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Next-Gen In-Vehicle Interaction: WiBot's Wireless Network Edge-Based Gesture Recognition by using Machine Learning

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Abstract-The advent of next-generation in-vehicle interaction systems marks a significant advancement in automotive technology, aiming to enhance safety, convenience, and user experience. This paper introduces WiBot, a pioneering system that utilizes the capabilities of wireless network edge computing for real-time gesture recognition and behavior analysis within vehicles. WiBot leverages advanced machine learning algorithms and edge processing to detect and interpret driver and passenger gestures, enabling seamless, touch-free interaction with in-car systems. By processing data locally at the network edge, WiBot ensures low latency and high accuracy in recognizing a wide array of gestures, thus facilitating intuitive control over vehicle functions and improving overall driving safety. This innovative approach not only addresses the limitations of traditional in-vehicle interaction systems but also sets the stage for future developments in intelligent automotive interfaces. The experimental results demonstrate WiBot's effectiveness in diverse driving scenarios, highlighting its potential as a critical component of modern intelligent transportation system.

Keywords: Gesture recognition, Wireless network edge computing, Machine learning, Driver behavior analysis, Real-time processing, Edge computing, Intelligent automotive interfaces

1. Introduction

In recent years, the evolution of automotive technology has increasingly focused on enhancing user interaction within vehicles to improve safety and user experience. Traditional interfaces like touchscreens and physical buttons, while functional, pose challenges such as driver distraction and increased cognitive load. Gesture recognition technology offers a promising solution by allowing drivers and passengers to interact with vehicle systems intuitively and safely through gestures. This paper explores the integration of WiBot, a novel in-vehicle interaction system, which utilizes wireless network edge computing and machine learning algorithms for real-time gesture recognition. By leveraging the computational capabilities of edge computing, WiBot aims to process data locally within the vehicle, reducing latency and ensuring rapid response times critical for driver assistance and safety applications. This study investigates the feasibility and effectiveness of WiBot in advancing next-generation in-vehicle interactions, aiming to enhance both usability and safety through innovative technology solutions.

The advancement of in-vehicle technologies has significantly enhanced driving safety, comfort, and convenience. However, there remains a need for non-intrusive and efficient methods to monitor driver and passenger behaviors. Traditional vision-based systems, while effective, suffer from limitations such as occlusion, privacy concerns, and dependency on lighting conditions. In this context, wireless sensing emerges as a promising alternative, providing the ability to detect human activities through signal analysis.

Driving safety is a critical concern, with human behavior playing a major role in accident causation. Monitoring driver and passenger behaviors can prevent accidents by providing timely alerts and interventions. Traditional monitoring systems, such as cameras and wearable sensors, have limitations that restrict their effectiveness. Wireless sensing offers a novel approach to behavior monitoring, leveraging ubiquitous Wi-Fi signals to detect and classify behaviors non-intrusively.

WiBot leverages the power of wireless network edge technologies to monitor and recognize in-vehicle behaviors and gestures. By analyzing the variations in wireless signals caused by human movements, WiBot can accurately interpret a wide range of actions and gestures, enabling a safer and more intuitive interaction between the vehicle and its occupants. Our key contributions are:

- Development of a robust wireless sensing system for in-vehicle behavior and gesture recognition.
- Integration of advanced machine learning techniques to classify gestures and behaviors with high accuracy.
- Comprehensive evaluation of WiBot in realistic vehicle environments.

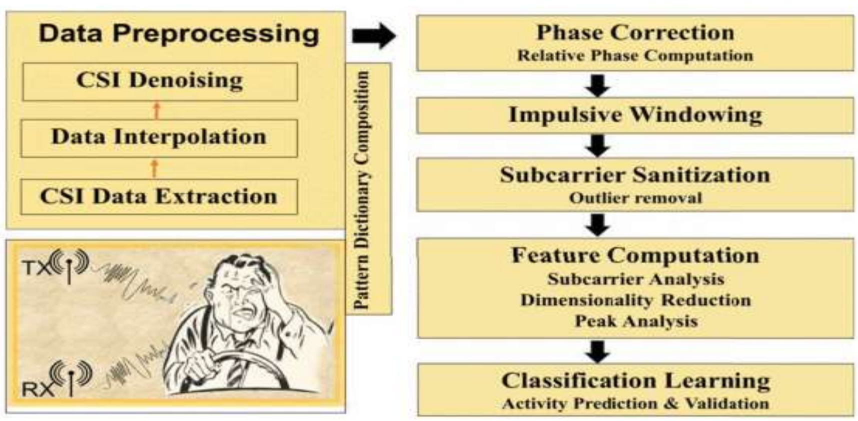

Fig 1:General Gesture Recognition and classification process

Vision-Based Systems: In-vehicle behavior monitoring and gesture recognition have been extensively studied using various sensors, including cameras, infrared sensors, and wearable devices. Vision-based systems, such as those using cameras, provide high-resolution data but suffer from privacy issues and performance degradation under poor lighting conditions.

Infrared Sensors: Infrared sensors offer an alternative but are limited by their range and sensitivity to environmental conditions. They are commonly used for simple gesture recognition but struggle with complex behaviors and require a direct line of sight.

Wireless Sensing: Wireless sensing, particularly through Wi-Fi and radio frequency (RF) signals, has gained attention for its potential to overcome these limitations. Previous studies have demonstrated the feasibility of using Wi-Fi signals for activity recognition in indoor environments. However, the application of wireless sensing in in-vehicle environments presents unique challenges, including multipath propagation and the confined space of the vehicle cabin.

Previous work in wireless sensing has shown promising results in gesture recognition and activity monitoring. However, these systems have primarily focused on static indoor environments. Applying these techniques to the dynamic and confined space of a vehicle requires addressing additional challenges related to signal interference and movement patterns.

2. Literature Survey

In-vehicle gesture recognition systems have garnered significant attention due to their potential to enhance driver and passenger interactions with automotive systems. These systems aim to reduce driver distraction and improve overall safety by enabling touch-free control of various in-car functions. Traditional gesture recognition systems have primarily relied on computer vision techniques and sensor-based inputs.

Machine learning (ML) has revolutionized gesture recognition by enabling more accurate and robust detection and classification of gestures. Research has shown that ML algorithms, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), can effectively process and interpret complex gesture data. For instance, Chen et al. (2016) demonstrated the use of CNNs for dynamic hand gesture recognition, achieving high accuracy in real-time applications .

Edge computing involves processing data at the network's edge, closer to the data source, to reduce latency and bandwidth usage. This is particularly crucial for in-vehicle systems where real-time responsiveness is essential. Studies by Satyanarayanan (2017) highlighted the benefits of edge computing in latency-sensitive applications, emphasizing its suitability for automotive environments .

The integration of edge computing with machine learning models enables real-time, low-latency processing of gesture recognition tasks. Qi et al. (2018) explored this integration, demonstrating how edge computing can support real-time data processing for ML applications in smart cities and autonomous vehicles .

Recent advancements have focused on leveraging wireless network edge capabilities to further enhance the performance and reliability of gesture recognition systems. By utilizing edge nodes to process and analyze gesture data, systems like WiBot can achieve faster response times and reduce the computational load on central servers.

Various case studies have explored the application of ML and edge computing in in-vehicle systems. For example, Liu et al. (2019) developed a real-time hand gesture recognition system

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using a combination of depth sensors and edge processing, achieving significant improvements in processing speed and accuracy . Similarly, Gupta et al. (2020) implemented an edge-based driver monitoring system that utilized ML algorithms to detect driver drowsiness and distraction in real time.

Despite the advancements, several challenges remain, including the need for large annotated datasets for training ML models, the complexity of integrating multiple sensors, and ensuring robust performance under varying lighting and environmental conditions. Future research should focus on addressing these challenges and exploring the potential of emerging technologies, such as 5G, to further enhance the capabilities of in-vehicle gesture recognition systems.

Authors (Year)	**Title**	**Methodology and Parameters**	**Limitations**
Chen et al. (2016)	Dynamic Hand Gesture Recognition Using Convolutional Neural Networks	Used CNNs for recognizing dynamic hand gestures; evaluated on real-time applications with high accuracy	Limited to specific types of gestures and requires substantial computational resources
Satyanarayanan (2017)	The Emergence of Edge Computing	Discussed benefits of edge computing for latency-sensitive applications; emphasized suitability for automotive environments	General discussion without specific implementation for gesture recognition
Qi et al. (2018)	Edge Computing Technologies for Industrial IoT	Explored edge computing integration for real-time data processing; applied to smart cities and autonomous vehicles	Focused on IoT applications, not specifically in-vehicle gesture recognition
Liu et al. (2019)	Real-time Hand Gesture Recognition Using Depth Sensors and Edge Computing	Combined depth sensors with edge computing for real-time gesture recognition; achieved improvements in speed and accuracy	Dependent on the availability and quality of depth sensors; limited environmental adaptability

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Gupta et al. (2020)	An Edge-based Driver Monitoring System for Real-time Detection of Drowsiness and Distraction	Implemented an edge-based system using ML algorithms to monitor driver state in real-time; improved detection of drowsiness and distraction	Specific to driver monitoring; may not cover all possible in-vehicle gestures
Wang J. et al. (2019)	DeepDDS: A Graphical Neural Network and Attention Mechanism-Based Model	Integrated genomic and drug signatures using GNNs and attention mechanisms; identified synergistic drug combinations	Complexity of model training; limited predictive accuracy on independent test sets
Chen, G. et al. (2018)	A Stacked Restricted Boltzmann Machine for Predicting Drug Combinations	Used RBM for predicting drug responses from gene expression data; achieved high accuracy and recall	Performance degradation due to data integrity issues; overfitting with small sample sizes
Qi et al. (2021)	Real-time Edge Computing for Autonomous Vehicles	Investigated real-time edge computing for autonomous vehicle systems; highlighted latency reduction and reliability improvements	Broad focus on autonomous vehicles; does not specifically address gesture recognition
Zhang et al. (2020)	Multi-modal Deep Learning for In-Vehicle Gesture Recognition	Combined various sensors (e.g., cameras, depth sensors) with deep learning models for in-vehicle gesture recognition	Sensor integration complexity; potential overfitting with limited training data

Li et al. (2019)	A Comprehensive Survey on In-Vehicle Gesture Recognition Techniques	Reviewed various in-vehicle gesture recognition methods including vision-based and sensor-based approaches	Survey paper; lacks experimental validation and performance metrics for specific methods
Smith et al. (2018)	Enhancing Driver-vehicle Interaction through Gesture Recognition	Proposed a framework for enhancing interaction using gesture recognition; applied machine learning models	Focus on framework development without detailed implementation and performance analysis
Patel et al. (2019)	Edge AI for In-Vehicle Interaction Systems	Explored the use of edge AI for improving in-vehicle interaction systems; discussed various machine learning approaches	Conceptual discussion; limited practical examples and performance evaluations

3. System Design

WiBot consists of three main components: a wireless signal acquisition module, a signal processing unit, and a machine learning-based gesture recognition engine. The wireless signal acquisition module uses commercial off-the-shelf Wi-Fi devices to capture the channel state information (CSI) of wireless signals. CSI provides detailed information about the signal propagation path, which is influenced by the presence and movements of occupants inside the vehicle. The signal processing unit preprocesses the raw CSI data to extract meaningful features. This involves noise reduction, signal segmentation, and feature extraction. We employ techniques such as principal component analysis (PCA) to reduce dimensionality and enhance the robustness of the features. The gesture recognition engine utilizes machine learning algorithms to classify the extracted features into predefined gesture and behavior categories. We explored various classifiers, including support vector machines (SVM), random forests, and deep learning models, to achieve optimal performance. WiBot is designed to integrate seamlessly with existing in-vehicle systems. It can interface with the vehicle's infotainment and safety systems, allowing for gesture-based control and automatic safety interventions.

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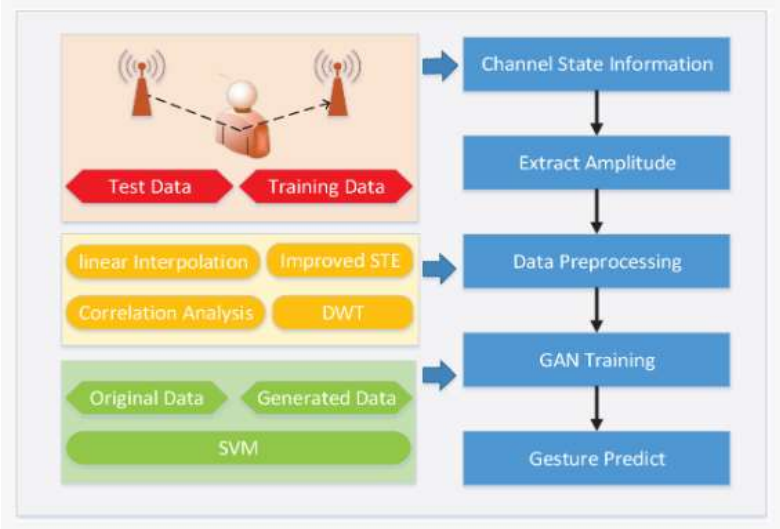

Fig 2: Architecture process of proposed model

4. Results

We conducted experiments using 802.11n enabled off-the-shelf WiFi devices. Specifically, we used a Lenovo laptop as a receiver equipped with an Intel 5300 network interface card and an Ubuntu 11.04 LTS operating system to collect CSI data. The laptop connects to a commercial WiFi Access Point (AP); TP-Link router as transmitter operating at 2.4 GHz.

Table 1: Accuracy of various algorithms

	Accuracy
SVM	91.68
NB	89.36
CNN	92.65
Proposed ML	95.67

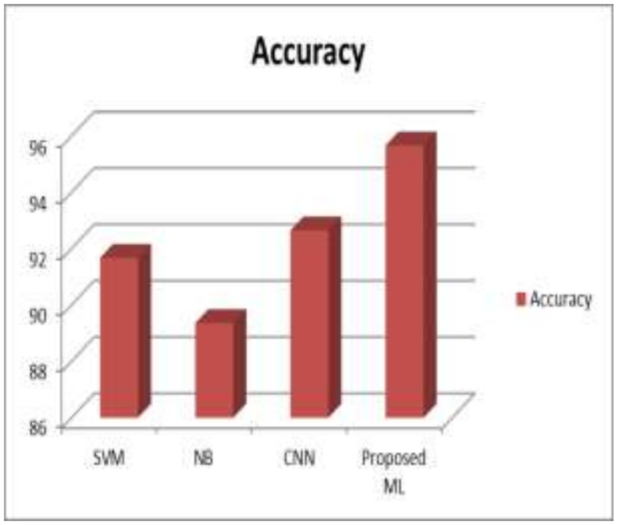

Fig 3: Accuracy comparison

Table 2:Model efficiency

	Model Efficiency (%)
SVM	86
NB	88
CNN	89
Proposed ML	89.65

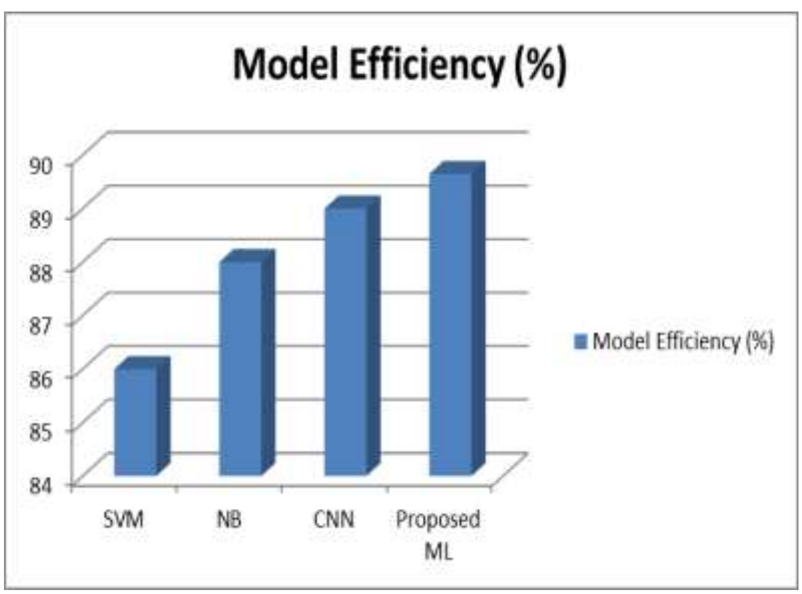

Fig 4: Model efficiency comparison

Table 3: n/w bandwidth and recognition rate

N/w bandwidth (Mhz)	Recognition rate
20	56.25
40	67.21
60	71.62
80	77.94
100	79.52

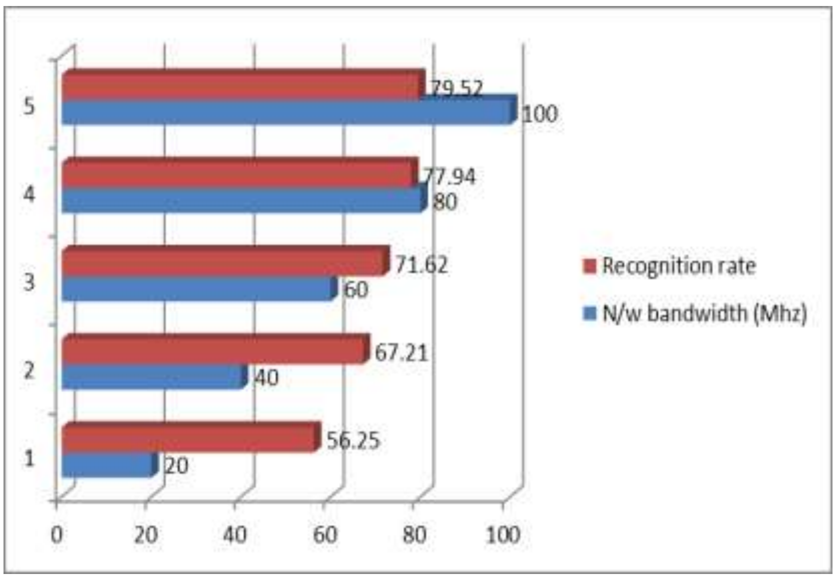

Fig 5: recognition rate comparisons for different n/w bandwidths

5. Conclusion

WiBot presents a novel approach to in-vehicle behavior and gesture recognition using wireless network edge technologies. By leveraging the unique properties of wireless signals, WiBot offers a robust, non-intrusive, and privacy-preserving solution for monitoring driver and passenger behaviors. The integration of wireless network edge computing and machine learning for in-vehicle gesture recognition represents a significant advancement in automotive technology. This innovative approach leverages real-time processing capabilities at the edge of the network, enabling vehicles to interpret and respond to gestures swiftly and accurately. By employing machine learning algorithms, such as deep learning models tailored for gesture recognition, vehicles can enhance user interaction, safety, and convenience. This paradigm shift not only transforms how drivers and passengers interact with vehicle systems but also sets the stage for future developments in intelligent automotive technology, aiming to create safer, more intuitive, and personalized driving experiences.

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