Bulletin of Electrical Engineering and Informatics
Vol. 15, No. 2, April 2026, pp. 1473~1483
ISSN: 2302-9285, DOI: 10.11591/eei.v15i2.9437

Improved no-line-of-sight static and dynamic sensor data classification using KNN algorithm with PLS model

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Article Info

Article history:

Received Oct 13, 2024
Revised Feb 18, 2026
Accepted Mar 5, 2026

Keywords:

Classification
Detection
K-nearest neighbour
No-line-of-sight
Search and rescue

ABSTRACT

The rising cases of structural collapses across the world have aggravated the problem of finding people under rubble as part of search and rescue (SAR) effort. The conventional search techniques, namely drill operation and the use of dog searching, are usually slow, labour-intensive and unsuccessful in difficult debris setting. Radar systems, though non-invasive, are limited by attenuation and multipath interference in non-line-of-sight (NLOS) environments. The proposed research will contribute to the improvement of victim recognition by creating an advanced machine learning (ML) model that will operate in the most challenging environmental settings. It suggests a modular prediction model combining both the K-nearest neighbor (KNN) and partial least squares (PLS) to extract features and reduce the dimensions. The procedure includes the derivation of essential signal characteristics, dataset validation, PLS application to get limited and discriminative feature amounts, and KNN classification under conditions of both fixed and dynamic conditions. Experimental findings indicate classification scores of 87.87 and 75.70 respectively in case of static and dynamic data. These results validate the practicability of the suggested solution in enhancing the forecasting accuracy during NLOS circumstances and emphasize its possible use in enhancing quicker, more dependable, and evidence-based official choices during the actual SAR operations.

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1. INTRODUCTION

The increasing frequency of artificial structure collapses worldwide has resulted in a rising number of individuals becoming trapped under rubble during such disasters [1], [2]. Locating victims in crises, especially when buried under debris, presents a significant challenge for search and rescue (SAR) personnel [3]. Traditional techniques, including drilling, canine search, and acoustic sensors, are time-consuming and often ineffective. In response, radars have been considered for their non-invasive, fast, and robust nature. However, the complex debris environment leads to signal attenuation and multipath interference [4].

Efficient post-disaster rescue actions are crucial for reducing fatalities in the face of natural catastrophes. Ongoing studies focus on effective techniques for reliable robotic navigation and monitoring in uncharted settings, emphasizing security, rescue missions, and protection [5]. Ultra-wide band (UWB) radar technology has shown good promise in identifying human targets through walls for various applications, including counterterrorism and emergency recovery efforts [6]. UWB radar, with its high definition, great penetrability, and low power consumption, is particularly suitable for detecting hidden objects and survivors under debris [7].

Despite advancements in sensor systems, current approaches using microphones, optical/thermal cameras, and doppler radar have limitations in accurately detecting human victims [8]. The rapid progress of artificial intelligence (AI) and machine learning (ML) offers new possibilities for making instant, data-driven decisions in disaster relief scenarios [9]. Techniques like locating stranded victims during non-line-of-sight (NLOS) SAR operations. The study's optimized dimensionality reduction framework scenarios make use of support vector machine (SVM) classification, independent component analysis (ICA), genetic algorithms (GA), and an adaptive human presence detector (AHPD) [10]. Feature selection strategies, tailored approaches for domain-specific applications [11]. Methods that integrate many algorithms also showed an increase in the accuracy of detection in difficult situations [12]. However, challenges such as dimensionality issues and overfitting persist.

Overfitting and the curse of dimensionality have been reported to impair the classification capacities of high-dimensional input spaces in the context of NLOS data processing. To address these issues, several dimensionality reduction techniques have been proposed in the literature to identify the best subset of genetic elements that can improve the interpretability of ruins and help uncover hidden patterns [13]. Finding a small subset of features that can enhance prediction performance is the aim of dimensionality reduction, which is essential for SAR operations in localization and decision-making [14]. By picking pertinent features, several researchers have tackled the curse of dimensionality by using various dimensionality reduction techniques in the analysis of NLOS human detection data. For feature selection and classification, hybrid dimensionality reduction techniques and metaheuristics have also been suggested.

However, they suffer from issues such as correlation, complexity, and increased computational time [15], [16]. A systematic approach for selecting an optimal subset of data is a crucial issue. Additionally, dimensionality reduction techniques, like as feature extraction [17], [18] (both linear and nonlinear), have been developed to boost performance and improve models [19].

To address these challenges, this study explores the application of ML, particularly dimensionality reduction techniques, to improve the accuracy of human detection during SAR missions. While various ML techniques, including convolutional neural networks (CNNs) and deep learning methods, have been proposed, documented experimental results suggest the need for further improvement [3].

Additionally, many detection-based techniques include pre-processing stages based on heuristics. These techniques use a database of well-known human models for training and detection, comparing attributes from the scene with those in the database. They primarily depend on reliable and descriptive qualities and are trained to recognize specific body postures. One ML technique for predicting group membership for data examples is classification, with various approaches available [20]. Techniques for reducing dimensionality have been developed and reported [21], [22]. Although current methods can produce results with high accuracy, they still need optimization for better performance, especially when dealing with large feature dimensions and massive datasets.

Several methods, including clutter removal, can enhance the ability to find people concealed behind debris. After removing insignificant scattering signals, the target reflections are retained. The efficiency of this strategy depends on the trajectory of the human target, despite its popularity due to simplicity. Some techniques rely on concepts such as subspace projection, compressed sensing, and spatial filtering [23], [24]. Optimization of exponentially weighted cancellation using the LMS method can efficiently handle target loss while the target is moving, though its design is intricate [25]. The singular value decomposition method requires significant computation but has a poor coupling degree with the target's movement form [26].

The objective of this study is to carry out an enhanced predictive performance of human detection classification through a dimensionality reduction model for predicting human victims trapped under rubble. This study presents an enhanced human detection predictive model through dimensionality reduction for detecting human victims trapped under debris. Partial least squares (PLS) is used to extract a subset of relevant features for more effective decision-making in SAR operations. The research also conducts a comparative performance analysis of data collected through static and dynamic sensors, examining the effect of uncorrelated features on sensor data collection.

2. MATERIALS AND METHOD

Several materials and techniques were employed in this study to enhance performance and improve human detection capabilities. The general workflow is described in Figure 1.

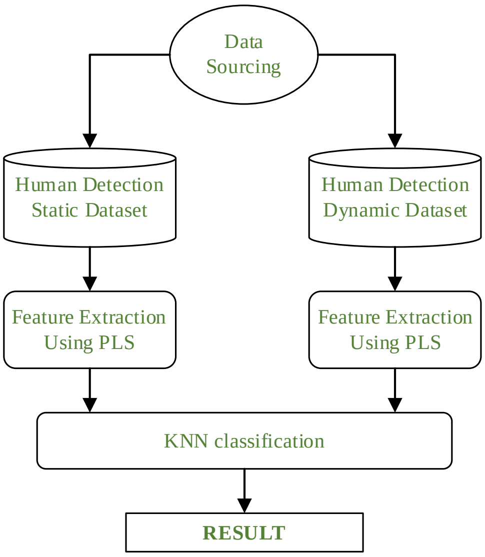

Figure 1. Workflow of the proposed technique

2.1. Materials

The dataset used in this study consists of 17,408 static and 23,522 dynamic instances, each containing 256 samples per attribute. The data was sourced from the Cesena campus of the University of Bologna and includes diverse elements such as various human body orientations, different building materials, and radar measurements at different distances, both in static and dynamic scenarios [27]. The dataset, openly accessible (GitHub - disi-unibo-nlp/uwb-nlos-human-detection: Dataset for "Human Being Detection from UWB NLOS Signals: Accuracy and Generality of Advanced Machine Learning Models") and previously utilized in [27], provides a comprehensive representation of real-world conditions.

This diverse dataset serves as a valuable resource for evaluating the proposed dimensionality reduction techniques. The inclusion of human body orientation, construction materials, and radar distances provides a realistic representation of the challenges encountered in NLOS environments.

2.2. Method

The study employs PLS regression and the K-nearest neighbor (KNN) classification algorithm for dimensionality reduction. These techniques are chosen for their capability to handle high-dimensional datasets and their potential to enhance the performance of human detection in NLOS scenarios. Table 1 gives a full description of the dataset used in this research.

Table 1. Dataset description

Attribute	Description
Dynamic instance	23,522
Sample per observation	256
Source	University of Bologna's Cesena Campus School of Engineering
Characteristics	Human body orientation, building materials, debris, and radar distances
Accessibility	Openly accessible dataset [27]

MATLAB was used as the experimental tool for evaluating the dataset obtained from [27]. PLS regression was applied to extract relevant features from the dataset. This step is crucial for keeping the most instructive aspects of the data while lowering its dimensionality.

After feature extraction, the reduced feature set was subjected to the KNN classification algorithm. This approach aims to leverage the strengths of both PLS and KNN to achieve an optimal balance between feature reduction and accurate classification in NLOS conditions [28]. By combining PLS for feature extraction and KNN for classification, the study seeks to increase the accuracy and efficiency of human detection in complex environments, such as those involving debris and obstructions.

2.3. Partial least squares feature extraction

A popular supervised feature extraction method for characterizing relationships between blocks of experimental variables using latent variables is PLS. PLS looks for high covariance linear transformations that are uncorrelated with the response variables, or latent components, of the original predictor variables [29]. Creating a linear relationship between the response variable (y) and the explanatory variables (x) is the main objective of PLS [30].

$$Y = X\beta + € \tag{1}$$

Where Y denotes the response variable, β is the loading, scores (latent variables), and € is the exceptional matrices that the original variables produced. PLS integrates the response parameter during the dimensionality reduction process, in contrast to other feature extraction techniques. This feature sets PLS apart as a supervised technique and closely matches it to the particular needs of this research. Crucially, PLS has been proven to perform better in analyzing and assessing NLOS human detection data [31].

2.4. K-nearest neighbor

Given its versatility and reliability, KNN was employed to classify features extracted through PLS. This is to achieve accurate classification in complex NLOS scenarios, where traditional line-of-sight methods may falter [29]. The steps taken for the execution are defined in phases 1 to 10 as depicted in Figure 2.

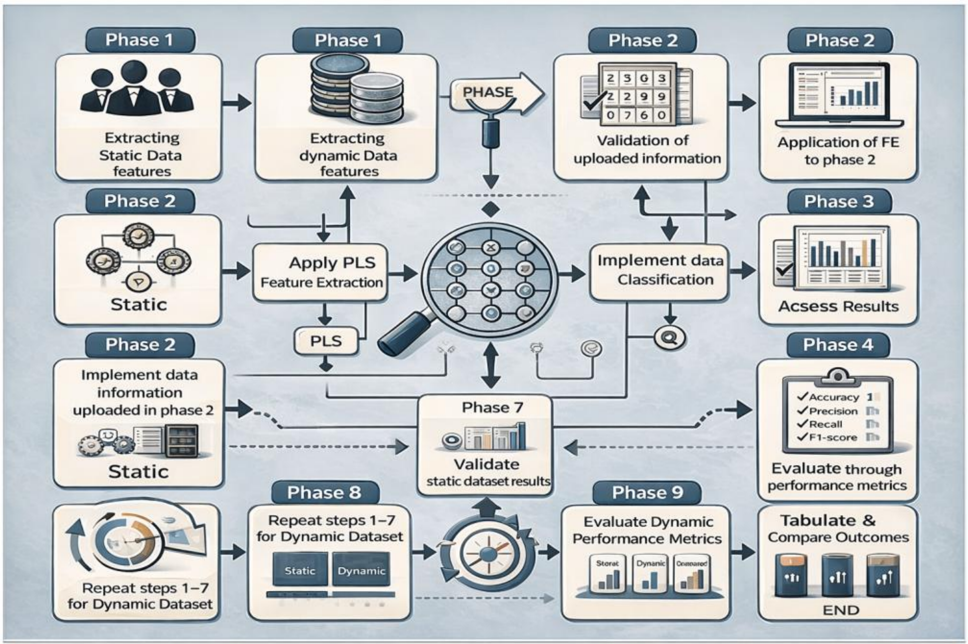

Figure 2. Flow diagram of the steps taken for the execution KNN classifier

Phase 1: extracting data feature parameters (static)
Phase 2: validate the static dataset information uploaded using MATLAB
Phase 3: application of the feature extraction (PLS) algorithm to the information from phase 2
Phase 4: implement the KNN classification on the phase 3 results
Phase 5: assess the results
Phase 6: evaluate the outcomes through performance metrics
Phase 7: validate the information uploaded
Phase 8: repeat steps 1 to 7 using the dynamic dataset
Phase 9: evaluate the outcomes through performance metrics
Phase 10: tabulate and compare outcomes

The process flow for the technique is as follows: features from static data are extracted, validated, and processed using MATLAB; PLS is used for feature extraction; KNN classification is implemented; results are assessed and evaluated; the same stages are then repeated for dynamic data, and the results are finally compared.

The flow diagram in Figure 2 illustrates the complete workflow of the KNN classifier utilized for features extracted alongside PLS. Effective dimensionality reduction, along with data reliability and robust classification performance, was achieved in the execution process, which consisted of ten sequential phases, for both static and dynamic datasets.

Phase 1: feature data extraction (static). The relevant parameters that were used as potential classification features (amplitude, time delay, phase, and signal strength) are all extracted in this initial phase, where raw radar or signal measurements from the static dataset are collected.

Phase 2: static data validation. The next step is data verification for missing values, normalization of the data, and ensuring reliability in the static dataset before proceeding with further processing. MATLAB was used for both preprocessing and feature extraction.

Phase 3: application of the feature extraction (PLS) algorithm to the information from phase 2. The validated data were reduced by applying PLS for dimensionality through regression. PLS identifies latent components that best describe the variance amongst input features and class labels, creating a compact, information-rich feature set.

Phase 4: implementation of KNN classifier. The KNN algorithm used the reduced features from the output PLS for prediction and data classification. KNN classifies each model by relating it to its nearest neighbors in the feature space, assigning it to the majority class among them.

Phase 5: initial result assessment. This stage ensures that the classification outputs are reviewed to ensure the model performs as projected. Misclassifications or anomalies are noted for further analysis.

Phase 6: performance evaluation. The key performance metrics used for the evaluation are and computation are accuracy, precision, recall, and F1-score. These metrics help to determine how the classifier (KNN) model performs in identifying victims in NLOS data signals.

Phase 7: static dataset validation. This phase helps in cross-checking for consistency and completeness of the validated and evaluated static dataset. The accuracy of the feature class and its associated is confirmed before applying it to the next process of the dynamic dataset.

Phase 8: dynamic data processing. Steps 1 to 7 are repeated using the dynamic dataset, which includes measurements at different time intervals representing moving targets or changing environments.

Phase 9: dynamic performance evaluation. Similar performance metrics are calculated for the dynamic instance. This permits direct contrast of KNN’s performance in static as opposed to dynamic NLOS settings.

Phase 10: comparative analysis and tabulation. The results obtained from the two datasets (static and dynamic) are tabulated and compared. Differences in classification accuracy, robustness, and reliability between static and dynamic conditions are highlighted to assess the overall efficiency of the KNN classifier and PLS dimensionality reduction.

3. PERFORMANCE EVALUATION

Assessing the performance of a ML model necessitates the use of validation metrics, with the confusion matrix being a fundamental tool, particularly in classification models. The confusion matrix allows for the analysis of four key features: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). These metrics unveil the correctly and incorrectly classified instances within the dataset sample used to test the model [32].

A model's accuracy is determined using four metrics: TP, FP, TN, and FN. When a human is present, the state is found via the TP product. When a person is absent, the state is determined by the output of FP. When there are no humans present, the TN product cannot locate the state. When humans are present, the FN product is unable to determine the state.

Accuracy: $(TP + TN) \,/\, (TP + TN + FP + FN)$ (2)

The number of appropriately identified cases with positive results is calculated by:

Sensitivity. $TP/(TP + FN)$ is the sensitivity (3)

Specificity determines the proportion of appropriately identified cases that have real drawbacks.

Specificity: $TN/(FP + TN)$ (4)

Particularity: $TN/(FP + TN)$ Accuracy: $TP/(TP + FP)$ Remember: $TP/TP + FN$

F1-Score: $2\ x\ (Precision\ x\ Recall) \,/\, (Precision + Recall)$ (5)

These metrics collectively offer a comprehensive assessment of the model's classification performance, considering both false and true positives and negatives. Proceeding with the evaluation, these metrics will be instrumental in gauging the efficacy of the PLS and KNN approaches in enhancing human detection accuracy in NLOS scenarios.

4. RESULTS AND DISCUSSION

The NLOS human detection dataset provides a valuable resource for identifying individuals trapped behind rubble, with potential applications across various domains. Leveraging ML technology, specifically advanced techniques implemented in MATLAB and optimized computer configurations, forms the basis for successful experimentation and analysis in predicting technology outcomes based on the NLOS human detection dataset. This study aims to synergize sophisticated methodologies, cutting-edge tools like MATLAB, and an appropriately configured computing environment to advance our understanding and application of NLOS human detection technology.

The effectiveness of the classification models is evaluated through KNN classification validation. 70% of the data is used for training, with 30% set aside for testing. To mitigate sample biases, a 10-fold cross-validation is implemented in MATLAB. Computational performance indicators, including accuracy, specificity, sensitivity, precision, F-score, and recall, are crucial metrics forming the basis of the evaluation's results. The performance metrics study was then used to assess the KNN confusion matrix. Figure 3 depicts the outcomes of the confusion matrix for dynamic datasets.

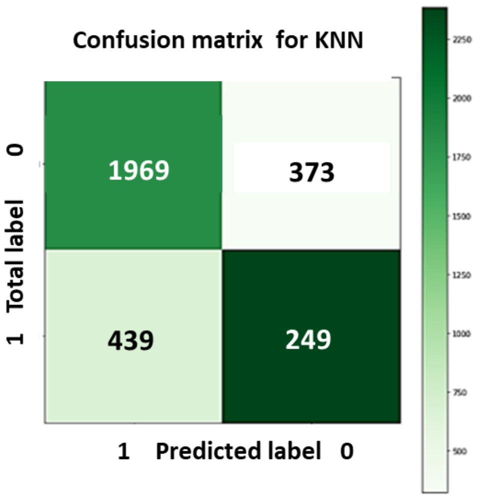

Figure 3. A confusion matrix outcome for the dynamically loaded dataset

The model is successful in identifying real victims, which is essential for disaster response, as demonstrated by the high TP (1969) result. Missing victims in actual disasters could mean the difference between life and death, even while FN is moderate. Additionally, an imbalance in classification power is suggested by the low TN of 249 cases, which may be the result of more positive than negative instances. Although the model is accurate at locating trapped people, it runs the danger of overlooking some (FN=439). Since saving lives outweighs the expense of false alarms, it is frequently appropriate in disaster response to prioritize recall above specificity. This outcome emphasizes the well-known trade-off between precision, recall, and specificity in ML for high-stakes situations (rubbles). Figure 4 describes the results of the confusion matrix for static datasets. This performance outlines that a smaller neighborhood size enhanced sensitivity to variations and noise typical of complex environments. Accordingly, the Kth value of 5 was determined to be optimal for the dynamic dataset, improving recall of victim signals, notwithstanding a slight increase in FP.

The model is quite good at accurately identifying non-victims, reducing the amount of rescue efforts spent, as evidenced by its high TN (3890) and specificity of less than 91%. The results indicate that a good TP of 994 is used to detect the majority of victims. A confusion matrix performance shows a FN of 281, meaning that 1 in 5 are missed. A balanced model across all classes is reflected in the overall performance. The confusion matrix for both static and dynamic datasets provide a detailed breakdown of the classifier's performance. The static dataset shows a higher accuracy (87.87%) compared to the dynamic dataset (75.70%), reflecting the challenges posed by the dynamic environment, such as noise and uncorrelated information. Table 2 presents the findings alongside the confusion matrix. These outcomes represent the model's training with a moderately high Kth value for the static dataset. This also smoothens the decision boundaries and minimizes overfitting. Consequently, the Kth value of 9 was identified as the optimal value for the static dataset, balancing the trade-off between bias and variance. This helps by reducing FP, but potentially misses some TP.

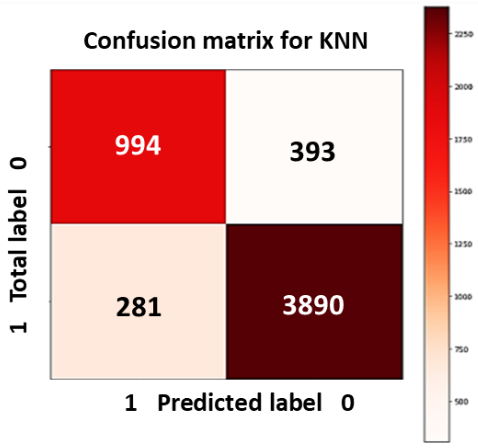

Figure 4. An outcome of the confusion matrix for the static loaded dataset

Table 2. Classification performance outcome

Performance metrics (%)	KNN classification (static)	KNN classification (dynamic)
Accuracy	87.87	75.70
Sensitivity	77.96	81.77
Specificity	90.82	41.70
Precision	71.67	87.82
Recall	93.26	36.19
F1-score	74.68	84.69
Matthew's correlation coefficient	66.83	26.60

The differences in optimal Kth values for static and dynamic settings underscore the impact of environmental stability on model behavior. Static scenarios benefit from broader neighborhood averaging for reliable classification, while dynamic conditions necessitate a narrower neighborhood to capture localized variations in signal reflections due to noise. These findings align with prior studies [33], which emphasize adaptive Kth value selection approaches for enhancing model generalization in NLOS detection tasks. Scholarly studies, as indicated by the performance measures in Figure 3, consistently demonstrate that employing a dimensionality reduction model through PLS enhances the output of KNN classification [34]. Figure 5 represents the comparative outcomes of the performance obtained from the confusion matrix for both dynamic and static datasets. The precision-recall-specificity trade-off that is essential to ML for crucial applications is demonstrated by the comparison of the dynamic and static outcomes derived from CFs. Life preservation (a few victims missing) is prioritized by a recall-optimized algorithm with a dynamic dataset, although rescue logistics are burdened. In a static dataset, a specificity-optimized model prioritizes efficiency (few false alarms), but it runs the risk of missing actual victims.

Applying traditional PLS improves performance by eliminating deformed and uneven data, with dynamics potentially more impacted by noise and uncorrelated information. Despite using the same sensor but in different configurations (static and dynamic), the static configuration exhibits better accuracy. Sensor attenuation may be caused by unfavorable weather, environmental factors that affect sensor technology, topography, sensor network topology, natural catastrophes, emergencies, physical or internal interference, or a lack of human presence. The evaluation suggests that KNN performs well for static data characteristics, highlighting the algorithm's suitability for specific scenarios.

The effectiveness of PLS feature extraction combined with KNN classification in improving human detection accuracy in NLOS scenarios is demonstrated in this study, with static datasets showing higher performance due to fewer dynamic interferences.

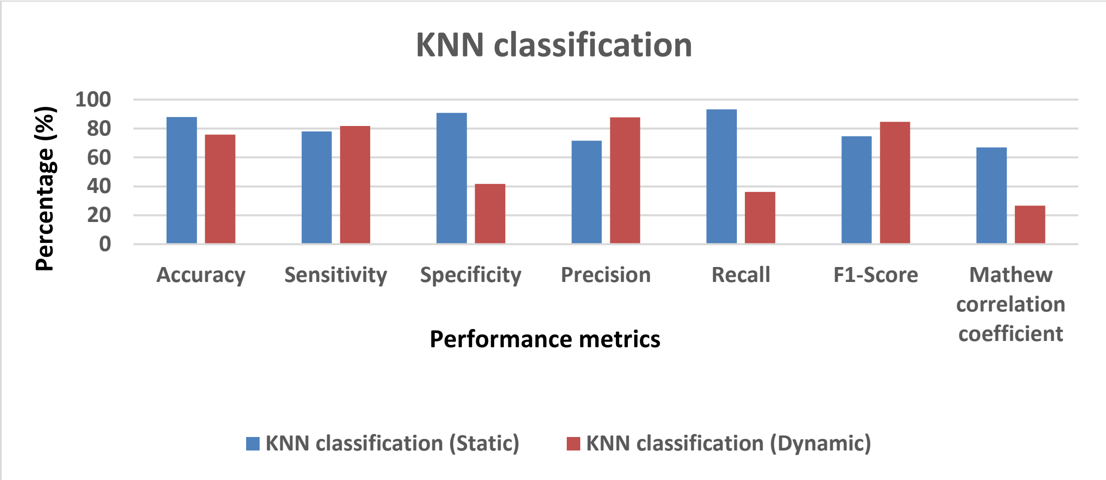

Figure 5. PLS feature extraction and KNN classification for static and dynamic output performances

4.1. Comparative analysis

Table 3 displays an evaluation and comparison of state-of-the-art methods for victim localization, highlighting the performance of various techniques as reported in the literature.

Table 3. The comparative methods

Methods	Accuracy (%)
SVM and ensemble [35]	81
KNN [36]	66
ANN [36]	66
SVM+autoencoder [37]	86.98
CNN+stacked-LSTM [11]	82.14
Proposed method	87.87

By integrating advanced algorithms and optimizing model architecture, this method enhances predictive accuracy and robustness. Unlike other methods, this technique offers computational effectiveness, which qualifies it for real-time victim localization during SAR missions. According to the accuracy metric in the NLOS dataset, the model outperforms alternative methods. In particular, the accuracy for static data increased to 87.87%, above the baselines with the greatest performance. We attribute the noteworthy enhancement to the proficient amalgamation of dimensionality reduction and hybridization methodologies, which enhance the precision and pertinence of localization. Additionally, its interpretability and adaptability to various environmental conditions further enhance its practical utility.

5. CONCLUSION

By combining PLS-based feature extraction and KNN classification for precise prediction, this study has improved the detection and prediction of human victims buried beneath debris with ML approaches. The findings suggest that data-driven techniques can be employed to enhance the precision and effectiveness of SAR operations.

Future research may focus on integrating this model with wearable sensors, autonomous systems, and smart environments to enhance situational awareness and facilitate real-time victim detection. Additionally, by including adaptive learning processes, the system will be able to help adapt to changing sensor settings and environments. At the same time, maintaining reliable performance in uncertain disaster scenarios will require controlling cross-sensor consistency and guaranteeing data reliability.

This research lays the groundwork for next-generation SAR technologies—systems that are not only more accurate but also responsive, durable, and prepared for real-world deployment—by connecting sophisticated algorithms with intelligent, adaptable platforms.

ACKNOWLEDGMENTS
The author expresses gratitude to Landmark University and the Faculty of Electrical Technology and Engineering, Universiti Teknikal Malaysia Melaka, for providing support for all necessary experiments conducted throughout this research work.

FUNDING INFORMATION
The authors gratefully acknowledge the support provided by the Faculty of Electrical Technology and Engineering, Universiti Teknikal Malaysia Melaka.

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

CONFLICT OF INTEREST STATEMENT
The authors declare that they have no competing interests.

DATA AVAILABILITY
The data that support the findings of this study are openly available at https://github.com/disiunibo-nlu/uwb-nlos-human-detection.

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