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Optimized human detection in NLOS scenarios using hybrid dimensionality reduction and SVM with UWB signals

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ABSTRACT

Trapped victim localization in search and rescue (SAR) operations is especially difficult in non-line-of-sight (NLOS) conditions, where traditional techniques fail due to debris and signal distortion. Ultra-wideband (UWB) NLOS signal datasets offer a promising alternative but are often high-dimensional and noisy. This study proposes an optimized dimensionality reduction framework combining an adaptive human presence detector (AHPD) with genetic algorithms (GA) and independent component analysis (ICA), followed by support vector machine (SVM) classification. The approach is tested on a public NLOS dataset comprising 23,522 dynamic instances, each with 256 signal samples per attribute, simulating complex SAR scenarios including rubble and dynamic obstacles. The results indicate that the AHPD+GA+SVM model reached an accuracy of 85.78%, sensitivity of 80.00%, and specificity of 96.46%, which is better than the AHPD+ICA +SVM model that had an accuracy of 79.20%, sensitivity of 73.07%, and specificity of 81.05%. These findings demonstrate the framework's robustness and scalability, making it a strong candidate for real-time human detection in disaster recovery missions.

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1. INTRODUCTION

A notable challenge in the analysis of search and rescue (SAR) operations lies in the aggregation of information originating from fast, independent, and severe-impact sources [1]. A prominent characteristic of the dataset is its extensive sample size, which encompasses a considerable quantity of redundant and superfluous noisy features [2], [3]. The presence of these arbitrary input signals detracts from the efficacy of classification-based learning approaches [4]. Methods for minimizing dimensionality have been employed on numerous occasions. Extracting relevant discriminative subsets from the data representation reduces computational demands and enhances the precision of classification predictions [5].

In the realm of dataset analysis, the phenomena of model overfitting and issues related to high-dimensional data are recognised as significant obstacles to optimal classification performance. The structure consists of a high-dimensional input space, often denoted as the curse of dimensionality. Numerous dimensionality reduction strategies have been used in the literature to overcome the curse of dimensionality challenges [6]. To uncover hidden elements and improve the interpretability of the images, the best feature combination must be chosen [7], [8]. The goal of dimensionality reduction is to identify a trivial subset of data that may improve prediction performance, which will aid engineers and SAR in localisation and decision-making [9].

The issues surrounding the curse of dimensionality have been covered by numerous writers. Although metaheuristics have also been presented, methods for collecting no-line-of-sight (NLOS) signal data subsets are challenged by strong correlations, high processing rates, and prolonged computation durations [10], [11]. Methodically identifying the ideal subset of data attributes is a major problem. The widely recognized methods for reducing dimensionality in feature extraction (FE) [12], [13] (supervised and unsupervised) and feature selection strategies, including filter, wrapper, and embedded methods [14] have resolved performance enhancement; however, further advancements in hybrid models and optimisation are required to achieve even better results [15]-[17]. The objective is to identify the best selected portion of data attributes aimed at managing high-dimensional optimisation problems and provide feasible solutions [6], [13].

Although GA has been widely utilised and is good at identifying the best-performing feature groups within high-dimensional datasets, it is computationally costly and susceptible to overfitting. To get around this limitation, optimisation techniques have been applied to provide improved outcomes in terms of choosing the best selected feature groups and the precision of classification [18]. A legitimate feature extraction technique that has been widely used as a capable standard method for extracting groups of feature samples used for classification purposes is independent component analysis (ICA) (linear), which has recently attracted more attention [19]. The hybrid approach's remarkable results and advantages demonstrate its value in addressing dimensional issues that hinder classification. Identifying or categorizing NLOS signal data and the analysis of expression data depend on the creation of effective models that are simple to use and compute quickly [20].

Numerous studies have been conducted and reported in the literature [21], [22]. However, given the prevalence of building collapses and trapped victims in West Africa, these studies need to be improved to aid in making decisions regarding the reduction of victim mortality in the region [23]. The commonly employed conventional target location and classification (TLC) methods depend heavily on understanding signal behavior and surrounding environmental conditions, despite their effectiveness in controlled situations. Because the manual calibration procedure can occasionally be time-consuming, it is not appropriate for erratic, extreme situations like earthquake debris. In addition, TLC modes exhibit reduced performance, especially when distinguishing low-reflective or stationary targets, since they lack the sophisticated methods for eliminating or minimizing signal interference needed to manage the greater degree of obstruction naturally present in non-line-of-sight scenarios. To more closely resemble human-generated content, it must make several changes that can add complexity and diversity.

To anticipate NLOS data signals, this paper suggests a hybrid dimensionality reduction method. Hybrid systems outperformed conventional methods based on scenario-specific parameterisation in each instance. Increased adaptability across a range of settings will result from the use involving adaptive noise suppression, self-adjusting parameter tuning, and continuous feature optimisation. When compared to other systems, the hybrid solution shown here has several advantages over traditional tracking localisation settings. However, the suggested under-rubble adaptive human presence detector (AHPD) method eliminates the need for intricate mathematical calculations or parameter searches by combining a genetic algorithm (GA) with ICA to flexibly respond to variations in environmental conditions. This is in line with new research findings that emphasise the necessity of machine learning-infused flexible models to attain higher generalisations in a range of situations.

Following the methods, the GA and ICA are applied after pertinent data subsets are extracted using an AHPD pseudocode that filters out noise and permits automated adjustments in amplitude to identify hidden components. AHPD with GA and AHPD with ICA combinations under rubble are classified using support vector machines (SVM) on an NLOS dataset. To help engineers and SAR teams make better judgments, this effort seeks to minimize challenges in prediction, including computational expenses, obtaining pertinent portions of the dataset, and interrelationships among variables. The other portions of this study consist of existing research, relevant materials, and methodology, the findings, discussions, and the conclusions.

2. ADAPTIVE ALGORITHM FOR HUMAN PRESENCE DETECTION IN UNDER-RUBBLE ENVIRONMENTS

The emitted ultra-wideband (UWB) pulse is significantly weakened, altered, and bounced back several times due to the nature of the rubble. Radar finds it challenging to detect small features amid the noise because of these issues. Preprocessing the raw data gathered from the environment using processing techniques is the first step in removing these barriers. For the proposed study, Algorithm 1 shows a flexible, dynamic system for detecting human presence.

Algorithm 1. Proposed flexible adaptive human presence detector

```
Step 1: Main loop
First step: 512 * n_pulses
First step: 256 n_samples
Step 1.3: dtpulse = 0.014
In step 1.4, breath_freq = [0.2, 0.7].
Step 1.5: amp_thresh = 0.5
Step 2: Determine the amplitude’s minimal threshold
Step 2.1: noise_thresh = 0.3
In step 3.0, set the noise threshold.
Step 3.1: The NFFT is 1024.
Step 3.2: For n_measures, use 10.
Step 4.0: Replace the actual quantity of measurements
Step 4: actual_targets = np.random.choice([0,1],n_measures)
Step 5: Replace the existing target values
In Step 5.1, CF = np.zeros((2,2)).
Step 6.0: The feature of noise filtering
In step 6.1, define filter_noise(data,noise_thresh):
If noise_thresh > np.max(data) in step 6.2, then
6.3: filtered_data = data - np.median(data)
Step 6.4: Should it happen that
Data = filtered_data in step 6.5
In step 7.6, return filtered_data.
Step 7.0: The method by which the measure detects the presence of humans
Step 7.1 is defined as Def
verify_human_presence_in_measure(measure,amp_thresh,breath_freq,noise_thresh,n_pulses,dtpul
se,NFFT,n_samples).
Step 8.0: Subtract the row and column averages.
Measure in Step 8.1 [:,np.newaxis] - Mdiff_measure- np.mean(axis=0), + np.mean(measure),
np.mean(measure,axis=1)
In step 9.0, apply noise filtering.
Step 9.1: Mfiltered_measure = np.zeros_like(Mdiff_measure)
Step 9.2: For i in range(Mdiff_measure.shape[1]),
The formula for step 9.3 is Mfiltered_measure[:,i] =
filter_noise(Mdiff_measure[:,i],noise_thresh).
Step 10.0: Use the FFT to determine the amplitude spectrum
Step 10.1: n_samples = Mfft_measure* / np.abs(np.fft.fft(Mfiltered_measure,NFFT,axis=0))
Step 11.0: Find the maximum amplitude and pulse index
Step 11.1: max_amp,pulse_idxmax_amp = np.max(Mfft_measure),np.argmax(Mfft_measure)
Step 11.2: i,_ = np.unravel_index(pulse_idxmax_amp,Mfft_measure.shape)
Step 12.0: Ascertain whether the potential target
Step 12.1 if max_amp > amp_thresh
Step 12.2: pred_freq = (i - 1) / (n_pulses * dtpulses)
In case breath_freq[0] <= pred_freq <= breath_freq[1], as stated in clause 12.3,
Step 12.4: Respond Truthfully
Step12.5: Return the false
Step 13.0: Update the Confusion Matrix
Step 13.2: def update_cf(predicted_target,actual_target,cf) if actual_target:
13.3: Is predicted_target supposed to be true?
Step 13.4: Increase cf[0,0] by 1
Step 13.5: Should it happen that
Step 13.6: cf[1,0] + 1
Step 13.7: Should it happen that
13.8: Should predicted_target come true:
Step 13.9: Increase cf[0,1] by 1
Step 13.10: In the absence of
13.11 Step: 1 + cf[1,1]
Step 13.12: Return with vigor cf
Step 13.13: For k in range(n_measures):
Step 13.14: Measure = np.random.rand(n_pulses,n_samples)
Step 14.0: Use authentic measurement information
In step 14.1, actual_target = actual_targets[k].
The presence of humans in the measure
(measure,amp_thresh,breath_freq,noise_thresh,n_pulses,dtpulse,NFFT,n_samples) is confirmed
by the predicted_target function at step 14.2.
14.3: CF = update_cf(predicted_target,actual_target,CF)
In step 14.4, print("Confusion Matrix:").
In step 14.5, print(CF).
```

From several phases of approach that assess the possibility of human presence, the suggested method finds human whereabouts. The algorithm carefully analyses every measurement to ascertain the probability of human presence after noise filtering. This thorough analysis guarantees the detection system’s resilience and efficacy in a range of situations and applications.

An Intel Core 5 CPU consisting of a 64-bit operating system and 16 GB of RAM is used for the testing in this research. The algorithm was written using the Python environment. To verify comparable training and testing performances of the experiments in terms of accuracy and sensitivity, among other metrics, the confusion matrices were employed as the classification evaluation [7].

3. MATERIALS AND METHOD

This section explains the methodology used for the investigation and concurrently. Gives an all-inclusive discussion of the materials used. Figure 1 presents the technique flow chart. While Table 1 displays the dataset description.

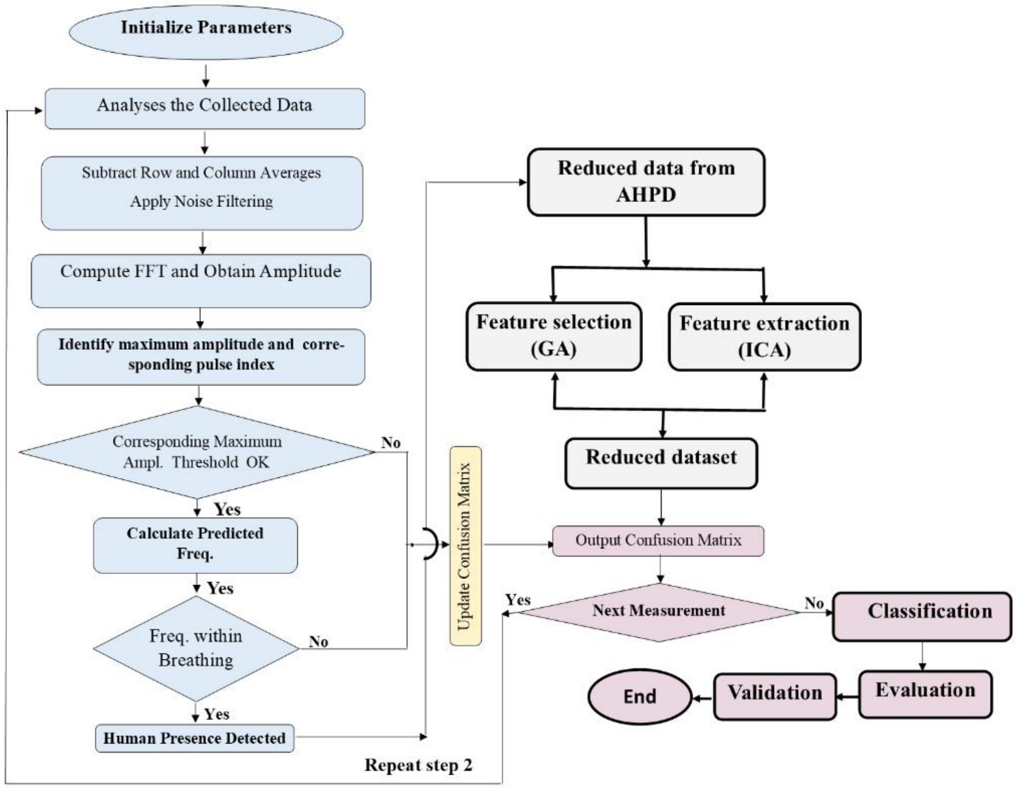

Figure 1. Proposed under-rubble AHPD for NLOS data human detection

3.1. Dataset

The investigation made use of the University of Bologna's freely available NLOS signal dataset collection for human detection buried under debris. It is composed of various types of detritus, ranging from glass cement-based materials and wood, and an oriented human body consisting 256 samples and 23,552 occurrences as described in Table 1.

Table 1. Features of the dataset

Dataset	Instances	Total number of samples collected per observed window
Dynamic radar values	23,552	256

3.2. Methodology

SAR, or through-wall human detection, is a widely used method for locating victims, particularly those hidden by debris. The ability to detect several aspects of hidden data is a key element of current high-throughput genetic factor technologies. It reacts to various training solutions and situations, generating sufficient sequencing data [24], and it detects subtle changes occurring in the conditions of buried victims, providing greater insight for inmates, rescue efforts, and improved detections [25]. People behind barriers can now be classified and evaluated thanks to the human detection prediction of NLOS signal data [26].

Due to the high-dimensional dataset, the detection problem is a key one that leads to unfitting conclusions for UWB data signals obtained from sensors. An NLOS signal dataset is used in this investigation. The Python application is used to analyse the data samples. The AHPD receives the samples. After that, a smaller sample is collected and fed into the GA and ICA independently. Training and testing sets are created using the reduced data. SVM is used for classification.

3.3. Dimensionality reduction

Dimensionality reduction is a widely used method for getting rid of extraneous features and undesirable noise. The high-dimensional features in the NLOS dataset are computationally intensive, which hinders the effectiveness of classification methods. Dimensionality reduction strategies are crucial for removing duplication and collecting unnecessary features that reduce activity efficiency by reducing the sample-to-feature ratios. This approach reduces the likelihood of overfitting. One important technique is feature extraction and collection, which lowers the dimensionality [27], [28].

3.4. Feature selection

Model testing and training depend on technologies such as NLOS signal data, which produce unique and pertinent feature IDs for transcript sequences. To improve classification performance, feature selection is crucial. Feature selection lessens the detrimental impacts of dimensionality and makes it possible to choose pertinent components for classification model performances by eliminating unnecessary and duplicate characteristics [29], [30]. It supports the learning process throughout the categorisation phase and improves the success model.

For example, both supervised and unsupervised decision-making learning are used in the massive information feature selection method that combines wall and SAR data. The prediction model's efficacy will be increased by using carefully chosen optimal rank attributes that communicate priority for categorisation jobs. One effective method known as a filter, wrapper, or embedded type is the collection of feature selection [31], [32].

3.5. Genetic algorithm

Engine optimisation problems are analysed using a genetic algorithm, which is an evolutionary method for choosing pertinent features based on wrappers. The persistence of the rightist paradigm-based genetic algorithms is built on real behaviours connected to human hereditary elements. Genetic algorithms include primary population advances, fitness evaluation, parent selection, crossover, and mutation [33], [34].

A GA is an exploratory discovery technique characterised by a straightforward procedure that generates a value appropriate for the primary objective of computing favourable findings by using a model of randomly generated results. In general, property sets that are represented as binary strings of 0 s and 1 s comprise wreckage or rubble [35]. Even though genetic algorithms are highly sensitive to the beginning population, they exhibit an optimality deficit. Although it has been revealed to yield sufficient eminence solutions to improve it for NLOS sampling, the quality of its output declines as the problem dimensions increase [36].

3.6. Feature extraction

Finding significant traits, attributes, or structures in data is known as feature extraction. Finding patterns and public events in an assembly of identifications are two examples of feature extraction strategies [37]. Feature extraction is used to obtain an additional detailed picture of the features while working with data that contains dimensional loads. The curse of dimensionality can be lessened by employing feature extraction to isolate revolutionary feature variables. In particular, there are two main categories of feature extraction techniques: linear (supposing a low-dimensional depiction resulting from high-dimensional features, comparably ICA) and non-linear (assuming data on a low-dimensional subspace, like PCA) for a non-linear relationship between features [19], [38].

3.7. Independent component analysis

By separating multivariate signals into distinct non-Gaussian components for statistically independent components, ICA can assist in revealing hidden features from multidimensional data. ICA embellishes the data by deleting or altering the relevant information to find a relationship amongst the bits of information [39]. A: ICA adopts opinion B as a straight-line combination of the individual parts. If B relates to the columns of C, then define the fundamental characteristic, the independent weighted matrix R, vectors of observation X.

$$A = RtoB, B = CtoS \quad (1)$$

ICA has been widely applied in information retrieval, recognition, through-wall applications, and SAR [40], [41]. GA is a non-linear optimization technique that reduces the number and dimensionality of features. Although GA is inherently non-linear, preprocessing enhances performance and allows ICA to operate as a linear technique [42].

4. CLASSIFICATION

One popular supervised learning tactic in data mining methods is classification. It entails class label assignment and prediction using predetermined class labels and available data. There are two steps in the categorisation procedure [43]. First, a class label and a collection of training data are used to develop a classification model. The accuracy of the SVM classifier is then assessed by using this model to predict class labels for data that has not yet been observed. The text provides definitions for the utilised equations.

4.1. Support vector machine

By identifying the best hyperplane in the input space, SVM aims to separate groups. By incorporating the kernel notions into high-dimensional workspaces, SVM, a linear classifier, is developed to handle non-linear scenarios. For non-linear scenarios, SVM uses a kernel to train the data in order to narrow the spread the dimension. When modifying the proportions, SVM should search for the best hyperplane that can distinguish one class from another [44]. By identifying the best hyperplane in the input space, SVM aims to separate groups. SVM, a linear classifier, is developed by combining the kernel concepts in high-dimensional workspaces to handle non-linear scenarios. SVM employs a kernel to train the data to narrow distribute the dimension for non-linear situations. SVM can find the optimal hyperplane and differentiate a class from other classes by adjusting the proportions [45].

The Gaussian kernel [46] is associated with the general assumption that all kth-order subordinates are smooth. To describe previous learning challenges, kernels that control a certain prior data recurrence material can be constructed. All of the polynomial extensions of the x components are included in the translation of each input vector, x, into an infinite-dimensional vector [47].

Adding dimensions to NLOS signal data is a major challenge to straightforward, trustworthy research techniques. When learning complex strategies on multiple levels that are influenced by morphological processes that are of interest, it is imperative to employ traditional ways. Most traditional approaches for handling high-dimensional data, like the NLOS signal data, have several problems. When a portion of data from one operation is added to the input of another, the application of different dimensionality reduction techniques can provide special advantages. Feature extraction techniques often employ feature selection or redundant signal data deletion to choose the original subset of data, respectively, so facilitate feature selection. It may be advantageous to extract primary subset features and combine many feature extraction techniques [38], [48].

This work proposed an efficient dimension reduction technique for NLOS signal data classification. This method has enormous promise for tracking down, identifying, and locating victims who are concealed beneath the ground. However, the structures become more apparent when the dimensionality is reduced. Data is still difficult to handle, though, and existing algorithms require improvement to exhibit the right characteristics. Although the fusion strategy offers benefits, it also necessitates the use of beneficial modelling techniques.

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The AHPD cypher text, features chosen, characteristics eliminated, and the class of the class are the four steps that have been suggested prior to the classification technique. The proposed hybrid system for the NLOS data human detection architecture, which predicts victims trapped behind debris using the NLOS signal dataset, is shown in Figure 1. Four subsystems make up the framework: one for class-based feature extraction, one for AHDP pseudocode, one for feature collecting, and one for classification. The function selection sub-system employs AHPD pseudocode, which filters noise using the first method and utilises GA to evaluate the fitness to identify an ideal subset. ICA is used by the function extraction subsystem due to its data projection of efficiency, invariance, and impertinent ordering. SVM is used to classify research standards.

The dynamic properties of the human detecting algorithm, which offer many search areas that independently and concurrently review the best result to produce a good result, are what make it important to optimise. To reduce the number of features in this study while preserving discriminating qualities, GA features were used. Reduced data are converted into latent components using the best feature extraction technique. Sadly, this reduces its productivity and invalidates both dimensionality reduction techniques for the dataset.

5. RESULTS AND DISCUSSION

Using a publicly available dataset containing 23,552 samples and 256 occurrences, as shown in Table 2, this research presents a Python-based tool for NLOS signal dataset classification [23]. A total of 481 features were extracted from the dynamic dataset as relevant features. The AHPD approach was employed to filter out noise and refine feature selection, thereby enhancing classification accuracy and efficiency. Figure 2 illustrates the proposed prediction framework for human detection data analysis.

Table 2. Comparative approaches

Methods employed	Accuracy (%)
CNN+stacked-LSTM [49]	82.14
AHPD+ GA+Bagged ensemble [50]	85.69
FE+SVM [51]	83.00
SVM+Ensemble [51]	81.00
AHPD+GA+SVM (proposed model)	85.78

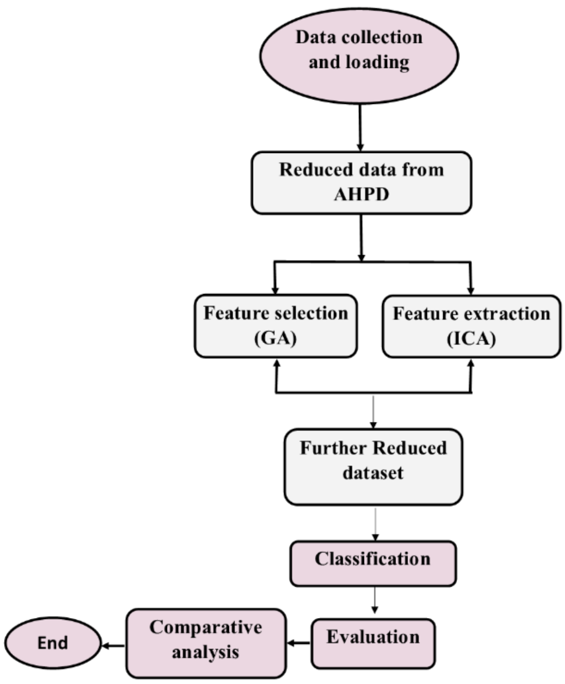

Figure 2. Proposed complete framework flow for human detection data analysis

A 0.5 threshold was applied as a decision boundary in classification tasks to determine whether a detected signal corresponds to human breathing. This thresholding mechanism ensures that only signals with sufficient confidence are classified as breathing, thereby improving detection reliability. By implementing this threshold, the system effectively minimizes false positives, which could misidentify non-human signals such as machinery vibrations or environmental noise as breathing. Additionally, false negatives, which occur when real human breathing is not detected, are reduced by optimizing the system’s sensitivity within the specified frequency range.

Furthermore, the breath frequency range was set at [0.2, 0.7] Hz to enhance SAR effectiveness, particularly in disaster scenarios where victims may have weakened or irregular breathing patterns. Individuals trapped under rubble due to structural collapses may experience slow or rapid breathing as a result of trauma, panic, or oxygen deprivation. By expanding the breath frequency range, the system becomes more adaptive to diverse physiological conditions, thereby improving its robustness in real-world search and rescue applications. The selected range ensures that even subtle respiratory signals are detected, increasing the likelihood of successful human presence identification in complex and noisy environments.

The dataset was evaluated using state-of-the-art machine learning classifiers, with an emphasis on optimizing hyperparameters for improved performance. GA-based feature selection was applied to refine the dataset by selecting only the most relevant features, thus reducing dimensionality and enhancing classification accuracy. Through this optimization process, the ideal number of neighbors (n_neighbors) was identified as 11 for the SVM classifier. This value provided the best trade-off between bias and variance, ensuring a balance between model complexity and generalization. The use of GA further enhanced classification performance by optimizing feature selection and ensuring robust generalization across dynamic datasets. This study underscores the effectiveness of integrating dimensionality reduction techniques with machine learning classifiers to improve NLOS human detection in search and rescue operations. Figure 3 shows the confusion matrices for AHPD+GA+SVM.

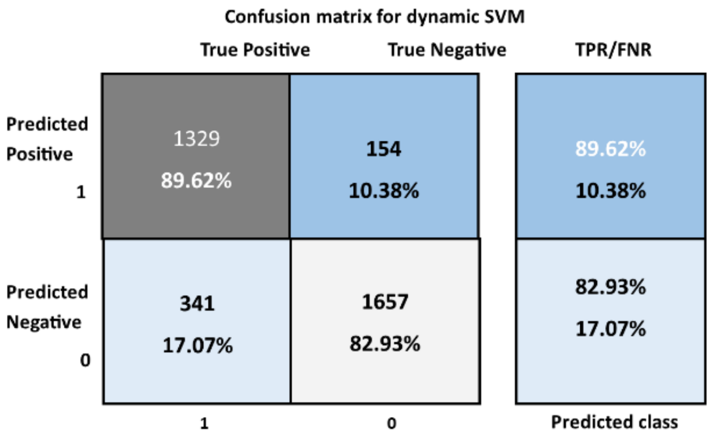

Figure 3. Confusion matrix for AHPD with GA and SVM (dynamic) TP=1329; TN=1657; FP=154; FN=341

The SVM classification technique with validation was used to predict the outcomes of the extracted features. To evaluate prediction models, this approach separates the given sample into training and testing sets. Performance indicators were then used to assess the SVM confusion matrix. Additionally, the filtered AHPD features were subjected to the GA method and the ICA variables. The confusion matrix was evaluated following the classification of the latent features using SVM with cross-validation. The algorithms AHPD +GA+SVM and AHPD+ICA+SVM were tested on the NLOS signal dataset. Figure 4 display the ROC for ICA-SVM performance

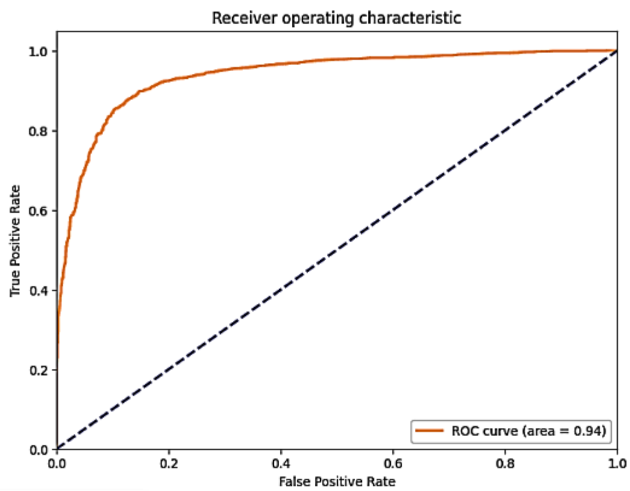

Figure 4. A ROC curve of the SVM attributes with ICA

Numerous researchers have employed machine learning approaches to address fundamental classification problems and develop reliable detection and prediction strategies for identifying trapped victims. Figure 5 depicts the confusion matrices for AHPD+ICA+SVM. The results presented in Figure 6 demonstrate an improvement over the previous method. Compared to the state-of-the-art, the accuracy improved (Table 2). When a GA for feature selection was used in conjunction with an SVM classifier, the AHPD system demonstrated significant performance improvements, particularly for the dynamic dataset.

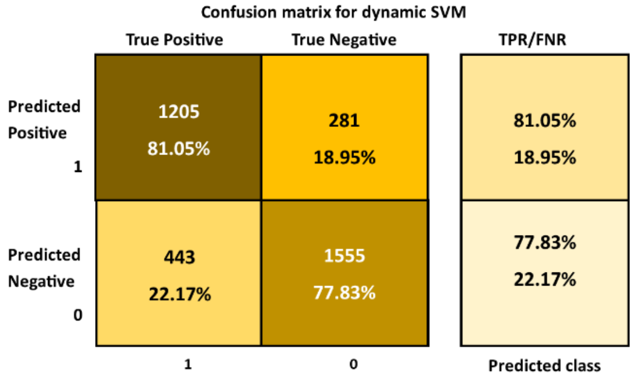

Figure 5. Confusion matrix for AHPD with ICA and SVM (dynamic data) TP=1202; TN=1555; FP=281; FN=443

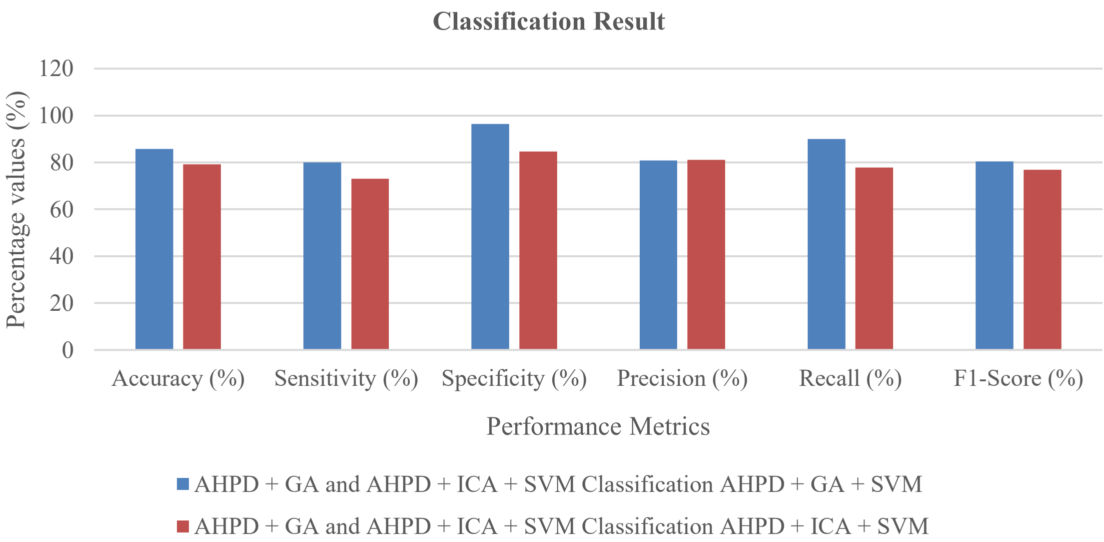

Figure 6. Performance metrics classification result for the experiment

The AHPD+GA+SVM model achieved the highest performance, with an accuracy of 85.78%. This implies that it has a strong ability to correctly predict both the presence and absence of humans trapped behind rubble. The high accuracy suggests that GA effectively selects the most relevant features while removing redundant or noisy data caused by NLOS signal reflections, leading to improved classification efficiency. The ability to correctly detect the presence of trapped victims (sensitivity) is 80.00%. This means the system is effective in minimizing false negatives, which is crucial in SAR missions where the inability to detect a trapped individual could have life-threatening consequences. The model is robust against false alarms, as it demonstrates a high capability (96.46%) in correctly identifying non-human presence (specificity), making it highly reliable for real-world deployment in disaster scenarios. This reduces unnecessary resource allocation, ensuring that rescue teams focus on actual human presence rather than false detections. Figure 6 contains the list of performance evaluation results from the experiments.

The precision of 80.82% indicates that 80.82% of the model's human presence classifications were correct, showing that the predictions made were generally reliable. The balance between precision and sensitivity is essential in applications where both minimizing false positives and maximizing true positives are necessary. The recall (90.00%) is the highest among all the evaluated metrics, highlighting that the model successfully identified a high proportion of true human presence cases. This is particularly important in SAR operations, where missing a trapped victim could delay rescue efforts and reduce survival chances. The F1-score of 80.41% confirms strong classification performance, showing a good balance between precision and recall. This means that the model maintains overall effectiveness, making it suitable for complex, noisy environments where accurate human presence detection is critical.

The AHPD+ICA+SVM model demonstrated slightly lower performance, achieving an accuracy of 79.20%. This suggests that while ICA is somewhat effective in extracting meaningful features, it may retain some redundant or noisy components, leading to reduced classification accuracy. The 73.07% sensitivity indicates that the model is less effective than the GA-based model in detecting human presence, which could increase the likelihood of false negatives. The model has a tendency (84.69%) to misclassify non-human signals as human presence (specificity), potentially leading to more false alarms. The precision of 81.05% suggests that when the model does classify human presence, it is relatively confident in its prediction. However, the recall (77.83%) indicates that the model is less effective at capturing all instances of human presence. The F1-score of 76.85% suggests a weaker overall balance between precision and recall.

The performance of AHPD+ICA+SVM suggests that ICA is less effective than GA in feature extraction for human detection in NLOS environments. However, the superior performance of AHPD+GA+SVM indicates that using a GA for feature selection enhances the model's ability to distinguish between relevant and irrelevant features, leading to improved generalization and robustness in classifying human presence in challenging NLOS conditions.

The accuracy of the GA-SVM hybrid increased significantly (by 6.58%) from 79.20% to 85.78% in a complex and dynamic scenario compared to ICA. Sensitivity rose from 73.07% to 80.00%, demonstrating GA's ability to optimize feature selection. Additionally, the F1-score (80.41) improved, indicating a better balance between precision and recall. These results emphasize the importance of feature selection in dealing with complex scenarios where irrelevant features could obscure important patterns.

The AHPD with GA and SVM appears to be a reliable technique for through-wall detection. To further improve performance, future work should focus on noise reduction strategies and additional feature refinement techniques. These findings highlight the potential of GA-enhanced SVM models for NLOS human detection, particularly in search and rescue applications where accurate victim identification is critical.

6. COMPARATIVE ANALYSIS

This work provides a better way to make observations than more traditional approaches. Furthermore, it can provide a more precise assessment of human detection and localization during search-and-rescue operations. Table 2 shows how this study compares to other approaches that have been reported in the literature.

7. CONCLUSION

This study proposes a hybrid dimensionality reduction approach combining AHPD, GA, and ICA, integrated with SVM classification, to enhance victim localization in NLOS scenarios for SAR operations. The AHPD+GA+SVM model achieved superior performance with an accuracy of 85.78%, demonstrating its potential as a scalable and robust solution for real-time disaster response.

Despite promising results, the model was tested on controlled datasets, and its real-time adaptability in unstructured environments remains to be validated. Limitations include potential computational overhead and challenges with sensor reliability in practical scenarios. Future research should explore real-world testing, lightweight model optimization, deep learning integration, and multi-sensor fusion to improve the system's robustness and deployability in actual SAR missions.

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C: **C**onceptualization
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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 competing interests.

DATA AVAILABILITY

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

REFERENCES

[1] D. Mishra and E. Natalizio, “A survey on cellular-connected UAVs: Design challenges, enabling 5G/B5G innovations, and experimental advancements,” *Computer Networks*, vol. 182, p. 107451, Dec. 2020, doi: 10.1016/j.comnet.2020.107451.
[2] X. Xu, X. Wu, F. Wei, W. Zhong, and F. Nie, “A general framework for feature selection under orthogonal regression with global redundancy minimization,” *IEEE Transactions on Knowledge and Data Engineering*, vol. 34, no. 11, pp. 5056–5069, Nov. 2022, doi: 10.1109/TKDE.2021.3059523.
[3] J. Maillo, I. Triguero, and F. Herrera, “Redundancy and complexity metrics for big data classification: towards smart data,” *IEEE Access*, vol. 8, pp. 87918–87928, 2020, doi: 10.1109/ACCESS.2020.2991800.
[4] J. Ko and S. Lee, “SAR image despeckling using continuous attention module,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 15, pp. 3–19, 2022, doi: 10.1109/JSTARS.2021.3132027.
[5] S. Velliangiri, S. Alagumuthukrishnan, and S. I. T. Joseph, “A review of dimensionality reduction techniques for efficient computation,” *Procedia Computer Science*, vol. 165, pp. 104–111, 2019, doi: 10.1016/j.procs.2020.01.079.
[6] W. Jia, M. Sun, J. Lian, and S. Hou, “Feature dimensionality reduction: a review,” *Complex and Intelligent Systems*, vol. 8, no. 3, pp. 2663–2693, 2022, doi: 10.1007/s40747-021-00637-x.
[7] J. A. Enoch, I. B. Oluwafemi, F. A. Ibikunle, O. K. Paul, I. O. Yusuf, and A. O. Michael, “An efficient no-line-of-sight learning approach for prediction of static victim detection using genetic algorithm and kth nearest neighbor data classification,” in *2024 International Conference on Science, Engineering and Business for Driving Sustainable Development Goals (SEB4SDG)*, IEEE, Apr. 2024, pp. 1–6. doi: 10.1109/SEB4SDG60871.2024.10630421.
[8] J. Podani, T. Kalapos, B. Barta, and D. Schmera, “Principal component analysis of incomplete data – A simple solution to an old problem,” *Ecological Informatics*, vol. 61, 2021, doi: 10.1016/j.ecoinf.2021.101235.
[9] W. Shi and G. Wu, “New algorithms for trace-ratio problem with application to high-dimension and large-sample data dimensionality reduction,” *Machine Learning*, vol. 113, no. 7, pp. 3889–3916, Jul. 2024, doi: 10.1007/s10994-020-05937-w.
[10] J. Liu, G. Teng, and F. Hong, “Human activity sensing with wireless signals: a survey,” *Sensors*, vol. 20, no. 4, p. 1210, Feb. 2020, doi: 10.3390/s20041210.
[11] S. Zekavat *et al.*, “An overview on position location: past, present, future,” *International Journal of Wireless Information Networks*, vol. 28, no. 1, pp. 45–76, Mar. 2021, doi: 10.1007/s10776-021-00504-z.
[12] A. M. Alhassan and W. M. N. Wan Zainon, “Review of feature selection, dimensionality reduction and classification for chronic disease diagnosis,” *IEEE Access*, vol. 9, pp. 87310–87317, 2021, doi: 10.1109/ACCESS.2021.3088613.
[13] G. Manikandan and S. Abirami, “Feature selection is important: state-of-the-art methods and application domains of feature selection on high-dimensional data,” in *EAI/Springer Innovations in Communication and Computing*, 2021, pp. 177–196. doi: 10.1007/978-3-030-35280-6_9.
[14] P. Boonyakitanont, A. Lek-uthai, K. Chomtho, and J. Songsiri, “A review of feature extraction and performance evaluation in epileptic seizure detection using EEG,” *Biomedical Signal Processing and Control*, vol. 57, p. 101702, Mar. 2020, doi: 10.1016/j.bspc.2019.101702.
[15] K. S. M. H. Ibrahim, Y. F. Huang, A. N. Ahmed, C. H. Koo, and A. El-Shafie, “A review of the hybrid artificial intelligence and optimization modelling of hydrological streamflow forecasting,” *Alexandria Engineering Journal*, vol. 61, no. 1, pp. 279–303, Jan. 2022, doi: 10.1016/j.aej.2021.04.100.
[16] M. Thirunavukkarasu, Y. Sawle, and H. Lala, “A comprehensive review on optimization of hybrid renewable energy systems

using various optimization techniques," *Renewable and Sustainable Energy Reviews*, vol. 176, p. 113192, Apr. 2023, doi: 10.1016/j.rser.2023.113192.
[17] H. Mengmeng, L. Fang, Y. Aihuan, and M. Xianfa, "Review of hybrid model used in SAR target recognition," in *2020 2nd International Conference on Information Technology and Computer Application (ITCA)*, IEEE, Dec. 2020, pp. 746–750. doi: 10.1109/ITCA52113.2020.00160.
[18] M. Chiesa, G. Maioli, G. I. Colombo, and L. Piacentini, "GARS: genetic algorithm for the identification of a robust subset of features in high-dimensional datasets," *BMC Bioinformatics*, vol. 21, no. 1, p. 54, Dec. 2020, doi: 10.1186/s12859-020-3400-6.
[19] M. P. Uddin, M. Al Mamun, and M. A. Hossain, "PCA-based feature reduction for hyperspectral remote sensing image classification," *IETE Technical Review*, vol. 38, no. 4, pp. 377–396, Jul. 2021, doi: 10.1080/02564602.2020.1740615.
[20] G. Moro, F. Di Luca, D. Dardari, and G. Frisoni, "Human being detection from UWB NLOS signals: accuracy and generality of advanced machine learning models," *Sensors*, vol. 22, no. 4, p. 1656, Feb. 2022, doi: 10.3390/s22041656.
[21] Z. Afroze and D. W. Matolak, "LOS-to-NLOS channel transition measurements, analysis and characterization for the 90 GHz band," *IEEE Transactions on Vehicular Technology*, vol. 73, no. 5, pp. 6073–6082, May 2024, doi: 10.1109/TVT.2023.3347074.
[22] F. Che *et al.*, "Feature-based generalized Gaussian distribution method for NLoS detection in ultra-wideband (UWB) indoor positioning system," *IEEE Sensors Journal*, vol. 22, no. 19, pp. 18726–18739, Oct. 2022, doi: 10.1109/JSEN.2022.3198680.
[23] R. W. Byard, "Environmental issues," in *Forensic and Legal Medicine*, Boca Raton: CRC Press, 2023, pp. 235–243. doi: 10.1201/9781003138754-31.
[24] Cristin R, "Hybridized algorithm: spectrum sensing and minimization of PAPR in the MIMO system," *Journal of Networking and Communication Systems (JNACS)*, vol. 3, no. 2, pp. 18–26, Apr. 2020, doi: 10.46253/jnacs.v3i2.a3.
[25] N. Feiner, M. Brun-Usan, and T. Uller, "Evolvability and evolutionary rescue," *Evolution & Development*, vol. 23, no. 4, pp. 308–319, Jul. 2021, doi: 10.1111/ede.12374.
[26] B. Deng, M. Yan, and T. Xu, "A parallel deep learning based NLOS identification method using CIR signal," in *2023 42nd Chinese Control Conference (CCC)*, IEEE, Jul. 2023, pp. 8312–8317. doi: 10.23919/CCC58697.2023.10240284.
[27] P. Selvaraj and S. Sivaprakash, "Feature extraction and feature selection in medical images," in *Intelligent Computing Techniques in Biomedical Imaging*, Elsevier, 2025, pp. 83–97. doi: 10.1016/B978-0-443-15999-2.00008-6.
[28] M. Zulfiqar, M. Kamran, M. B. Rasheed, T. Alquthami, and A. H. Milyani, "A hybrid framework for short term load forecasting with a navel feature engineering and adaptive grasshopper optimization in smart grid," *Applied Energy*, vol. 338, p. 120829, May 2023, doi: 10.1016/j.apenergy.2023.120829.
[29] U. M. Khaire and R. Dhanalakshmi, "Stability of feature selection algorithm: a review," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 4, pp. 1060–1073, Apr. 2022, doi: 10.1016/j.jksuci.2019.06.012.
[30] R.-C. Chen, C. Dewi, S.-W. Huang, and R. E. Caraka, "Selecting critical features for data classification based on machine learning methods," *Journal of Big Data*, vol. 7, no. 1, p. 52, Dec. 2020, doi: 10.1186/s40537-020-00327-4.
[31] O. O. Ogundile, A. M. Usman, O. P. Babalola, and D. J. J. Versfeld, "Dynamic mode decomposition: A feature extraction technique based hidden Markov model for detection of Mysticetes' vocalisations," *Ecol. Inform.*, vol. 63, p. 101306, 2021.
[32] V. C P and A. A. Chikkamannur, "Redundancy and complexity metrics for big data classification: towards smart data," *International Journal of Engineering Trends and Technology*, vol. 69, no. 2, pp. 165–170, Feb. 2021, doi: 10.14445/22315381/IJETT-V69I2P223.
[33] W. Shu, Z. Yan, J. Yu, and W. Qian, "Information gain-based semi-supervised feature selection for hybrid data," *Applied Intelligence*, vol. 53, no. 6, pp. 7310–7325, 2023, doi: 10.1007/s10489-022-03770-3.
[34] B. Alhijawi and A. Awajan, "Genetic algorithms: theory, genetic operators, solutions, and applications," *Evolutionary Intelligence*, vol. 17, no. 3, pp. 1245–1256, 2024, doi: 10.1007/s12065-023-00822-6.
[35] A. Vie, A. M. Kleinnijenhuis, and D. J. Farmer, "Qualities, challenges and future of genetic algorithms: a literature review," 2020, [Online]. Available: http://arxiv.org/abs/2011.05277
[36] T. M. Shirajuddin, N. S. Muhammad, and J. Abdullah, "Optimization problems in water distribution systems using non-dominated sorting genetic algorithm II: an overview," *Ain Shams Engineering Journal*, vol. 14, no. 4, p. 101932, Apr. 2023, doi: 10.1016/j.asej.2022.101932.
[37] X. Zhao, Z. Tang, F. Cao, C. Zhu, and J. Periaux, "An efficient hybrid evolutionary optimization method coupling cultural algorithm with genetic algorithms and its application to aerodynamic shape design," *Applied Sciences*, vol. 12, no. 7, p. 3482, Mar. 2022, doi: 10.3390/app12073482.
[38] W. K. Mutlag, S. K. Ali, Z. M. Aydam, and B. H. Taher, "Feature extraction methods: a review," *Journal of Physics: Conference Series*, vol. 1591, no. 1, p. 012028, Jul. 2020, doi: 10.1088/1742-6596/1591/1/012028.
[39] R. Zebari, A. Abdulazeez, D. Zeebaree, D. Zebari, and J. Saeed, "A comprehensive review of dimensionality reduction techniques for feature selection and feature extraction," *Journal of Applied Science and Technology Trends*, vol. 1, no. 1, pp. 56–70, May 2020, doi: 10.38094/jastt1224.
[40] M. Wu, S. Hu, B. Wei, and Z. Lv, "A novel deep learning model based on the ICA and Riemannian manifold for EEG-based emotion recognition," *Journal of Neuroscience Methods*, vol. 378, p. 109642, Aug. 2022, doi: 10.1016/j.jneumeth.2022.109642.
[41] C. Hashemi, R. Avelar, and J. Leger, "Isolating signals in passive non-line-of-sight imaging using spectral content," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 47, no. 9, pp. 7328–7339, Sep. 2025, doi: 10.1109/TPAMI.2023.3301336.
[42] S. Shahrestani, D. R. Cohen, and A. R. Mokhtari, "A comparison of PCA and ICA in geochemical pattern recognition of soil data: the case of Cyprus," *Journal of Geochemical Exploration*, vol. 264, p. 107539, Sep. 2024, doi: 10.1016/j.gexplo.2024.107539.
[43] S. Verma, O. Ahmad, and A. Sharan, "Multilabel text classification in biomedical domain," in *Text Mining Approaches for Biomedical Data. Transactions on Computer Systems and Networks*, A. Sharan, N. Malik, H. Imran, and I. Ghosh, Eds., Singapore: Springer, 2024, pp. 299–326. doi: 10.1007/978-981-97-3962-2_14.
[44] H. Aydadenta and Adiwijaya, "On the classification techniques in data mining for microarray data classification," *Journal of Physics: Conference Series*, vol. 971, no. 1, p. 012004, Mar. 2018, doi: 10.1088/1742-6596/971/1/012004.
[45] S. Lukman, "Optimal kernel function for high speed rail received signal level dataset," *International Journal on Electrical Engineering and Informatics*, vol. 16, no. 3, pp. 442–454, Sep. 2024, doi: 10.15676/ijeei.2024.16.3.7.
[46] C. D. A. Vanitha, D. Devaraj, and M. Venkatesulu, "Gene expression data classification using support vector machine and mutual information-based gene selection," *Procedia Computer Science*, vol. 47, no. C, pp. 13–21, 2015, doi: 10.1016/j.procs.2015.03.178.
[47] A. M. Olaolu, S. O. Abdulsalam, I. R. Mope, and G. A. Kazeem, "A comparative analysis of feature selection and feature extraction models for classifying microarray dataset," *Computing and Information Systems*, vol. 22, no. 2, pp. 29–39, 2018.
[48] S. Djosic, I. Stojanovic, M. Jovanovic, and G. L. Djordjevic, "Multi-algorithm UWB-based localization method for mixed

LOS/NLOS environments," *Computer Communications*, vol. 181, pp. 365–373, Jan. 2022, doi: 10.1016/j.comcom.2021.10.031.
[49] C. Jiang, J. Shen, S. Chen, Y. Chen, D. Liu, and Y. Bo, "UWB NLOS/LOS classification using deep learning method," *IEEE Communications Letters*, vol. 24, no. 10, pp. 2226–2230, Oct. 2020, doi: 10.1109/LCOMM.2020.2999904.
[50] E. A. Jiya and I. B. Oluwafemi, "Advanced genetic algorithm (GA)-independent component analysis (ICA) ensemble model for predicting trapped humans through hybrid dimensionality reduction," *Scientific African*, vol. 27, p. e02564, Mar. 2025, doi: 10.1016/j.sciaf.2025.e02564.
[51] R. Thakur and P. Panse, "Classification performance of land use from multispectral remote sensing images using decision tree, k-nearest neighbor, random forest and support vector machine using EuroSAT data," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 10, no. 1s, pp. 67–77, 2022.

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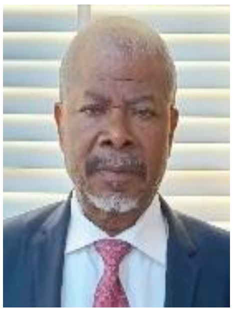

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