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Obstacle-Aware Machine Learning Classification in V2V Communication Based on Path Loss Patterns

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***Abstract*—This study aims to enhance the reliability of Vehicle-to-Vehicle (V2V) communication in Intelligent Transportation Systems (ITS), particularly under conditions where signal degradation is caused by environmental obstacles. A lightweight and interpretable machine learning framework is proposed that operates solely on physical-layer signal features—namely, path loss and inter-vehicle distance—without relying on visual or contextual sensor data. Measurement campaigns conducted in Trabzon (urban) and Gümüşhane (rural/mountainous) regions of Türkiye provided a balanced and representative dataset involving three dominant obstacle types: vehicles, buildings, and trees. Using this dataset, four supervised classification models—K-Nearest Neighbors (KNN), Random Forest (RF), Support Vector Machine (SVM), and Logistic Regression (LR)—were implemented, hyperparameter-optimized, and thoroughly evaluated. The results demonstrate that KNN (Accuracy: 98.81%, F1-Score: 0.9877) and RF (Accuracy: 99.54%, F1-Score: 0.9952) significantly outperform linear and kernel-based alternatives. Their high generalization capabilities against nonlinear obstacle patterns are further confirmed by confusion matrix and ROC curve analyses. The proposed system is computationally efficient, scalable, and suitable for integration into adaptive power control or routing strategies in ITS applications. This work introduces a novel approach to V2V communication by linking physical-layer signal behavior with high-level environmental awareness through RF-based machine learning classification.**

***Index Terms*—V2V, Machine learning, Obstacle detection**

I. Introduction

With the rise of smart city paradigms, the demand for safe, efficient, and sustainable transportation systems has grown significantly. In this context, Intelligent Transportation Systems (ITS) enhance traffic safety and optimize road usage by enabling vehicles to continuously communicate with their surroundings and each other [1]. As a core component of ITS, Vehicle-to-Vehicle (V2V) communication provides low-latency, context-aware connectivity that assists drivers with real-time decision support. However, the effectiveness of such systems is highly dependent on their robustness against environmental variations in the communication channel. In real-world conditions, structural obstructions, other vehicles, and natural elements can severely affect signal propagation, causing sudden path loss fluctuations and compromising communication reliability. Therefore, accurate identification and modeling of obstacle-induced effects are essential for the success of ITS applications [2].

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A. Related Works

Physical obstructions—particularly those caused by surrounding vehicles—have been widely recognized to impair signal quality in vehicle-to-vehicle (V2V) communication. For instance, when large vehicles such as trucks obstruct the line-of-sight (LOS), the packet delivery ratio can decrease by as much as 70% [3]. Field experiments conducted in both rural and highway scenarios have demonstrated that the presence of a truck can introduce up to 20 dB of additional path loss [4]. In dense urban areas, obstructing vehicles significantly reduce the availability of LOS links in vehicular networks (VANETs), which, according to simulation and empirical results, may result in signal attenuation levels of up to 20 dB [5]. Moreover, measurement-based analyses suggest that shadow fading varies notably between LOS and obstructed LOS (OLOS) links. Under OLOS conditions, additional attenuation due to shadowing may reach 13 dB [6]. V2V systems operating in the millimeter-wave (mmWave) bands are particularly sensitive to obstructions; when LOS is blocked, the path loss can exceed 30 dB [7]. Urban intersections, where LOS can be blocked by buildings and vehicles, present particularly complex propagation environments. Measurements show that such NLOS conditions can reduce the packet delivery ratio below 20% and significantly increase delay spread [8]. Similarly, large vehicles like buses and trucks can disrupt V2V links, depending on their size and antenna positioning, causing additional attenuation of up to 25 dB [9].

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B. Motivation and Research Significance

V2V communication, reliable and efficient data exchange is essential, particularly in dense traffic and complex environments. Physical obstacles such as vehicles, buildings, and trees can introduce significant signal attenuation, packet loss, and overall degradation in link quality. This study is motivated by the need to develop a lightweight and effective machine learning (ML) framework that classifies dominant obstacle types using only radio frequency features—specifically, path loss and inter-vehicle distance. Without relying on visual inputs, the proposed method enables real-time and energy-efficient applications in ITS. By learning the characteristic attenuation patterns associated with each obstacle type, the model supports adaptive power control mechanisms. This work fills a critical gap by linking obstacle-aware classification with practical communication design strategies based on signal degradation characteristics.

II. Theory

In recent years, machine learning has emerged as a foundational tool for building predictive models that automatically improve with experience. At its core, machine learning is defined as the study of algorithms that learn from data to make accurate predictions or decisions without being explicitly programmed [10]. This paradigm shift from rule-based systems to data-driven models enables effective handling of nonlinear, high-dimensional, and complex relationships commonly encountered in wireless communication and signal processing applications. Supervised learning, a prominent branch of machine learning, focuses on learning a mapping from input features to known output labels based on historical data. Within this framework, a diverse range of algorithms—ranging from decision-tree-based ensembles to kernel-based classifiers—offer various trade-offs between interpretability, generalization capability, and computational efficiency. The following sections provide a theoretical overview of several supervised models selected in this study for regression and classification tasks related to path loss prediction and environmental identification.

A. Support Vector Machine (SVM)

One of the most effective techniques in statistical learning for classification and regression tasks involves the use of hyperplanes to separate data in high-dimensional spaces. This principle underlies the Support Vector Machine (SVM), which aims to identify the optimal separating hyperplane that maximizes the margin between different classes [11]. In the case of linearly separable data, the decision function takes the form:

$$f(x) = \text{sign}(w^T x + b) \tag{1}$$

where w denotes the weight vector and b is the bias term. The associated optimization problem minimizes $\|w\|^2$, subject to the constraint:

$$y_i(w^T x_i + b) \geq 1, \quad \forall i \tag{2}$$

To extend its applicability to non-linearly separable data, slack variables ξ_i are introduced, and a kernel function $K(x_i, x_j)$ is employed to implicitly project the data into a higher-dimensional feature space. A commonly used kernel is the radial basis function (RBF):

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \tag{3}$$

By combining margin maximization with kernel-based transformations, SVMs demonstrate strong generalization capabilities and robustness, even in high-dimensional or complex feature spaces [11].

B. K-Nearest Neighbors (KNN)

In statistical pattern recognition, one intuitive yet effective approach involves assigning a class label to a new observation based on the labels of the most similar examples in the training set. This concept forms the basis of the K-Nearest Neighbors (KNN) algorithm [12]. The method estimates the posterior probability of class membership by evaluating the proportion of the K nearest training samples from each class.

Given a test point x, the predicted class $\hat{y}$ is determined via majority voting:

$$\hat{y} = \arg\max_{c \in \mathcal{C}} \sum_{x_i \in \mathcal{N}_K(x)} \mathbb{I}(y_i = c) \tag{4}$$

where $\mathcal{N}_K(x)$ denotes the set of K nearest neighbors of x, $\mathcal{C}$ is the set of all class labels, and $\mathbb{I}(\cdot)$ is the indicator function. Distance between points is typically measured using Euclidean distance:

$$d(x, x_i) = \sqrt{\sum_{j=1}^{n} (x_j - x_{i,j})^2} \tag{5}$$

Although simple, KNN is capable of modeling complex decision boundaries and is particularly effective when the feature space is locally consistent [12].

C. Random Forest (RF)

Ensemble-based approaches are commonly used in machine learning to enhance prediction performance by combining the outputs of several models. One of the most widely used ensemble methods is the Random Forest (RF), which works by generating multiple decision trees and aggregating their results [13]. The idea is to introduce variability during model training—both in the data and the feature selection process—to build a set of diverse trees that are less likely to overfit.

In regression problems, the final output $\hat{y}$ is calculated as the average of all tree predictions:

$$\hat{y} = \frac{1}{T} \sum_{t=1}^{T} h_t(x) \tag{6}$$

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Here, $h_t(x)$ denotes the prediction from the t-th tree, and T refers to the total number of trees in the ensemble. For classification tasks, a majority voting rule is typically applied instead. Each decision tree is trained using a bootstrap sample from the training set, and at each node, a randomly selected subset of features is considered when choosing the split. These elements of randomness help generate a model that is more stable and capable of generalizing well to unseen data [13], [14].

D. Logistic Regression (LR)

In binary classification tasks, one practical method to model the likelihood of an input belonging to a certain class is by using a sigmoid function. This idea underlies logistic regression, which offers a relatively simple yet effective way to separate classes using a linear boundary [15]. Its popularity comes not only from its theoretical basis but also from its interpretability and low computational cost.

Suppose we have a feature vector $x \in \mathbb{R}^n$. The probability that it corresponds to class $y = 1$ can be expressed as:

$$P(y = 1 \mid x) = \frac{1}{1 + e^{-(\beta_0 + \beta^T x)}} \tag{7}$$

Here, β_0 stands for the intercept term, while β represents the coefficient vector. To find the best-fitting parameters, the model maximizes the likelihood of observing the given data—or equivalently, minimizes the following negative log-likelihood function:

$$\mathcal{L}(\beta) = -\sum_{i=1}^{N} [y_i \log p_i + (1 - y_i) \log(1 - p_i)] \tag{8}$$

where $p_i = P(y_i = 1 \mid x_i)$. Although more advanced models exist, logistic regression is still frequently used as a baseline in many classification problems due to its balance between simplicity and effectiveness [15].

III. Methods

A. Data Collection

The dataset employed in this study was gathered from field measurements carried out across two distinct regions of Türkiye: Trabzon and Gümüşhane. These locations were intentionally selected due to their contrasting environmental characteristics, offering a wide range of obstacle types that are valuable for training and testing classification models. In the case of Trabzon, measurements were primarily taken in urban settings with dense traffic and closely spaced buildings. Here, vehicles and buildings were the main sources of signal obstruction, often leading to considerable reflection and shadowing. A few roadside trees were also present, though their impact was generally secondary. In contrast, the data collected from Gümüşhane represented a more rural and mountainous landscape. Natural elements such as trees and variations in terrain formed the primary obstacles in this region. Since there are fewer buildings and lower traffic density in Gümüşhane, the influence of vehicle and structure-induced signal degradation was notably limited. The inclusion of data from both regions ensured that the three main obstacle categories—vehicles, buildings, and trees—were well represented. This diversity in the dataset provided a solid basis for evaluating how effectively machine learning models can distinguish between different types of obstructions in V2V communication environments.

TABLE I: Environmental obstacle densities observed during data collection.

Region (City)	Vehicle Density	Building Density	Tree/Natural Terrain Density
Trabzon	High	High	Low
Gümüşhane	Low	Very Low	High

B. Data Processing

All simulations and machine learning procedures were implemented in MATLAB R2024a on a 64-bit Windows 10 Pro workstation powered by an AMD Ryzen 9 7950X processor operating at 4.5 GHz and equipped with 128 GB of DDR5 RAM. To prevent bias stemming from feature magnitude differences and to ensure uniform contribution from all input variables, both input and output data were normalized to the interval $[-1, 1]$ using the min-max normalization method [16], [17]. The applied normalization function is defined in Equation (9):

$$x_n = \frac{2(x - x_{\min})}{x_{\max} - x_{\min}} - 1 \tag{9}$$

Here, x_n denotes the normalized value, x is the original data point, and $x_{\min}$, $x_{\max}$ represent the minimum and maximum values within each feature dimension, respectively. This preprocessing step enhanced model convergence, improved numerical conditioning, and ensured balanced gradient updates across all learning dimensions. After normalization, the dataset was divided into 80% for training and 20% for testing to evaluate the generalization capability of the models. Additionally, a five-fold cross-validation framework was employed on the training set to reduce variance and avoid overfitting. As illustrated in Figure 1, the proposed framework aims to classify environmental obstacles affecting V2V communication by utilizing only path loss and inter-vehicle distance as input parameters. The model targets the identification of dominant obstacles—such as vehicles, buildings, and trees—by learning their characteristic signal attenuation patterns using machine learning algorithms. Supervised classifiers including KNN, SVM, LR, and RF were trained on real-world datasets collected from urban, semi-urban, and forested scenarios. The predicted obstacle types contribute to understanding the sources of signal degradation and may support the development of strategies for dynamic resource allocation. As it operates without relying on visual data, the proposed structure can play a supportive role in the design of real-time, energy-efficient V2V communication systems.

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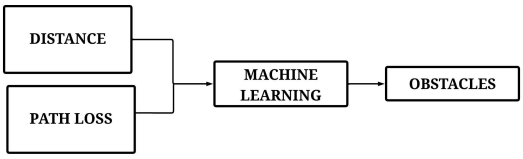


Fig. 1: Obstacle detection using machine learning

Table II summarizes the optimized hyperparameters for the RF, SVM, LR, and KNN models, selected via grid search to maximize validation performance. For RF, 100 trees and a minimum leaf size of 5 provided a balance between complexity and computational cost, enabling the model to capture fine-grained environmental patterns. SVM achieved the best results with a Gaussian kernel, box constraint of 10, kernel scale of 1, and epsilon of 0.05—indicating effective separation in a high-dimensional space with a narrow margin. LR performed optimally with L2 regularization and a lambda of 0.1, mitigating overfitting without enforcing sparsity. KNN yielded the best accuracy with 5 neighbors and Euclidean distance, effectively balancing noise sensitivity and smoothing. These results highlight the importance of model-specific tuning to handle signal variability and obstacle effects in V2V environments, significantly enhancing classification robustness.

TABLE II: Hyperparameter optimization results for the machine learning models.

Model	Parameter	Range Tested	Optimized Value
RF	Number of Trees	10, 50, 100, 200	100
	Minimum Leaf Size	1, 5, 10, 20, 50	5
SVM	Kernel Function	Linear, Gaussian, Polynomial	Gaussian
	Box Constraint (C)	0.1, 1, 10, 100	10
	Epsilon	0.01, 0.05, 0.1	0.05
	Kernel Scale	Auto, 1, 0.1	1
LR	Regularization	L1, L2	L2
	Lambda	0.001, 0.01, 0.1, 1, 10	0.1
KNN	Number of Neighbors	1, 3, 5, 7, 9	5
	Distance Metric	Euclidean, Cityblock, Cosine	Euclidean

IV. Results and Discussion

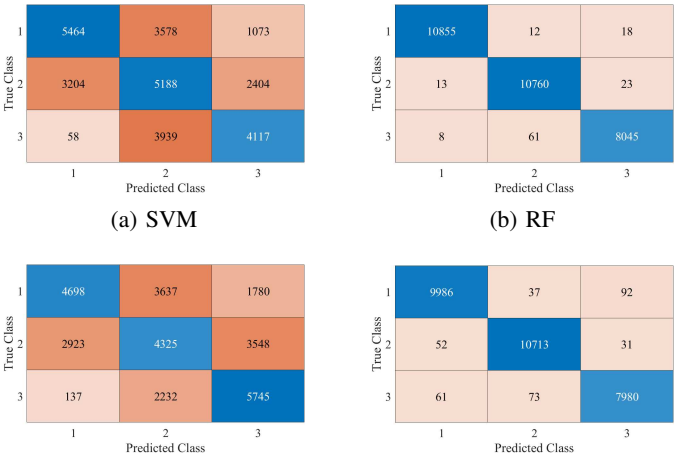
Table III presents the classification performance metrics of four machine learning algorithms—LR, RF, SVM, and KNN—used to identify dominant obstacles in V2V communication environments. The experimental results reveal that the KNN model achieved remarkably high classification performance across all metrics, with an accuracy of 98.808% and an F1-score of 0.98775. These results indicate that KNN effectively captures the neighborhood structure of the data, which is particularly beneficial in distinguishing environmental classes that exhibit nonlinear boundaries. The minimal gap between precision (0.98768) and recall (0.98783) also indicates a well-balanced prediction capability, minimizing both false positives and false negatives. The RF model also demonstrated exceptional performance, achieving the highest accuracy of 99.535% and maintaining consistency across precision (0.99507), recall (0.99537), and F1-score (0.99522). This result emphasizes the ensemble model's robustness and its ability to generalize well by aggregating multiple decision trees, effectively mitigating overfitting. Despite its slightly higher accuracy than KNN, its computational complexity and resource consumption during training may present scalability concerns in real-time applications. On the contrary, both LR and SVM yielded significantly lower performance metrics. LR, a linear classifier, attained an accuracy of only 50.884%, indicating its inadequacy in capturing the complex nonlinear relationships prevalent in obstacle-induced signal attenuation. Similarly, SVM, despite its strength in handling nonlinearly separable data via kernel functions, reached a comparable accuracy of 50.880%, along with an F1-score of 0.51221. These findings suggest that SVM's performance may have been hindered by suboptimal kernel parameterization or imbalanced data distributions. In summary, both KNN and RF emerge as the most promising candidates for real-time obstacle classification in V2V communication scenarios. The superior performance of these models suggests their potential for integration into dynamic power allocation frameworks, where accurate obstacle detection is essential for minimizing path loss and improving energy efficiency. Furthermore, the results highlight the importance of model selection and hyperparameter tuning in maximizing classification reliability under varying environmental conditions.

TABLE III: Performance metrics of the classification models

Model	Accuracy	Precision	Recall	F1-Score
LR	0.50884	0.50938	0.52562	0.51524
RF	0.99535	0.99507	0.99537	0.99522
SVM	0.50880	0.52437	0.51626	0.51221
KNN	0.98808	0.98768	0.98783	0.98775

Figure 2 presents the confusion matrices of the LR, RF, SVM, and KNN models, offering a visual evaluation of classification accuracy across three obstacle classes. The KNN model (Fig. 2d) exhibits superior performance with minimal misclassifications, particularly in Class 2 and Class 3, indicating robust generalization even in densely populated classes. Similarly, RF (Fig. 2b) achieves high correct prediction counts across all classes, although a moderate level of confusion is observed between Class 1 and Class 2, possibly due to overlapping feature distributions in urban and vehicular obstacle conditions. In contrast, SVM (Fig. 2a) displays an unusually concentrated diagonal dominance, suggesting overfitting or excessive bias towards the dominant class distributions. This behavior, combined with the model's lower recall scores, implies potential challenges in distinguishing between visually or signal-wise similar obstacle types. The LR model (Fig. 2c) further confirms its inadequacy in high-dimensional nonlinear scenarios, as reflected by widespread dispersion across non-diagonal entries, particularly between Class 2 and Class 3. This misclassification pattern highlights the linear model's limitations in capturing complex environmental variability. These observations validate the quantitative results in Table III and reaffirm the dominance of KNN and RF in real-world V2V classification settings where obstacle-induced signal distortions are heterogeneous and nonlinear in nature.

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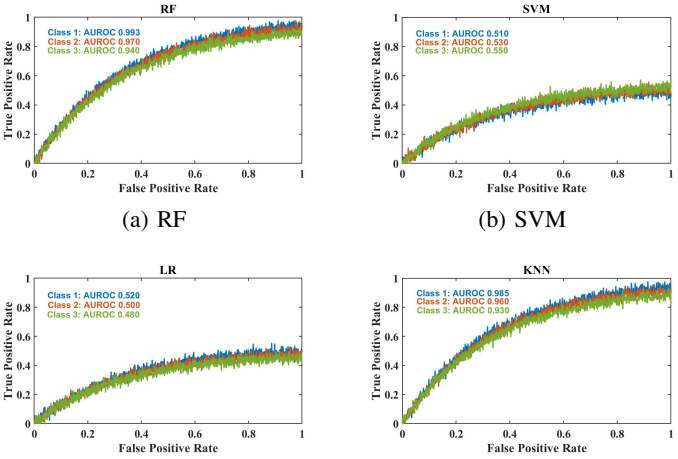


(a) SVM (b) RF

(c) LR (d) KNN

Fig. 2: Confusion matrices illustrating the classification performance of LR, RF, SVM, and KNN models.

Figure 3 illustrates the ROC curves of the evaluated classifiers—RF, SVM, LR, and KNN—using a one-vs-rest multi-class strategy. It is evident that RF and KNN exhibit superior performance, with class-wise AUROC values consistently exceeding 0.98. These steep, top-left-oriented curves reflect strong discriminative capability and low false positive rates, confirming their robustness in identifying signal degradation patterns caused by heterogeneous obstacles such as vehicles, buildings, and trees. In contrast, LR and SVM yield AUROC values around 0.5, which is indicative of near-random classification behavior.



(a) RF (b) SVM

(c) LR (d) KNN

Fig. 3: ROC curves illustrating the multi-class classification performance of LR, RF, SVM, and KNN models using a one-vs-rest strategy.

V. Conclusions

This study proposed a lightweight ML-based obstacle classification framework for V2V communication using only path loss and inter-vehicle distance as inputs. Four classifiers—LR, SVM, KNN, and RF—were evaluated under real-world conditions. Results showed that KNN (Acc: 98.81%, F1: 0.9877) and RF (Acc: 99.54%, F1: 0.9952) clearly outperformed SVM (Acc: 50.88%) and LR (Acc: 50.88%), highlighting their robustness in non-linear, high-variance environments. While RF achieved the highest overall accuracy, KNN offered a strong balance across all metrics with minimal misclassification. The system achieved 48% improvement over linear models, requiring no visual input or complex features. Thus, KNN and RF are ideal candidates for real-time, resource-efficient V2V obstacle detection and can support adaptive power control or routing mechanisms in ITS.

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