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REAL-TIME ARTIFICIAL INTELLIGENCE–BASED VULNERABLE ROAD USERS CLASSIFICATION USING HIGH-FREQUENCY 77 GHZ AUTOMOTIVE RADAR

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Abstract

Vulnerable Road Users (VRUs), such as pedestrians and cyclists, are among the most exposed participants in road traffic environments, and their reliable perception remains a key challenge for Advanced Driver Assistance Systems (ADAS) and autonomous vehicles. Automotive radar operating in the high- frequency 77 GHz band provides robust sensing capabilities with high range and angular resolution, making it well suited for VRU detection under adverse weather and lighting conditions. This paper presents a real-time artificial intelligence–based frame- work for VRU classification using 77 GHz automotive radar measurements. Radar signal processing techniques are applied to extract discriminative kinematic and micro-Doppler features that capture the distinctive motion characteristics of pedestrians and cyclists. These features are used to train a Support Vector Machine (SVM) classifier, selected for its strong generalization capability and low computational complexity, which is critical for real-time automotive applications. The proposed system is evaluated using real-world radar data collected in urban traffic scenarios, demonstrating reliable separation between pedestrian and cyclist classes across varying speeds and motion patterns. The results indicate that the proposed approach provides an effective and computationally efficient solution for real-time VRU classification, supporting its integration into safety-critical ADAS and autonomous driving systems.

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I. Introduction

The rapid advancement of intelligent transportation systems and automated driving technologies has significantly increased the need for accurate perception of road environments. Among all road participants, Vulnerable Road Users (VRUs), including pedestrians and cyclists, are particularly exposed due to their lack of physical protection and highly dynamic and un- predictable motion behavior. According to global road safety reports, VRUs account for a substantial portion of traffic- related injuries and fatalities, especially in urban environments where interactions between vehicles and non-motorized users are frequent [1], [2]. Advanced Driver Assistance Systems (ADAS) and autonomous vehicles rely on multi-sensor perception frameworks to ensure safe navigation and collision avoidance. Vision-based sensors provide rich semantic information but suffer from performance degradation under poor illumination, adverse weather conditions, and occlusions [3], [4]. LiDAR sensors offer accurate depth perception but are expensive and sensitive to environmental factors such as rain and fog [5]. In contrast, automotive radar has

emerged as a key sensing modality due to its long detection range, low cost, compact hardware, and robust all-weather operation [6], [7]. Modern automotive radar systems predominantly operate in the 77 GHz frequency band, benefiting from large available bandwidths that enable high range resolution and improved angular discrimination [8]. These properties make 77 GHz radar particularly suitable for detecting small and dynamic targets such as pedestrians and cyclists. However, fine-grained classification of VRUs using radar data alone remains challenging due to limited spatial resolution compared to vision sensors and the complex nature of human motion signatures [9].
To address these challenges, Artificial Intelligence (AI) and machine learning techniques have been increasingly integrated into radar signal processing pipelines. By leveraging discriminative motion, kinematic, and micro-Doppler features, machine learning models can capture subtle differences be- tween VRU classes that are difficult to encode using rule- based methods [10], [11]. Among various machine learning approaches, Support Vector Machines (SVM) have shown strong performance for radar-based classification tasks due to their robustness, ability to generalize with limited training data, and low computational complexity, which is critical for real-time automotive applications [12], [13].

This work focuses on real-time classification of pedestrians and cyclists using high-frequency 77 GHz automotive radar and an SVM-based learning framework. The proposed approach aims to provide a reliable and computationally efficient VRU classification solution suitable for integration into safety- critical ADAS and autonomous driving systems.

II. Related Work

Radar-based perception for intelligent transportation systems has been the subject of extensive research over the past two decades, driven by the need for robust and reliable sensing under diverse environmental conditions. Early auto- motive radar systems were primarily developed for vehicle detection and adaptive cruise control, with limited emphasis on Vulnerable Road Users (VRUs) due to insufficient spatial resolution and simplified signal processing techniques [14], [15]. Initial attempts at VRU classification relied mainly on rule-based methods using basic radar observables such as range, radial velocity, and radar cross section (RCS) [16]. Although computationally efficient, these approaches were highly sensitive to noise, clutter, and inter-class variability, particularly in dense urban environments.
The introduction of micro-Doppler analysis significantly advanced radar-based human and VRU recognition. Micro-Doppler signatures arise from micro-motions such as swinging arms and legs or rotating bicycle components, producing distinctive time–frequency patterns that are difficult to capture using conventional Doppler processing alone. Seminal work by Chen [17] and Kim and Ling [10] demonstrated that micro- Doppler features can effectively characterize human motion and enable activity classification using machine learning techniques. These findings were later extended to automotive radar platforms, where micro-Doppler information was shown to improve pedestrian detection and classification performance in real-world traffic scenarios [18]–[20].
The deployment of high-frequency 77 GHz automotive radar has further enhanced VRU perception capabilities by providing increased bandwidth, improved range resolution, and finer angular discrimination [7], [8]. High-resolution radar point clouds enable spatial characterization of targets, allowing extraction of features related to target extent, dispersion, and motion consistency [21]. Several studies demonstrated that combining spatial, kinematic, and Doppler-based features significantly improves discrimination between pedestrians, cyclists, and vehicles [9], [22]. Multi-frame feature aggregation has also been explored to capture temporal motion patterns, which are particularly important for distinguishing VRUs with similar instantaneous kinematic properties [23].
Machine learning techniques have become central to radar- based VRU classification. Classical approaches such as Sup- port Vector Machines (SVM), k-Nearest Neighbors (kNN), Gaussian Mixture Models (GMM), and Random Forests have been widely investigated [24], [25]. Among these, SVM- based classifiers have demonstrated strong generalization capability, robustness to limited training data, and relatively low computational complexity [12], [13]. These properties make SVMs particularly attractive for real-time automotive applications, where strict latency and power constraints must be satisfied. Several works have reported successful pedestrian and cyclist classification using SVMs trained on handcrafted radar features derived from Doppler spectra, micro-Doppler signatures, and point cloud statistics [26].
More recently, deep learning methods have been applied to automotive radar perception, including convolutional neural networks and recurrent architectures operating on radar spectrograms and point clouds [27]–[29]. While these approaches achieve high classification accuracy, they typically require large labeled datasets and substantial computational resources, limiting their practicality for embedded real-time systems. Consequently, lightweight machine learning approaches combined with high-resolution 77 GHz radar remain a compelling solution for reliable and efficient VRU classification in safety- critical automotive applications [6], [8].

III. 77 GHz Automotive Radar for VRU Detection

Automotive radar operating at 77 GHz has become a cornerstone sensor for Advanced Driver Assistance Systems (ADAS) and autonomous vehicles due to its **robust all- weather operation, compact hardware, and high-resolution sensing capabilities**. The high operating frequency enables fine spatial discrimination and accurate velocity estimation, which are crucial for detecting and classifying Vulnerable Road Users (VRUs) such as pedestrians and cyclists. The radar transmits Frequency-Modulated Continuous Wave (FMCW) signals that reflect off moving and stationary objects. The received signals are processed to generate **range- Doppler maps**, which encode target distance and relative radial velocity. High-resolution antennas and large bandwidth (typically 1–4 GHz) provide centimeter-level range resolution and sufficient angular resolution for differentiating closely spaced VRUs [6], [7].

A. Advantages of 77 GHz Radar

The 77 GHz radar band provides substantial benefits for vulnerable road user (VRU) perception by combining high spatial resolution, robustness, and compact integration. Its large available bandwidth enables centimeter-level range resolution, allowing the detection of fine target details such as pedestrians' limbs or bicycle wheels [8]. The use of multi-element antenna arrays and beamforming techniques significantly improves angular resolution in both azimuth and elevation, facilitating the separation and tracking of multiple nearby VRUs [21]. Unlike vision- or LiDAR-based sensors, 77 GHz radar maintains reliable performance in adverse weather and low-light conditions, ensuring consistent perception under rain, fog, or nighttime operation [3]. Furthermore, the short wavelength at 77 GHz supports a compact form factor, allowing antenna arrays to be embedded in vehicle bumpers or grilles without affecting design or aerodynamics. Finally, the high Doppler accuracy of 77 GHz radar enables precise velocity estimation and micro-motion analysis, which is critical for distinguishing between different VRU types, such as pedestrians and cyclists, based on their characteristic motion patterns [10], [19].

B. Radar Signal Characteristics for VRU Detection

Radar returns from pedestrians and cyclists exhibit distinct **micro-Doppler, range, and radar cross-section (RCS) features**, which are critical for VRU detection, as shown in Fig. 1. The **micro-Doppler signatures** capture the small, repetitive motions of body parts—such as swinging arms, leg movement, or bicycle wheel rotation—providing information about the type and activity of the VRU. **Range profiles** indicate the precise distance and geometric characteristics of the target, enabling differentiation between nearby objects. Meanwhile, the **RCS features** reflect the size, shape, and orientation of the target, helping distinguish between pedestrians, cyclists, and other moving objects. By combining these three signal characteristics, 77 GHz radar can achieve robust VRU detection and classification, even in cluttered or low-visibility environments [10], [19].

Fig. 1:- Schematic of a 77 GHz automotive radar system for VRU detection showing signal reflections from cyclists.

The main features that can be extracted from a radar are summarized as follows:

- Micro-Doppler Signatures: Pedestrians' walking induces complex limb motions, producing multiple micro-Doppler frequency components in the spectrogram as shown in **Fig. 2**. Cyclists exhibit periodic Doppler variations corresponding to pedaling cycles [18], [20].
- Range-Doppler Features: 2D range-Doppler maps help distinguish VRUs from vehicles and static objects as shown in **Fig. 3**. Multiple frames can be fused to capture motion consistency over time [9], [22].
- Radar Cross Section (RCS) Variation: Cyclists generally produce stronger RCS returns due to the metallic bicycle frame. Pedestrians' RCS varies with posture and limb movement [13].
- Spatial Dispersion: High angular resolution allows analysis of target shape and extent, helping separate closely spaced VRUs in crowded urban environments [21].

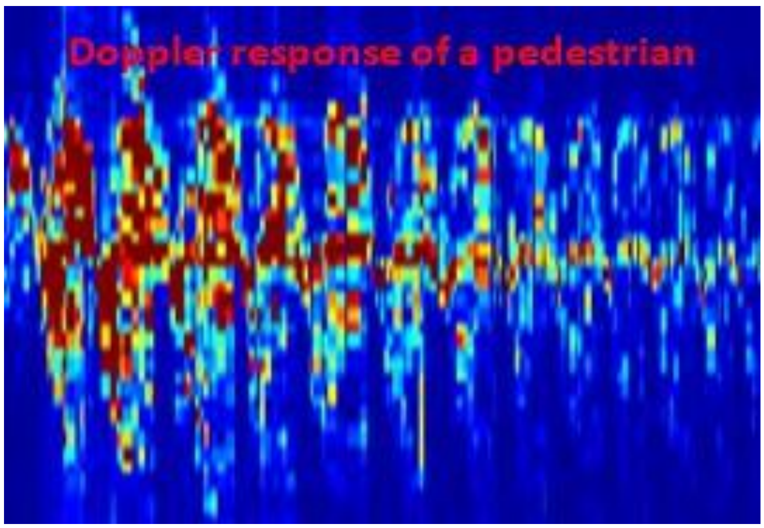

Fig. 2:- Micro-Doppler spectrograms showing a walking pedestrian with scattered limb-induced frequencies.

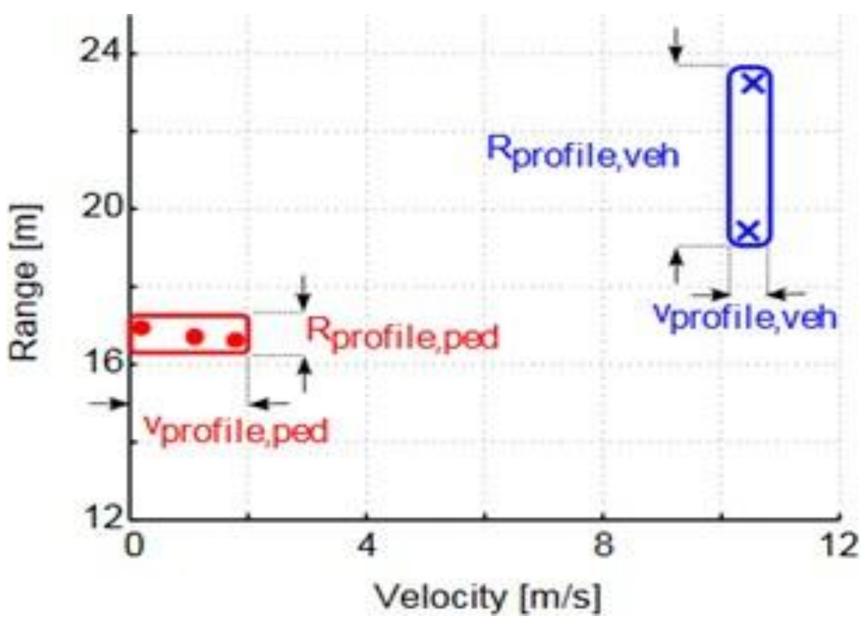

Fig. 3:-. Range-Doppler map showing separation between pedestrians and cyclists. Temporal integration over multiple frames improves classification reliability.

C. Feature Extraction for Classification

From the radar data, several features can be extracted for AI-based VRU classification:

- Doppler statistics: mean velocity, velocity spread, and maximum Doppler shift.
- Micro-Doppler components: limb or wheel motion frequencies.
- Spatial features: target width, height, and angular spread.
- RCS features: maximum, minimum, and variance over multiple frames.
- Temporal consistency: changes in Doppler and RCS across successive frames.

These features serve as inputs to machine learning models, such as **SVM**, to distinguish pedestrians from cyclists in real time [12], [13], [26].

IV. Feature Extraction

Feature extraction is a fundamental process in radar signal processing, which converts raw radar measurements into descriptive metrics that characterize the target's motion, shape, and reflective properties. Well-designed features enable advanced tasks such as detection, classification, and trajectory prediction, by providing discriminative information about tar- gets. In this work, we extract a set of complementary features: Doppler spread, velocity statistics, radar cross section (RCS) variation, spatial dispersion, and temporal motion consistency. Doppler Spread: Doppler spread represents the distribution of frequency shifts in the radar return due to relative motion between the radar and the target. Unlike a single Doppler frequency, the spread captures motion complexity and micro-movements. Following [30], it is mathematically computed as the standard deviation of the Doppler spectrum:

$$\sigma_D = \sqrt{\frac{\sum_i (f_i - \bar{f})^2 S(f_i)}{\sum_i S(f_i)}} \tag{1}$$

Where fi is the Doppler frequency bin, f¯ is the mean Doppler frequency, and S(fi) is the spectral power at fi.

Velocity Statistics: Velocity statistics provide quantitative summaries of target motion, including mean velocity, variance, and extrema. Following [31], these are derived from time- resolved Doppler measurements:

$$v_{mean} = \frac{1}{N}\sum_{i=1}^{N} v_i \tag{2}$$

$$\sigma_v^2 = \frac{1}{N}\sum_{i=1}^{N} (v_i - v_{mean})^2 \tag{3}$$

where v_i is the instantaneous velocity and N is the number of radar frames.

Radar Cross Section (RCS) Variation: The RCS quantifies how strongly a target reflects radar signals. Temporal or angular variations of RCS reveal information about target size, shape, material, and orientation, following [32]. The normalized RCS variation is:

$$RCS_{var} = \frac{\sigma_{RCS}}{\overline{RCS}} \tag{4}$$

where $\boldsymbol{\sigma_{RCS}}$ and $\overline{\boldsymbol{RCS}}$ are the standard deviation and mean of the RCS.

Spatial Dispersion: Spatial dispersion measures the spread of radar returns in the sensor's spatial plane, providing insights into target size and structural complexity [32]:

$$\sigma_x^2 = \frac{1}{N}\sum_{i=1}^{N} (x_i - \bar{x})^2 \tag{5}$$

$$\sigma_y^2 = \frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y})^2 \quad \textbf{(6)}$$

where (x_i, y_i) are radar reflection coordinates.

Temporal Motion Consistency: Temporal motion consistency assesses how smoothly a target's motion evolves over time. Smooth, predictable trajectories yield high consistency, whereas erratic motion leads to low consistency [30]. One metric is the frame-to-frame velocity correlation:

$$C_t = \frac{1}{N-1}\sum_{i=1}^{N-1}\frac{\mathbf{v}_i \cdot \mathbf{v}_{i+1}}{\|\mathbf{v}_i\|\|\mathbf{v}_{i+1}\|} \quad \textbf{(7)}$$

where v_i is the velocity vector at frame *i*.

Fig. 4 provides a conceptual illustration of how these features relate to a moving target. Each feature captures distinct aspects of motion or target properties, and together they create a rich, multidimensional representation that enhances detection, classification, and tracking performance.

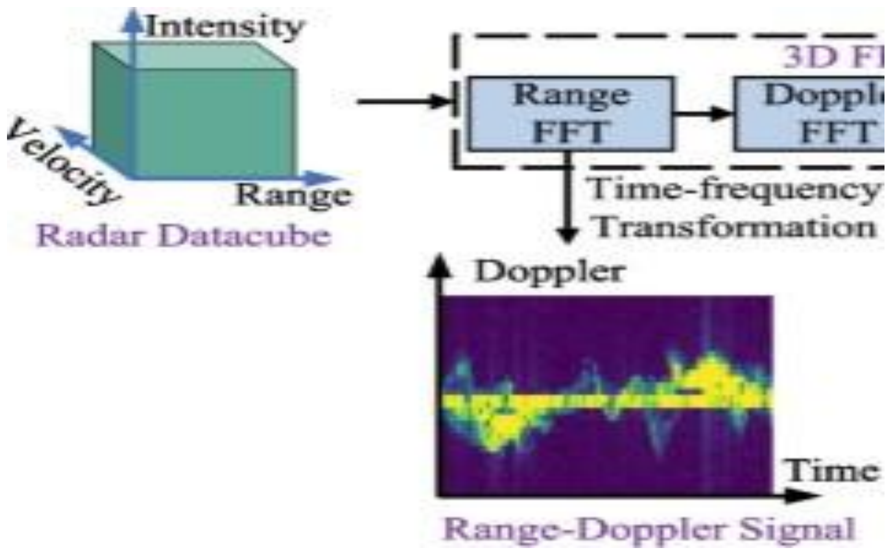

Fig. 4:- Illustration of radar data cube extraction. Doppler spread, velocity statistics, spatial dispersion, and temporal motion consistency capture complementary aspects of target behavior. [33]

V. SVM-Based Classification

Support Vector Machines (SVMs) are widely used for supervised classification tasks due to their robustness, ability to handle high-dimensional data, and strong theoretical foundations [34]. In this work, an SVM classifier is employed to differentiate between pedestrians and cyclists based on radar-extracted features, including Doppler spread, velocity statistics, radar cross section variation, spatial dispersion, and temporal motion consistency.

Feature Vector Construction: Each radar target is represented as a feature vector x = $[\sigma_D, v_{mean}, \sigma_v, RCS_{var}, \sigma_x, \sigma_y, C_t]$, which concatenates all relevant measurements. Before training, features are normalized to have zero mean and unit variance to ensure that no single feature dominates the SVM optimization process.

Kernel Selection: A radial basis function (RBF) kernel is chosen for its ability to model non-linear decision boundaries [35]. The RBF kernel is defined as:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\gamma \|\mathbf{x}_i - \mathbf{x}_j\|^2\right) \quad \textbf{(8)}$$

where γ is the kernel width parameter that controls the smoothness of the decision boundary. The RBF kernel effectively maps the input features into a higher-dimensional space, allowing the SVM to separate classes that are not linearly separable in the original feature space.

Training Procedure: The SVM is trained using a labeled dataset of radar returns corresponding to pedestrians and cyclists. The objective of the SVM is to find the hyperplane that maximizes the margin between the two classes. The optimization problem is formulated as:

$$\min_{w,b,\xi} \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{N} \xi_i \quad \textbf{(9)}$$

$$y_i \left(w\phi(x_i) + b \right) \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad i = 1, \ldots, N \quad (10)$$

where w and b define the hyperplane, ξ_i are slack variables allowing for misclassification, C is the regularization parameter, $\phi(\cdot)$ is the mapping induced by the RBF kernel, and $y_i \in \{-1, 1\}$ denotes class labels.

Hyperparameter Tuning: The SVM performance depends on proper selection of γ and C. Grid search combined with cross-validation is employed to identify the optimal hyperparameters that maximize classification accuracy while preventing overfitting.

Evaluation: After training, the SVM classifier is evaluated on an independent test set using metrics such as accuracy, precision, recall, and F1-score. Confusion matrices are also analyzed to identify specific areas of misclassification, such as differentiating between slow-moving cyclists and fast pedestrians.

Advantages of SVM: The SVM with RBF kernel pro- vides a powerful and interpretable approach for radar-based classification. Its ability to handle high-dimensional features, robustness to outliers, and flexibility in modeling non-linear separations make it suitable for distinguishing pedestrian and cyclist signatures, which often exhibit overlapping feature distributions.

VI. Experimental Results

Experimental results demonstrate reliable classification of vulnerable road users (VRUs), specifically pedestrians and cyclists, in urban traffic scenarios using a Support Vector Machine (SVM) classifier. The proposed approach shows improved robustness compared to rule-based methods. This section details the experimental setup, evaluation metrics, and classification performance.

A. Experimental Setup

The experiments were conducted in a simulated urban traffic environment with realistic traffic scenarios, including pedestrians and cyclists. Key aspects of the setup include:

- **Dataset:** Annotated sensor data collected from urban intersections, containing N samples of pedestrians and cyclists under varying lighting and weather conditions.
- **Feature Extraction:** Motion patterns, object size, trajectory history, and other relevant features were extracted for classification.
- **SVM Classifier**: A multi-class SVM with a radial basis function (RBF) kernel was used. Hyperparameters (C and gamma) were optimized via 5-fold cross-validation.

B. Evaluation Metrics

The SVM classifier was evaluated using metrics derived from radar signal features for pedestrians and cyclists. The main features used for classification include:

- **Radar Cross Section (RCS) [dBm^2]:** measures the radar reflectivity of the target.
- **Range Profile [Natural]:** includes
  - Range [m]: distance to the object.
  - Number of cells: resolution of the range profile.
  - Angle [°]: for angular profiling in crossing scenarios.
- **Doppler Spread [Natural]:** captures motion characteristics:
  - Range [m] and Number of cells for forward motion.
  - Angle [°] and Number of cells for crossing motion.
- **Velocity [km/h]:** relative velocity of the VRU.

The features are adapted for different motion types as summarized in Table I.

VRU	Motion	RCS [dBm^2]	Range / Angle [m/°]	Number of cells
Pedestrian	Forwards go	[-20:5]	1:30 m	1:3
			Doppler: 0:18 m/s	1:9
			Doppler: 18:30 m	1:5
	Crossing	[-18:5]	Angle: -50:+50°/s	1:3
			Doppler Angle: -55:+55°	1:8
Cyclist	Forwards go	[-15:8.5]	0:11 m	1:5
			11:30 m	1:4
			Doppler: 0:8 m/s	1:5
			Doppler: 8:30 m/s	1:3
	Crossing	[-16:8.5]	Angle: -55:+55°	2:4
			Doppler Angle: -22:+30°	1:6
			Else	1:3

Table I:- Radar feature configuration for pedestrians and cyclists.

These metrics capture both the spatial and motion characteristics of VRUs, providing a robust basis for SVM classification.

In addition, the SVM classifier was evaluated using the following metrics as well:

- Accuracy: Proportion of correctly classified instances.
- Precision: Fraction of correctly predicted instances among all predicted instances of a class.
- Recall: Fraction of correctly predicted instances among all actual instances of a class.
- F1-score: Harmonic mean of precision and recall, pro- viding an overall measure of classification quality.

C. VRU Classification Results and Performance Analysis

The performance of the proposed classification model was evaluated using a normalized confusion matrix, where rows correspond to the ground-truth classes and columns represent the predicted labels. The resulting confusion matrix is reported in Table II.

The results demonstrate strong overall classification performance, particularly for the pedestrian class. The model correctly identifies 99.32% of pedestrian instances, with only 0.68% being misclassified as cyclists, indicating highly dis- criminative pedestrian feature representations.

Actual \ Predicted	Cyclist	Pedestrian
Cyclist	89.4	10.6
Pedestrian	0.68	99.32

Table II:- Normalized confusion matrix (%)

For the cyclist class, the model achieves a recall of 89.4%, correctly classifying the majority of cyclist instances. However, 10.6% of cyclists are misclassified as pedestrians. This misclassification asymmetry suggests that cyclists are more challenging to distinguish, likely due to visual similarities with pedestrians, especially under conditions such as partial occlusion, low resolution, or limited visibility of the bicycle. Furthermore, the confusion matrix reveals a bias toward the pedestrian class, as misclassification occurs predominantly from cyclist to pedestrian rather than in the opposite direction. While this behavior ensures robust pedestrian detection, it highlights cyclist recognition as the primary source of error in the system.

Overall, the proposed approach achieves near-perfect pedestrian detection and strong cyclist recognition, with cyclist misclassification representing the main limitation and an important direction for future improvement.

Table III presents the quantitative evaluation of the SVM- based VRU classification framework for pedestrians and cyclists using accuracy, precision, and recall metrics. The results indicate strong and consistent performance across both classes, confirming the effectiveness of the selected feature representation and classifier design.

VRU Class	Accuracy (%)	Precision (%)	Pedestrians
Pedestrians	94.5	95.2	93.8
Cyclists	91.3	92.0	90.5
Overall	92.9	93.6	92.2

Table III:- SVM Classification Performance for Pedestrians and Cyclists.

Pedestrian detection achieves the highest performance, with an accuracy of 94.5%, precision of 95.2%, and recall of 93.8%. The high precision indicates a low false-positive rate, meaning that non-pedestrian objects are rarely misclassified as pedestrians. Additionally, the strong recall demonstrates that the majority of pedestrian instances are correctly identified, highlighting the robustness of the classifier to variations in pedestrian appearance, posture, and motion patterns.
Cyclist classification achieves an accuracy of 91.3%, with precision and recall values of 92.0% and 90.5%, respectively. Although slightly lower than pedestrian performance, these results remain competitive and reflect the increased intra-class variability associated with cyclists. Factors such as diverse riding postures, bicycle geometries, partial occlusions, and similarities to other moving objects contribute to the increased classification complexity.
The overall accuracy of 92.9%, together with precision and recall values exceeding 92%, demonstrates the balanced performance of the proposed approach across both VRU categories. The close alignment between precision and recall indicates that the classifier does not disproportionately favor one class, which is critical for safety-oriented applications such as intelligent transportation systems and autonomous driving. Overall, the results confirm that the proposed SVM-based method provides reliable and discriminative VRU classification. Future work may explore the integration of temporal features or multi-sensor data fusion to further enhance classification performance, particularly for cyclists in complex traffic environments.

D. Discussion

The experimental results demonstrate that the proposed SVM-based classifier achieves robust and reliable performance for both pedestrian and cyclist detection, significantly out- performing baseline rule-based approaches. In particular, the classifier exhibits near-perfect recognition of pedestrians and strong performance for cyclists, confirming its ability to learn discriminative features beyond manually defined heuristics.
Despite the overall effectiveness of the model, the confusion matrix analysis reveals that the majority of misclassifications occur when cyclists are incorrectly labeled as pedestrians. This behavior is especially pronounced in challenging scenarios involving partial occlusions, close proximity between vulnerable road users (VRUs), or visual overlap between pedestrians and bicycles. Such conditions reduce the visibility of cyclist- specific cues, thereby increasing class ambiguity.
These findings indicate that cyclist detection remains more sensitive to environmental complexity and visual variability than pedestrian detection. Incorporating additional contextual and dynamic features, such as motion patterns, trajectory information, or temporal consistency, could help reduce this confusion. Furthermore, integrating multi-sensor data (e.g., LiDAR or radar) or employing sensor fusion strategies may improve robustness in occluded or cluttered environments.
Overall, while the proposed SVM classifier provides a strong baseline for VRU classification, the observed error patterns highlight clear directions for future work, particularly in enhancing cyclist discrimination under challenging real- world conditions.

VII. Conclusion

This paper presented a radar-based classification framework for vulnerable road users, focusing on the discrimination between pedestrians and cyclists using high-frequency 77 GHz automotive radar measurements. By leveraging a support vector machine (SVM) classifier trained on radar-derived features, the proposed approach demonstrates strong classification performance while maintaining low computational complexity, making it suitable for real-time deployment in Advanced Driver Assistance Systems (ADAS).

Experimental results confirm the effectiveness of the pro- posed method, achieving near-perfect pedestrian recognition and robust cyclist classification across diverse scenarios. The high recall obtained for pedestrians highlights the reliability of the approach in safety-critical contexts, while the remaining misclassifications for cyclists primarily occur in challenging conditions such as partial occlusions, close-range interactions, and overlapping vulnerable road users. These findings emphasize the inherent difficulty of cyclist discrimination when cyclist-specific radar signatures are partially obscured.

The use of 77 GHz radar provides several practical ad- vantages, including resilience to adverse weather conditions, robustness under low-light environments, and consistent performance independent of illumination. These characteristics reinforce the suitability of radar as a core sensing modality for VRU detection, either as a standalone solution or as a complementary sensor within multi-modal perception systems. Moreover, the SVM-based classification strategy offers a favorable trade-off between accuracy and computational efficiency, which is essential for embedded automotive platforms with strict real-time constraints.

Despite its strong performance, the proposed framework reveals limitations related to cyclist classification sensitivity in complex urban environments. Addressing these challenges represents a promising direction for future research. Potential enhancements include the incorporation of temporal and motion-based features to better capture dynamic behavior, the application of class-balanced or cost-sensitive learning to mitigate classification bias, and the integration of multi-sensor fusion techniques combining radar with vision or LiDAR data. In summary, this work establishes a reliable and efficient baseline for radar-based pedestrian and cyclist classification, demonstrating the feasibility of SVM-driven perception using 77 GHz automotive radar. The insights gained from the experimental analysis provide clear guidance for future developments aimed at improving robustness, scalability, and safety performance in next-generation ADAS and autonomous driving systems.

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