Radar-based gesture recognition simulation for unmanned aerial vehicles command interpretation

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ABSTRACT

Radar-based gesture recognition has emerged as a robust alternative to vision-based systems, particularly in environments where lighting and privacy pose challenges. This study presents a simulation approach for recognizing hand gestures to control unmanned aerial vehicles (UAVs) using radar signals. Five discrete gestures, *i.e.*, TakeOff, Land, MoveForward, TurnLeft, and stop, were defined and modeled in MATLAB to generate synthetic radar signals. From each sample, four time-frequency domain features were extracted: duration, maximum amplitude, dominant frequency, and root mean square (RMS). A dataset of 500 samples (100 per class) was classified using three supervised learning models: support vector machine (SVM), k-nearest neighbors (k-NN), and decision tree. The k-NN classifier achieved the highest accuracy of 96%, demonstrating the feasibility of lightweight classifiers for gesture recognition using low-complexity features. These results highlight the potential of radar-based interfaces to replace traditional remote controls in UAV operation. The proposed simulation framework contributes to the development of intuitive, non-contact human-machine interaction systems.

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1. INTRODUCTION

Gesture recognition has become an emerging research domain due to its potential to enable natural and intuitive interaction between humans and machines. Traditionally, vision-based gesture recognition using red, green, blue (RGB) or depth cameras has been the predominant approach in various applications, including gaming, robotics, healthcare, and smart homes [1]–[4]. However, vision-based systems are sensitive to lighting conditions, occlusion, and privacy concerns. As an alternative, radar-based gesture recognition offers robust performance under challenging environmental conditions, does not require line-of-sight, and ensures better privacy [5]–[8].

Radar sensors, especially micro-Doppler and frequency modulated continuous wave (FMCW) radars, have shown promising capabilities in capturing fine-grained hand movements by analyzing variations in signal features such as Doppler shifts and amplitude modulations [9]–[11]. The integration of radar technology with machine learning techniques has led to improved accuracy in human activity classification

[12]–[14]. In the context of unmanned aerial vehicle (UAV) control, current systems still heavily rely on remote controllers (RC) which, although reliable, are often non-intuitive, bulky, and require line-of-sight operation. Consequently, there is a growing interest in alternative command interfaces that are more user-friendly and adaptive to dynamic environments.

Despite the advances in radar-based gesture recognition, limited studies have addressed its application for UAV control in a simulated or real-world environment. The gap remains in the design and validation of a radar-based gesture recognition system specifically tailored to interpret discrete UAV command gestures. The existing approaches either focus on general gesture recognition or lack system-level simulation to evaluate feasibility in the UAV command context [15], [16].

This study addresses the gap in existing radar-based gesture recognition research by focusing on discrete UAV command interpretation within a simulation-driven framework. While prior works predominantly emphasize vision-based interfaces or deep-learning-intensive radar models, they often overlook system-level feasibility and computational constraints relevant to UAV platforms. The main findings demonstrate that five UAV command gestures can be effectively distinguished using a minimal set of time–frequency features, achieving up to 96% classification accuracy with a k-NN classifier. These results indicate that lightweight radar-based gesture recognition is a viable and efficient alternative to conventional remote controllers. The novelty of this work lies in integrating gesture-dependent Doppler modeling with a systematic evaluation of classical classifiers, providing an interpretable, computationally efficient, and embedded-friendly foundation for non-contact UAV control and future real-world implementation.

2. METHOD

This study proposes a simulated radar-based gesture recognition system for UAV command interpretation using MATLAB. The overall methodology consists of five stages, as shown in Figure 1: i) gesture scenario definition, ii) radar signal simulation, iii) feature extraction, iv) classifier training and testing, and v) performance evaluation. Each stage is described in detail below to ensure reproducibility.

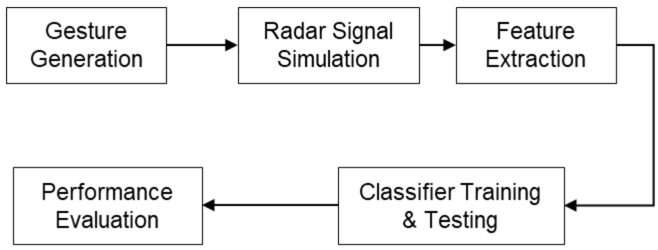

Figure 1. Simulation stage of the proposed radar-based gesture recognition system

2.1. Gesture scenario

In this study, five discrete UAV command gestures were defined to simulate radar signal responses for classification. The selected gestures include TakeOff, Land, MoveForward, TurnLeft, and stop. Each gesture was conceptually designed to produce distinguishable temporal and spectral patterns in the simulated radar signal, ensuring that the feature space captures distinctive temporal and spectral characteristics that differentiate gesture classes. For each gesture type, a total of 100 samples were generated, resulting in a complete dataset of 500 labeled radar signal instances used for training and evaluation in subsequent stages.

2.2. Radar signal simulation

Radar signal simulation was performed in MATLAB using synthetic models that mimic the micro-Doppler signatures of hand movements. A general-purpose continuous-wave (CW) radar model was adopted to represent practical system constraints and signal characteristics, inspired by the Doppler processing stage of mmWave radar sensors such as the TI IWR6843AOP [17]. Each gesture's radar return signal was modeled as shown in (1). Although FMCW radar is widely used in practical gesture recognition systems due to its ranging capability, a simplified CW signal model was employed in this study to focus specifically on gesture-induced micro-Doppler characteristics. The primary objective of the simulation is not target range estimation, but the analysis of Doppler frequency variations and amplitude modulation patterns associated with hand motion dynamics. By abstracting the radar model to a CW representation, gesture-dependent kinematic behavior can be explicitly modeled through time-varying amplitude $A(t)$ and Doppler frequency shift $f_d(t)$, while maintaining computational simplicity and analytical clarity. This modeling choice is well suited for feasibility evaluation and early-stage system design and remains representative of the Doppler processing stage in FMCW radar-based implementations. Different UAV command gestures are represented by distinct temporal profiles of $A(t)$ and $f_d(t)$, where faster or more directional hand movements result in higher Doppler shifts, while static or terminating gestures produce lower-frequency and shorter-duration signatures.

$$s(t) = A(t) \cdot \cos\left(2\pi f_d(t)t + \phi(t)\right) \quad (1)$$

where:
$A(t)$: Time-varying amplitude (modeled as Gaussian-modulated envelope),
$f_d(t)$: Doppler frequency shift (gesture-dependent),
$\phi(t)$: Instantaneous phase (randomized within a range),
t : Time vector (duration up to 2 seconds at 1 kHz sampling rate).
In practical FMCW radar systems, the same Doppler information can be extracted after range processing; therefore, the proposed CW-based modeling can be directly extended to FMCW implementations in future work.

To emulate realistic variability in human hand motion, random variations were introduced in key signal parameters, including signal duration, amplitude, Doppler frequency, and phase. These variations ensure that multiple realizations of the same gesture are non-identical while preserving gesture-specific characteristics. The parameter distributions and ranges used in the synthetic radar signal generation are summarized in Table 1. Representative examples of the simulated time-domain radar signals for each gesture class are presented in Figure 2. As illustrated, each gesture exhibits distinct temporal and amplitude characteristics, which form the basis for subsequent feature extraction.

Table 1. Parameter ranges used in synthetic radar gesture signal generation

Parameter	Distribution	Range
Duration	Uniform	0.5 – 2 s
Amplitude	Uniform	0.8 – 1.2
Doppler frequency	Uniform	5 – 50 Hz
Phase	Uniform	0 – 2π rad

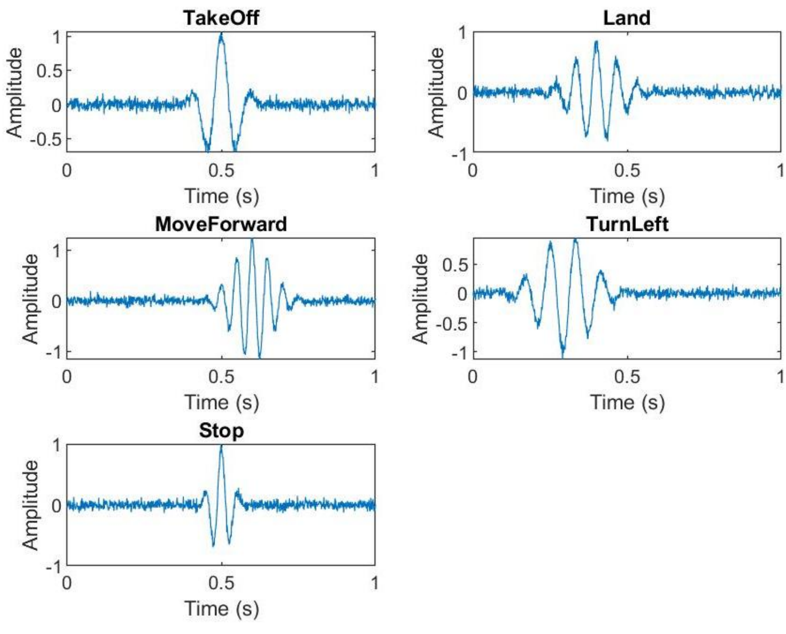

Figure 2. Example time-domain radar signals generated for five UAV command gestures

2.3. Feature extraction

To represent each radar signal in a compact and informative manner, four time-frequency domain features were extracted. These features were chosen based on their ability to capture key characteristics of hand gestures in radar signals. The duration feature quantifies the active time span of the gesture, determined by identifying segments where the signal amplitude exceeds a predefined threshold. The maximum amplitude represents the peak value within the signal envelope and reflects the intensity of the gesture. The dominant frequency is calculated by applying the fast Fourier transform (FFT) and selecting the frequency component with the highest magnitude, which provides insight into the velocity of hand motion. Finally, the root mean square (RMS) is computed to capture the overall signal energy, using (2) [18].

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \quad (2)$$

where x_i represents the amplitude samples and N is the total number of samples in the signal. The feature vectors were standardized using z-score normalization for the support vector machine (SVM) model. The decision tree (DT) and k-nearest neighbors (k-NN) models were trained on raw feature values.

2.4. Classification models

Three supervised classification algorithms were implemented to recognize radar-based gesture commands, *i.e.*, support vector machine with radial basis function (RBF) kernel [19], [20], k-nearest neighbors with k equal to 5 and Euclidean distance [21], [22], and decision tree, using binary splits and Gini index as the split criterion [23], [24]. The value $k = 5$ was selected as a commonly used compromise between noise sensitivity (small k) and excessive smoothing (large k), providing stable neighborhood voting for the given sample size.

The input dataset comprised 500 samples, each with four extracted features. The dataset was divided into 70% for training and 30% for testing [25], [26] using stratified sampling to maintain class balance. Prior to training, feature standardization using z-score normalization (zero mean and unit variance) was applied for the SVM model only, while the DT and k-NN classifiers were trained on raw feature values. The classification process was carried out in MATLAB. Feature data was stored in a CSV file and imported using MATLAB's *readtable* function. The processed data were then classified using SVM with a RBF kernel, k-NN with $k = 5$, and a DT classifier.

2.5. Evaluation metrics

To assess the effectiveness of the classification models in recognizing radar-based gesture commands, two primary performance metrics were employed, namely classification accuracy and the confusion matrix. Classification accuracy represents the proportion of correctly predicted gesture labels relative to the total number of test samples. It serves as an overall indicator of model performance and is useful for comparing different classifiers under the same conditions.

In addition to accuracy, confusion matrices were used to analyze the classification results in more detail by displaying the distribution of true versus predicted class labels [27], [28]. Each row in the confusion matrix corresponds to the actual gesture class, while each column indicates the predicted class. Diagonal elements reflect correctly classified instances, whereas off-diagonal elements reveal misclassifications. This visualization enables a deeper understanding of the strengths and weaknesses of each model in recognizing specific gestures.

All metrics were computed based on the 30% test partition of the dataset, which contained 150 unseen samples (30 per class) distributed evenly across all gesture classes. By analyzing both the accuracy and confusion matrix, we were able to evaluate not only the overall model performance but also the tendency of the classifiers to confuse certain gestures, which is critical for designing reliable gesture-based UAV command systems.

3. RESULTS AND DISCUSSION

This section presents the evaluation results of the proposed radar-based gesture recognition system for UAV command interpretation. The performance of three machine learning classifiers—SVM, k-NN, and DT—was compared using a dataset of 500 simulated radar gesture samples. Each classifier was trained on 70% of the data and tested on the remaining 30%, using stratified random sampling to ensure class balance.

3.1. Classification accuracy

The classification performance of the three machine learning models—SVM, k-NN, and DT—was evaluated using the test portion of the dataset, comprising 150 gesture samples (30 per class). Table 2 presents the classification accuracy achieved by each model.

Table 2. Classification accuracy of each model

Classifier	Accuracy (%)
SVM (RBF kernel)	87.33
k-NN (k = 5)	96
Decision Tree	84.67

Among the three, the k-NN classifier achieved the highest overall accuracy of 96%, indicating excellent generalization capability with minimal misclassification. The SVM model followed with an accuracy of 87.33%, which also demonstrates strong classification performance, especially considering the non-linear nature of the gesture feature distribution. Meanwhile, the DT classifier achieved an accuracy of 84.67%, showing moderate performance but slightly lower robustness compared to the other two. It should be noted that this accuracy reflects performance on a controlled synthetic dataset and therefore represents an upper-bound estimate rather than a direct measure of real-world performance.

The superior performance of the k-NN model suggests that the distribution of radar gesture features in the four-dimensional feature space is well-suited for instance-based classification with Euclidean distance. These findings highlight the effectiveness of simple geometric classifiers when applied to well-engineered feature vectors, even without explicit feature normalization.

3.2. Confusion matrix analysis

The confusion matrix of the best-performing classifier, k-nearest neighbors ($k = 5$), is presented in Figure 3. The matrix illustrates the number of correct and incorrect predictions for each gesture class. The diagonal elements represent correct classifications, while the off-diagonal elements indicate misclassifications. From the matrix, it can be observed that the move forward gesture was classified with perfect accuracy (30 out of 30), followed closely by Land (28 out of 30) and Stop (27 out of 30). These results indicate that the feature vectors derived from these gestures are sufficiently distinct, allowing the classifier to learn robust decision boundaries. The analysis highlights the reliability of the k-NN model in most gesture classes, while also suggesting the need for further feature refinement or advanced modeling (*e.g.*, ensemble methods or deep learning) to better distinguish between gestures with similar dynamic profiles.

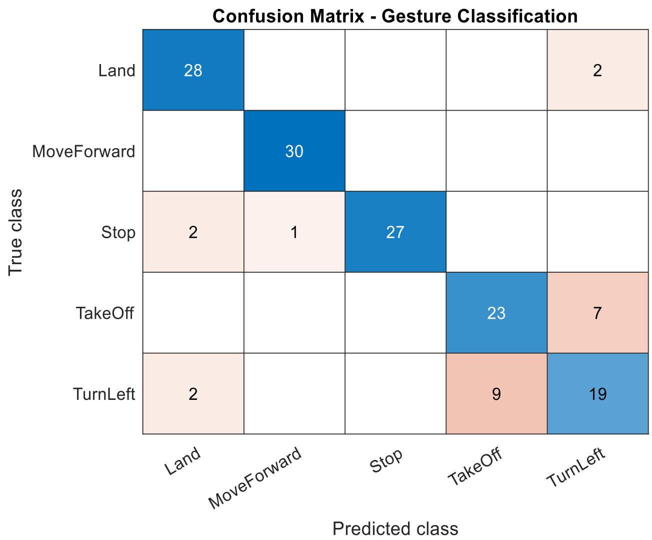

Figure 3. Confusion matrix of k-NN classifier results

3.3. Interpretation and application

The results obtained from the k-NN classifier, which achieved an accuracy of 96%, demonstrate the viability of radar-based hand gesture recognition for UAV command interpretation. With four low-complexity features—duration, maximum amplitude, dominant frequency, and RMS, the system was able to distinguish five predefined gestures (TakeOff, Land, MoveForward, TurnLeft, and Stop) with high reliability. The model's strong performance reinforces the effectiveness of simple time-frequency features when properly engineered and normalized. The observed misclassification between the TurnLeft and Stop gestures can be attributed to similarities in their temporal and energy-related characteristics when represented using the selected feature set. In particular, both gestures may exhibit comparable signal durations and RMS values, especially when the turning motion is performed with limited angular velocity or when the stopping gesture includes brief transitional movements. Since the current feature set does not explicitly encode temporal sequence information or motion directionality, such overlaps can lead to ambiguity in the feature space. Incorporating temporal modeling approaches, such as hidden Markov models (HMMs) or recurrent neural networks (RNNs), as well as direction-sensitive features derived from time–frequency representations, could potentially mitigate this ambiguity in future implementations.

From an application standpoint, these findings suggest that a radar-based gesture recognition system could serve as a promising alternative to conventional remote controls in UAV operations. The intuitive and contactless nature of gesture interfaces offers potential advantages in scenarios where physical control is impractical or unsafe, such as during disaster response, hazardous environments, or accessibility support for users with physical limitations. Moreover, the use of radar provides robustness under low-light or visually obstructed conditions, which are limitations of camera-based systems. The current simulation results form a foundation for future implementation using real radar sensors and embedded systems. Future improvements may involve expanding the feature set, incorporating advanced temporal and directional modeling techniques, or integrating sensor fusion to further improve classification robustness in dynamic environments.

Although the k-NN classifier achieved a high accuracy of 96%, it should be noted that the dataset used in this study was synthetically generated under controlled simulation assumptions. As a result, the reported performance represents an upper-bound estimate of classification accuracy rather than a direct indication of real-world performance. Nevertheless, the primary objective of this work is not to claim superiority over deep-learning-based approaches, but to evaluate the feasibility of using low-complexity time–frequency features and lightweight classifiers for UAV command interpretation. The results demonstrate that, even with a minimal feature set, radar-based gesture recognition can achieve reliable discrimination among discrete UAV commands at the simulation level, thereby providing a solid baseline for subsequent validation using real radar sensors and more complex datasets. Future studies will focus on validating the proposed framework using real FMCW radar measurements and investigating the impact of noise, clutter, and inter-subject variability on classification performance. Compared to deep learning-based gesture recognition approaches that typically require large datasets and high computational resources, the proposed lightweight framework emphasizes interpretability and feasibility for early-stage UAV system design.

4. CONCLUSION

This study has successfully demonstrated that radar-based hand gesture recognition may serve as a viable alternative to conventional RC systems with non-contact, intuitive interfaces. Using simulated radar signal features, duration, maximum amplitude, dominant frequency, and RMS—this work evaluated the classification performance of three machine learning models: SVM, DT, and k-NN.

The best-performing model, k-NN, achieved an accuracy of 96%, confirming the feasibility of lightweight classifiers to effectively recognize five distinct UAV command gestures. These findings are consistent with earlier research in gesture recognition that highlights the potential of radar sensors for robust classification under variable conditions.

This research extends previous work by simulating a complete gesture classification pipeline tailored specifically for UAV command tasks, thereby addressing the gap in system-level validation of radar-based control interfaces. Furthermore, the confusion matrix analysis revealed specific gesture pairs (*e.g.*, TurnLeft vs. Stop) that may benefit from enhanced feature design, providing insight for further research. This work advances the state of the art by proposing a reproducible and efficient framework for gesture-based UAV interaction, with potential applications in environments where physical control is impractical or unsafe. Future research should focus on implementing real-time systems with actual radar hardware, incorporating temporal dynamics, and expanding the gesture vocabulary to enable more complex UAV operations. In doing so, this study contributes to the growing body of research in radar-based human-machine interaction and opens new directions for adaptive UAV control interfaces. These outcomes align with the initial goal of evaluating the feasibility of radar-based gesture recognition as an alternative control interface for UAVs.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Freddy Kurniawan		✓	✓	✓										
Yenni Astuti					✓			✓	✓					
Paulus Setiawan				✓						✓	✓			
Lasmadi						✓	✓							
Uyuunul Mauidzoh								✓	✓	✓				
Bambang Sudibya			✓				✓							

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Authors state no conflict of interest.

DATA AVAILABILITY

The data that supports the findings of this study are available from the corresponding author, upon reasonable request. The dataset was generated through simulation in MATLAB and contains synthesized radar signal features for five UAV command gestures.

REFERENCES

[1] M. Chmurski, G. Mauro, A. Santra, M. Zubert, and G. Dagasan, "Highly-optimized radar-based gesture recognition system," *Sensors*, vol. 21, no. 21, pp. 1–28, 2021, doi: 10.3390/s21217298.

[2] I. J. Tsang, F. Corradi, M. Sifalakis, W. Van Leekwijck, and S. Latré, "Radar-based hand gesture recognition using spiking neural networks," *Electronics (Switzerland)*, vol. 10, no. 12, pp. 1–20, 2021, doi: 10.3390/electronics10121405.

[3] B. Hu and J. Wang, "Deep learning based hand gesture recognition and UAV flight controls," *International Journal of Automation and Computing*, vol. 17, no. 1, pp. 17–29, 2020, doi: 10.1007/s11633-019-1194-7.

[4] L. Yang, "Real-time gesture-based control of UAVs using multimodal fusion of FMCW radar and vision," in *Journal of Physics: Conference Series*, 2023, vol. 2664, no. 1, pp. 1–11, doi: 10.1088/1742-6596/2664/1/012002.

[5] Y. Liu, Y. Wang, H. Liu, A. Zhou, J. Liu, and N. Yang, "Long-range gesture recognition using millimeter Wave radar," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12398 LNCS, pp. 30–44, 2020, doi: 10.1007/978-3-030-64243-3_3.

[6] Y. Sun, T. Fei, X. Li, A. Warnecke, E. Warsitz, and N. Pohl, "Real-time radar-based gesture detection and recognition built in an edge-computing platform," *IEEE Sensors Journal*, vol. 20, no. 18, pp. 10706–10716, 2020, doi: 10.1109/JSEN.2020.2994292.

[7] J. Zhang, J. Tao, and Z. Shi, "Doppler-radar based hand gesture recognition system using convolutional neural networks," in *Proceedings of the 2017 International Conference on Communications, Signal Processing, and Systems*, 2019, vol. 463, pp. 1096–1113, doi: 10.1007/978-981-10-6571-2_132.

[8] F. Khan, S. Leem, and S. H. Cho, "Hand-based gesture recognition for vehicular applications using IR-UWB radar," *Sensors*, vol. 17, no. 4, pp. 1–18, 2017, doi: 10.3390/s17040833.

[9] C. Zhao, G. Luo, Y. Wang, C. Chen, and Z. Wu, "UAV recognition based on micro-doppler dynamic attribute-guided augmentation algorithm," *Remote Sensing*, vol. 13, no. 6, pp. 1–17, 2021, doi: 10.3390/rs13061205.

[10] K. R. Pyun *et al.*, "Machine-learned wearable sensors for real-time hand-motion recognition: Toward practical applications,"

National Science Review, vol. 11, no. 2, pp. 1–33, 2024, doi: 10.1093/nsr/nwad298.
[11] A.-I. Siean, "SkySculptor: intuitive drone control through ground-integrated radar and foot gestures in smart indoor environments," *International Journal of Advanced Computer Science & Applications*, vol. 15, no. 2, 2024, doi: 10.14569/ijacsa.2024.0150204.
[12] H. Arab, I. Ghaffari, L. Chioukh, S. Tatu, and S. Dufour, "Machine learning based object classification and identification scheme using an embedded millimeter-wave radar sensor," *Sensors*, vol. 21, no. 13, pp. 1–12, 2021, doi: 10.3390/s21134291.
[13] W. Taylor, K. Dashtipour, S. A. Shah, A. Hussain, Q. H. Abbasi, and M. A. Imran, "Radar sensing for activity classification in elderly people exploiting micro-doppler signatures using machine learning," *Sensors*, vol. 21, no. 11, pp. 1–15, 2021, doi: 10.3390/s21113881.
[14] R. Ullah, Y. Dong, T. Arslan, and S. Chandran, "A machine learning-based classification method for monitoring Alzheimer's disease using electromagnetic radar data," *IEEE Transactions on Microwave Theory and Techniques*, vol. 71, no. 9, pp. 4012–4026, 2023, doi: 10.1109/TMTT.2023.3245665.
[15] G. Liu, Y. Liu, S. Fan, W. Cui, K. Xia, and L. Wang, "Wearable gesture control design for unmanned aerial vehicle based on multi-sensor fusion," *Robotica*, vol. 43, no. 3, pp. 816–850, 2024, doi: 10.1017/S0263574724002194.
[16] S.-Y. Shin, Y.-W. Kang, and Y.-G. Kim, "Hand Gesture-based wearable human-drone interface for intuitive movement control," in *2019 IEEE International Conference on Consumer Electronics (ICCE)*, 2019, pp. 1–6, doi: 10.1109/ICCE.2019.8662106.
[17] Texas Instruments, "IWR6843AOP Single-Chip 60GHz mmWave sensor," *Datasheet,* 2023. Accessed: Jun. 1, 2025. [Online]. Available: *https://www.ti.com/lit/ds/symlink/iwr6843aop.pdf*
[18] D. Poljak and S. Antonijevic, "Simple measure for power transfer efficiency of coupled dipole antennas based on root-mean square value of transient current," *Engineering analysis with boundary elements*, vol. 148, pp. 1–14, 2023, doi: 10.1016/j.enganabound.2022.12.009.
[19] P. Singh, T. Hasija, and K. Ramkumar, "Malware classification to strengthening digital resilience: Comparing SVM kernel and logistic regression," in *Proceedings of the 3rd International Conference on Applied Artificial Intelligence and Computing (ICAAIC)*, 2024, pp. 1461–1466, doi: 10.1109/ICAAIC60222.2024.10575736.
[20] Z. Xia and M. Wu, "Radar automatic target open set recognition based on cluster boundary detection," *IEEE Access*, vol. 14, pp. 7365–7378, 2026, doi: 10.1109/ACCESS.2026.3652238.
[21] S. Mishra, H. Das, S. K. Mohapatra, S. B. Khan, M. Alojail, and M. Saraee, "A hybrid fused-KNN based intelligent model to access melanoma disease risk using indoor positioning system," *Scientific Reports*, vol. 15, no. 1, pp. 1–22, 2025, doi: 10.1038/s41598-024-74847-x.
[22] Y. Gong and X. Shen, "An algorithm for distracted driving recognition based on pose features and an improved KNN," *Electronics (Switzerland)*, vol. 13, no. 9, pp. 1–15, 2024, doi: 10.3390/electronics13091622.
[23] T. Daniya, M. Geetha, and K. S. Kumar, "Classification and regression trees with Gini index," *Advances in Mathematics: Scientific Journal*, vol. 9, no. 10, pp. 8237–8247, 2020, doi: 10.37418/amsj.9.10.53.
[24] J. Shafe-Purcell and A. D. Slepkov, "Boosted decision trees for non-resonant background removal in hyperspectral CARS microscopy," *Journal of Physics: Photonics*, vol. 7, no. 3, pp. 0–17, 2025, doi: 10.1088/2515-7647/adec28.
[25] Y. Lian, Y. Xu, L. Hu, Y. Wei, and Z. Wang, "Machine learning-based brain magnetic resonance imaging radiomics for identifying rapid eye movement sleep behavior disorder in Parkinson's disease patients," *BMC Medical Imaging*, vol. 25, no. 1, pp. 1–11, 2025, doi: 10.1186/s12880-025-01748-4.
[26] Y. E. Prawatya, N. H. Djanggu, R. Rahmahwati, and S. Lourensius, "Utilizing machine learning for predictive maintenance of production machinery in small and medium enterprises," *OPSI*, vol. 18, no. 1, pp. 91–100, 2025, doi: 10.31315/opsi.v18i1.13479.
[27] M. Heydarian, T. E. Doyle, and R. Samavi, "MLCM: multi-label confusion Matrix," *IEEE Access*, vol. 10, pp. 19083–19095, 2022, doi: 10.1109/ACCESS.2022.3151048.
[28] D. Valero-Carreras, J. Alcaraz, and M. Landete, "Comparing two SVM models through different metrics based on the confusion matrix," *Computers and Operations Research*, vol. 152, no. April 2022, p. 106131, 2023, doi: 10.1016/j.cor.2022.106131.

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