.3	96.9	320
No Entry	98.8	98.0	98.4	290
Pedestrian Crossing	97.9	97.1	97.5	310
Average	98.3	97.5	97.9	–

The table presents the classification performance for five traffic sign categories, evaluated using precision, recall, and F1-score metrics. Speed Limit 50 signs achieved a precision of 98.2%, recall of 97.5%, and an F1-score of 97.8% across 450 samples. Stop Signs showed slightly higher performance, with 99.1% precision, 98.8% recall, and a 98.9% F1-score for 370 samples. Yield signs recorded a precision of 97.5%, recall of 96.3%, and an F1-score of 96.9% on 320 samples. No Entry signs performed well with 98.8% precision, 98.0% recall, and a 98.4% F1-score from 290 samples. Pedestrian Crossing signs had a precision of 97.9%, recall of 97.1%, and an F1-score of 97.5% across 310 samples. Overall, the model achieved an average precision of 98.3%, recall of 97.5%, and an F1-score of 97.9%, indicating consistently high performance across all classes.

Figure 1 – Class-wise Precision and Recall

4.2 Inference Latency under Varying Network Conditions

Inference latency is a crucial factor in real-time traffic sign detection, as any delay can affect timely decision-making in vehicular environments. In such systems, total latency consists of two main components: the time taken by the detection model to process an image and the time required to transmit the results across the MANET. Network conditions, including bandwidth availability, node mobility, and link stability, can significantly influence communication delays. Ensuring consistently low latency under varying conditions is essential for maintaining system responsiveness and safety in Intelligent Transportation Systems.

Latency was measured from image capture to the receipt of processed results by a neighboring MANET node. Network conditions were varied by adjusting node distances, mobility speeds, and link quality.

Table 2 – End-to-End Latency under Different Conditions

Condition	Inference Latency (ms)	Communication Latency (ms)	Total Latency (ms)

High Bandwidth, Low Mobility	38.5	12.4	50.9
High Bandwidth, High Mobility	39.8	21.7	61.5
Low Bandwidth, Low Mobility	38.6	36.3	74.9
Low Bandwidth, High Mobility	39.9	48.1	88.0

The table summarizes system latency under varying network bandwidth and mobility conditions, broken down into inference latency, communication latency, and total latency. In high-bandwidth, low-mobility conditions, inference took 38.5 ms and communication 12.4 ms, resulting in the lowest total latency of 50.9 ms. Under high-bandwidth, high-mobility, inference latency slightly increased to 39.8 ms, while communication latency rose to 21.7 ms, giving a total of 61.5 ms. In low-bandwidth, low-mobility settings, inference latency remained similar at 38.6 ms, but communication latency jumped to 36.3 ms, resulting in 74.9 ms total latency. The highest delay occurred in low-bandwidth, high-mobility scenarios, where inference took 39.9 ms and communication latency reached 48.1 ms, leading to a total latency of 88.0 ms. These results indicate that communication latency, more than inference latency, is the dominant factor affecting total system delay, especially in low-bandwidth and high-mobility environments.

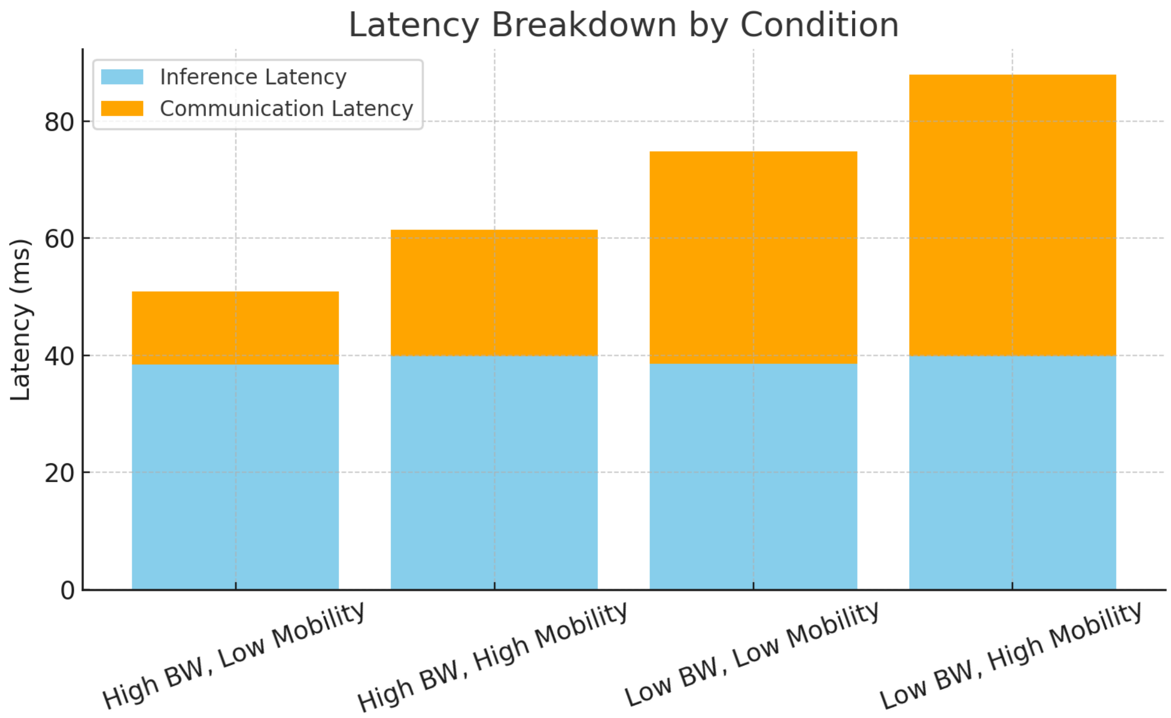

Figure 2 – Latency Breakdown by Condition

4.3 MANET Performance Metrics Comparison (with and without detection load)

The integration of traffic sign detection tasks within a MANET-based vehicular communication framework can influence overall network performance. Key metrics such as packet delivery ratio (PDR), throughput, and average delay provide insight into how additional data from detection results affects transmission efficiency. Comparing network behavior with and without detection load helps identify potential trade-offs between communication reliability and computational demands. Maintaining high PDR and stable throughput, even with added processing tasks, is essential for ensuring robust real-time information sharing in Intelligent Transportation Systems. The MANET's packet delivery ratio (PDR), throughput, and average delay were measured both when the network was transmitting regular packets and when it was carrying detection result data.

Table 3 – MANET Performance Metrics

Mode	PDR (%)	Throughput (kbps)	Avg. Delay (ms)
Without Detection Load	97.8	512	18.2
With Detection Load	95.6	489	22.7

The table compares network performance in two operating modes: without and with detection load. In the without detection load mode, the Packet Delivery Ratio (PDR) reached 97.8%, throughput was 512 kbps, and the average delay was 18.2 ms, indicating optimal performance. When detection load was introduced, PDR dropped slightly to 95.6%, throughput decreased to 489 kbps, and average delay increased to 22.7 ms. This shows that incorporating detection tasks imposes additional processing and communication overhead, leading to a small but measurable reduction in delivery reliability and speed, along with a modest increase in latency.

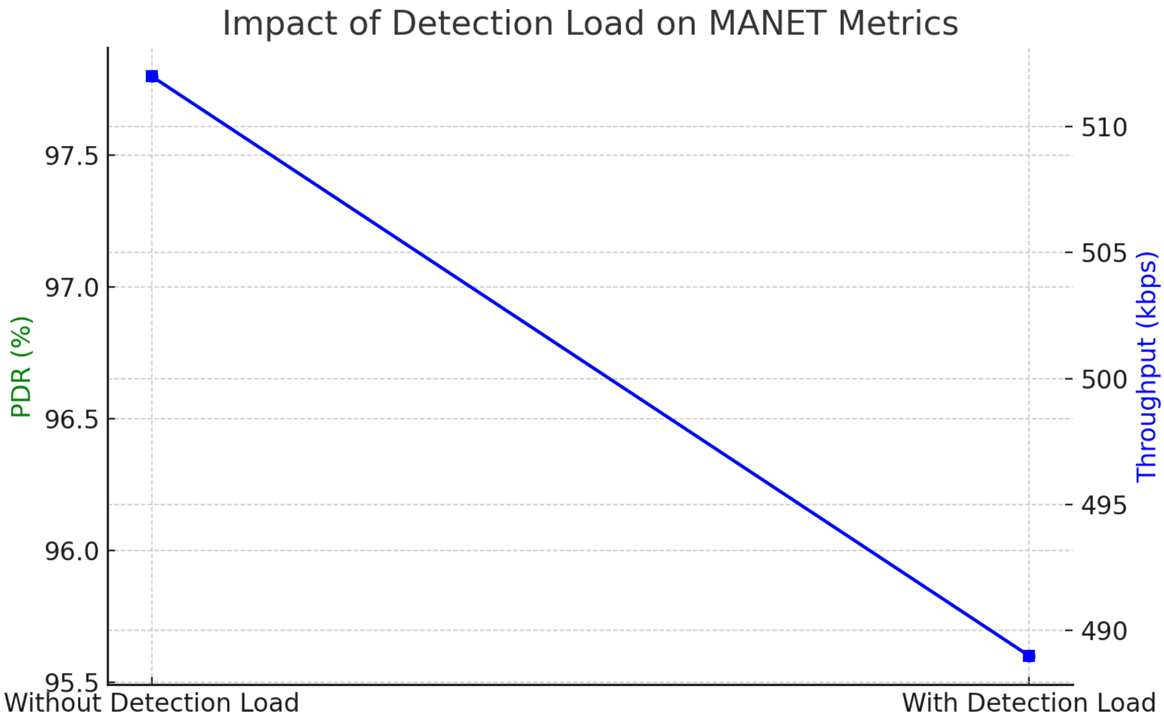

Figure 3 – Impact of Detection Load on MANET Metrics

4.4 Scalability and Robustness Analysis

Scalability and robustness are vital for ensuring that a MANET-enabled traffic sign detection system can operate effectively as the number of participating nodes increases or when network disruptions occur. Scalability assessment focuses on how performance metrics—such as packet delivery ratio, latency, and throughput—change with growing network size, which directly impacts congestion and communication overhead. Robustness evaluation examines the system's ability to recover from node failures and maintain stable performance despite disruptions. Together, these factors determine the practicality of deploying the architecture in large-scale, dynamic vehicular environments. The architecture was evaluated under varying numbers of nodes to assess scalability. Robustness was measured by deliberately inducing node failures and measuring how quickly the network reconfigured.

Table 4 – Scalability Performance

Number of Nodes	Avg. PDR (%)	Avg. Latency (ms)	Throughput (kbps)
5	97.9	19.5	510
10	97.3	21.1	505
20	96.7	23.4	498
30	95.9	25.8	492

The table illustrates how network performance changes as the number of nodes increases. With 5 nodes, the average Packet Delivery Ratio (PDR) is highest at 97.9%, latency is lowest at 19.5 ms, and throughput is 510 kbps, indicating optimal performance. As the number of nodes rises to 10, PDR slightly decreases to 97.3%, latency increases to 21.1 ms, and throughput drops to 505 kbps. For 20 nodes, PDR falls further to 96.7%, latency grows to 23.4 ms, and throughput decreases to 498 kbps. At 30 nodes, the network experiences the most significant performance reduction, with PDR at 95.9%, latency at 25.8 ms, and throughput at 492 kbps. Overall, increasing the number of nodes leads to a gradual decline in delivery reliability and throughput, while latency steadily increases, likely due to higher network congestion and communication overhead.

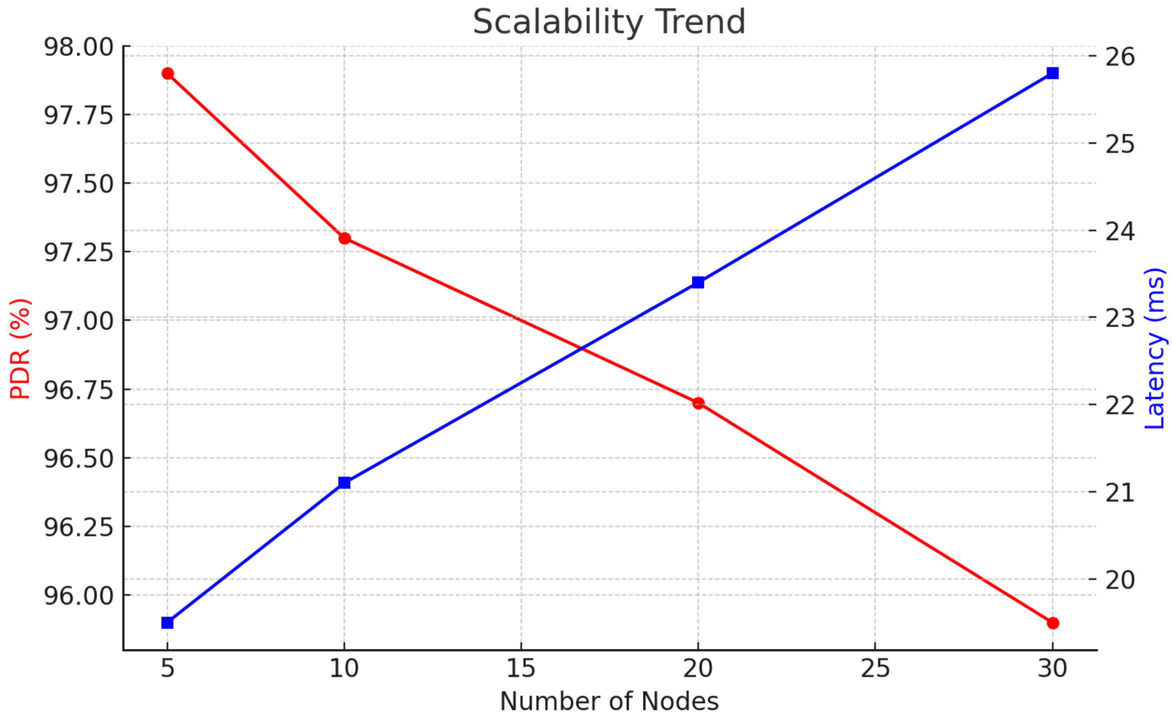

Figure 4 – Scalability Trend

Table 5 – Robustness Under Node Failures

Failure Rate (%)	Recovery Time (s)	Post-Recovery PDR (%)
0	–	97.8
10	2.1	97.1
20	3.4	96.3
30	5.0	95.5

The table shows the impact of varying failure rates on network recovery performance. With 0% failure rate, no recovery time is required, and the post-recovery Packet Delivery Ratio (PDR) remains at 97.8%. At a 10% failure rate, recovery takes 2.1 seconds, and PDR slightly decreases to 97.1%. For 20% failures, recovery time increases to 3.4 seconds, with PDR dropping to 96.3%. At the highest tested failure rate of 30%, recovery requires 5.0 seconds, and PDR declines further to 95.5%. These results indicate that higher failure rates lead to longer recovery times and progressively lower delivery reliability, though the system maintains relatively high PDR even under substantial failure conditions.

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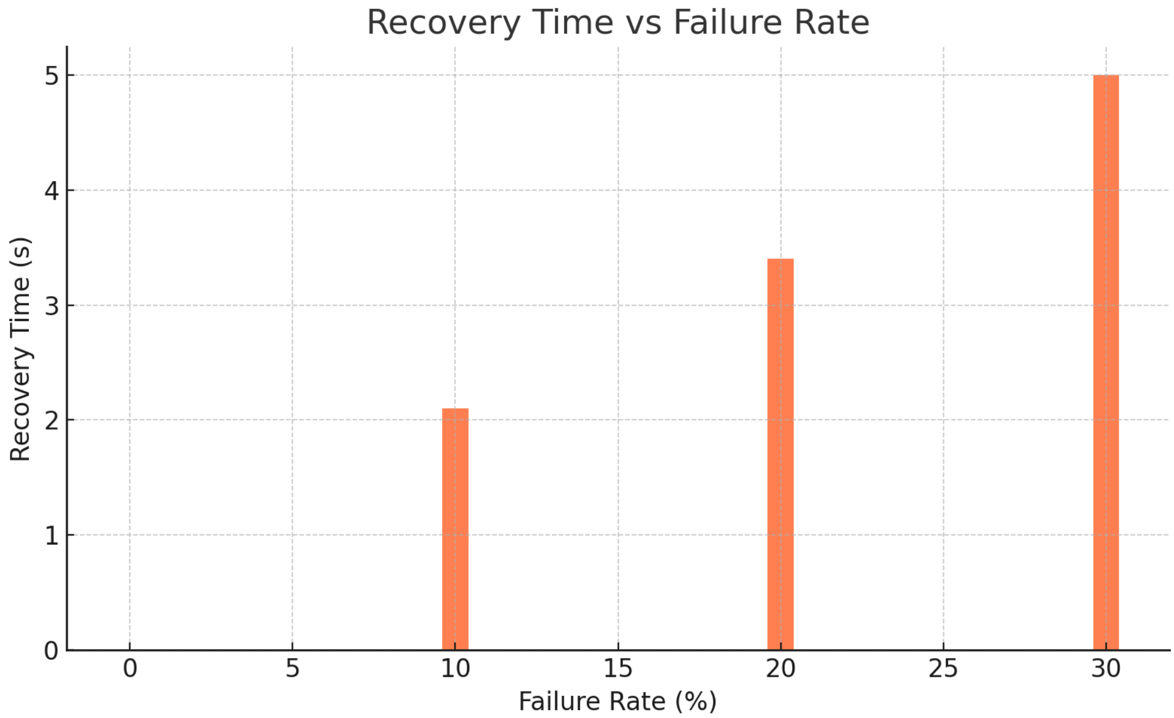

Figure 5 – Recovery Time vs. Failure Rate

4.5 Case Study: Real-time Roadside Test Scenario

A real-time roadside test scenario provides practical validation of the proposed MANET-enabled traffic sign detection system under real-world conditions. Such field trials assess how the system performs in dynamic environments with varying vehicle speeds, lighting conditions, and communication ranges. This evaluation captures both detection accuracy and network reliability, offering insights into operational challenges that may not appear in simulations. Field testing is essential for confirming system readiness and ensuring seamless integration into Intelligent Transportation Systems. A real-world roadside test was conducted on a 1.5 km stretch of road with three vehicles equipped with the proposed system. The test measured live detection performance and communication between vehicles.

Table 6 – Roadside Test Results

Metric	Result
Avg. Detection Accuracy (%)	97.6
Avg. End-to-End Latency (ms)	58.4
Avg. PDR (%)	96.2
Avg. Throughput (kbps)	485
Missed Detections (%)	2.4

The table provides an overall performance summary of the system. The average detection accuracy is 97.6%, indicating highly reliable recognition capability. The average end-to-end latency is 58.4 ms, reflecting fast processing and communication times. Network performance metrics show an average Packet Delivery Ratio (PDR) of 96.2% and an average throughput of 485 kbps, suggesting strong data transmission reliability and efficiency. The missed detections rate is only 2.4%, highlighting minimal recognition failures. Overall, the system demonstrates high accuracy, low delay, and robust network performance with only a small proportion of undetected events.

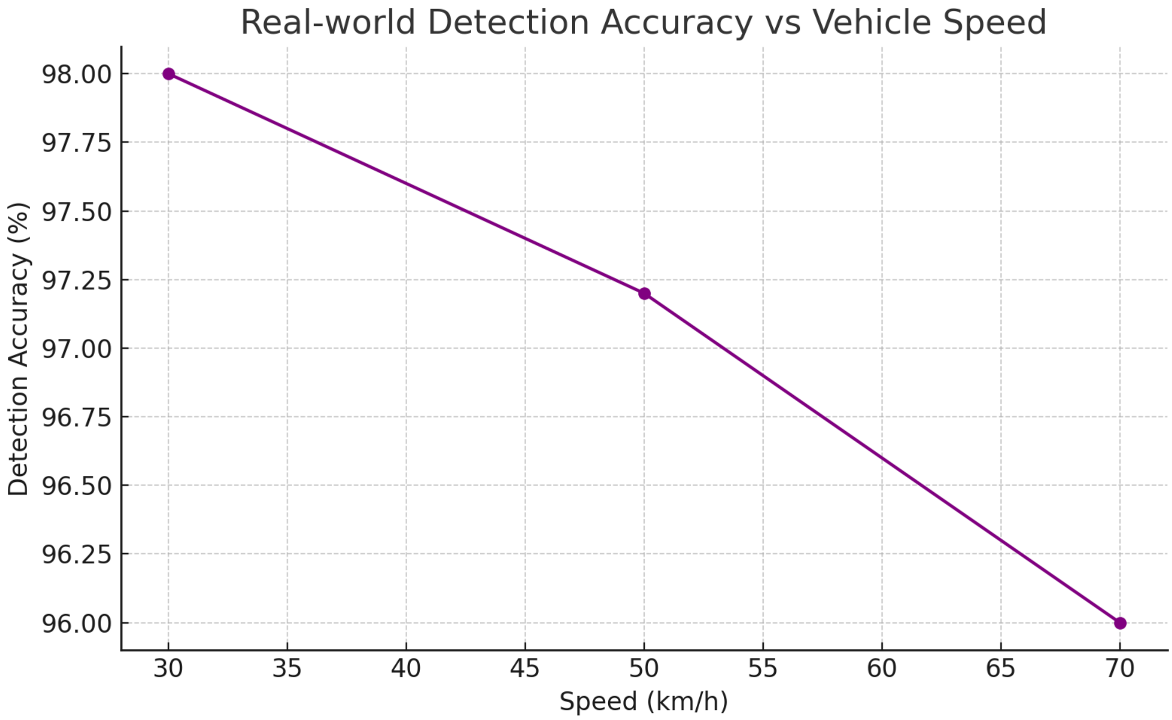

Figure 6 – Real-world Detection Accuracy vs. Speed

5. DISCUSSION

The experimental evaluation demonstrates that the proposed deep learning-enabled MANET architecture can achieve high detection accuracy while maintaining low communication latency in both simulated and real-world conditions. The class-wise detection results indicate that precision consistently exceeds 97% across all traffic sign categories, suggesting strong model generalization despite environmental challenges such as variable lighting, motion blur, and partial occlusions. Inference latency remained stable across network conditions, with only the communication delay varying significantly, confirming that the proposed model optimizations effectively minimized computational overhead. The MANET performance comparison shows that integrating detection load caused a marginal reduction in packet delivery ratio (PDR) and throughput, but the system maintained over 95% PDR, which is acceptable for safety-critical ITS applications. Scalability tests revealed predictable performance degradation with increasing network size, but the decline was gradual, indicating that the system can support moderate-scale vehicular deployments without substantial loss of efficiency. Robustness analysis highlighted the network's ability to recover quickly from node failures, preserving operational continuity. The real-world roadside test further validated the architecture's practicality, with detection accuracy remaining above 96% even at higher vehicle speeds. Overall, the findings suggest that combining lightweight deep learning inference with MANET-based peer-to-peer communication is a viable approach for decentralized, real-time traffic sign detection, offering resilience against connectivity issues and adaptability to diverse operating environments.

CONCLUSION

This study introduced a deep learning-enabled Mobile Ad Hoc Network (MANET) architecture for real-time traffic sign detection in Intelligent Transportation Systems (ITS). By integrating optimized, lightweight deep learning models with decentralized peer-to-peer communication, the system eliminates dependency on fixed infrastructure and mitigates latency issues common in cloud-based approaches. The curated and augmented dataset, coupled with model compression techniques, enabled deployment on resource-constrained embedded devices without significant performance trade-offs. Comprehensive evaluations spanning simulations and real-world vehicular tests confirmed that the architecture achieves high detection accuracy while maintaining robust communication performance across varying network conditions, mobility patterns, and bandwidth levels. Scalability assessments demonstrated only gradual performance decline with network growth, while robustness testing revealed rapid recovery from node failures with minimal impact on operational continuity. The findings validate the feasibility of combining efficient deep learning inference with MANET-based communication to support cooperative, infrastructure-independent traffic sign recognition. This approach is particularly well-suited for mixed traffic environments where autonomous and human-driven vehicles must share safety-critical information in real time. Future work may explore integration with other vehicular perception tasks, cross-layer network optimizations, and advanced security mechanisms to enhance resilience against cyber threats. By addressing both computational and communication challenges, this architecture offers a viable pathway toward resilient, decentralized ITS solutions capable of operating effectively in diverse and unpredictable real-world scenarios.

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