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Enhanced dimensionality reduction methods for classifying UWB NLOS signals dataset using KNN classifier

Enoch Adama Jiya[1], Ilesanmi B. Oluwafemi[2], Kazeem O. Oyebode[3], Oluwafemi Emmanuel Oni[3]
[1]Department of Electrical and Electronics Engineering, Niger State Polytechnic, Zungeru, Nigeria
[2]Department of Electrical and Electronic Engineering, Ekiti State University, Ado Ekiti, Nigeria
[3]Electrical and Computer Engineering, University of Zululand, Richards Bay Campus, Richards Bay, South Africa

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ABSTRACT

Ultra-wideband (UWB) radar-based non-line-of-sight (NLOS) signal analysis has great promise in the field of search and rescue (SAR) for detecting and identifying trapped victims who may be located outside of the line of sight (LOS). When UWB signals are transmitted, however, they may be distorted, attenuated, and multiply reflected by rubble and other obstructing materials, creating complex, noisy, high-dimensional datasets that may lower the accuracy and efficiency of human detection systems. This study is designed to propose an optimal hybrid dimensionality-reduction and classification method to increase the analysis accuracy of UWB NLOS data. The optimized adaptive human presence detector (AHPD), combined with the genetic algorithm (GA) feature selection and independent component analysis (ICA) feature extraction methods, were used to identify relevant feature subsets and the uncorrelated signal components in the signal. The reduced feature representations were then classified by using the k-nearest neighbour (KNN) algorithm. All proposed models have been tested by the standard classification performance measures and compared to each other to find the one more efficient in identifying human presence in complex NLOS environments. The accuracy, sensitivity, and specificity results obtained from the AHPD-ICA-KNN model was at 83.40%, 75.84%, and 91.04%, respectively. The results presented here show the feasibility of the proposed hybrid method of reducing feature dimensionality and improving NLOS human detection performance in SAR applications.

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Corresponding Author:

Enoch Adama Jiya
Department of Electrical and Electronics Engineering, Niger State Polytechnic
Zungeru, Nigeria
Email: adamajiya@gmail.com

1. INTRODUCTION

Many natural disasters, such as earthquakes, fires, hurricanes, tsunamis, and other seismic events, occur worldwide on a regular basis and frequently cause damage or collapse of built infrastructure, such as buildings and bridges [1]. Survivors in such conditions can be trapped under the debris, and the search and rescue teams have a difficult time. These teams frequently lack information about location and the number of people enclosed in collapsed buildings, and the fact that they are trapped. Effective and timely rescues are crucial, as survival after around 3 days of entrapment is highly improbable [2], [3].

In the realm of search and rescue (SAR) operation analysis, a noteworthy challenge lies in gathering data from uncorrelated and high-throughput catastrophic sources [1]. Large samples with a lot of redundant and unnecessary noisy features are one of the dataset's well-known characteristics [2], [3]. These erratic input

signals degrade the performance of categorization learning models [4]. Techniques for reducing dimensions have been applied numerous times. It reduces computational loads and increase classification prediction accuracy by retrieving relevant discriminative subsets from the data, such as the location and number of people trapped in collapsed buildings [5], [6].

Overfitting and the curse of dimensionality are known to impair classification capabilities in dataset analysis [7]. It consists of an input space with large dimensions, known as the "curse of dimensionality." Numerous dimensionality reduction strategies have been used in the literature to overcome the curse of dimensionality challenges [6]. It is essential to choose the ideal selection of features that can both improve the interpretability of the detritus and disclose hidden features [8]. The goal of dimensionality reduction is to find the optimal subset of data that might improve prediction performance; this will aid SAR and engineers in decision-making and localization [9].

Numerous writers have tackled the issues surrounding the curse of dimensionality. Although metaheuristics have also been suggested, methods for retrieving non-line-of-sight (NLOS) signal data subsets suffer from correlations, large throughputs, and longer calculation times [10], [11]. An important problem is to retrieve an ideal subset of data attributes in a methodical manner. The established dimensionality reduction approaches to feature selection, traditional filter-based methods (e.g., Mutual Information, Chi-square) identify relevant features based on statistical relevance but fail to capture interdependencies between features [12], [13] and feature extraction, genetic algorithms (GA) have been widely applied to optimize feature selection in high-dimensional datasets. GA effectively reduces redundancy but is computationally expensive and prone to local optima, limiting its efficiency in real-time SAR applications [14]. Supervised and unsupervised approaches have solved several issues, including performance enhancement; however, further advancements in hybrid models and optimization are required to achieve even better outcomes. Independent component analysis (ICA) has proven effective for extracting latent components from high-dimensional SAR data. ICA enhances classification by separating mixed signals into statistically independent components, making it a useful tool for processing noisy and occluded signals [15]-[17]. The goal is to identify the best subset of data features that can handle high-dimensional optimization problems and provide workable solutions [6], [13].

While these techniques have achieved success in dimensionality reduction, several challenges remain unresolved. Although GA has been widely utilized and is skilled at identifying optimal subsets on high-dimensional data, it is computationally costly and prone to overfitting. To get around this restriction, optimization techniques have been applied to guarantee improved results in terms of determining the best feature subsets and classification accuracy [18]. An acceptable feature extraction technique that has been widely used as a standard competent method for retrieving subsets of feature samples for classification is ICA (linear), which has recently attracted increasing attention [19]. The outstanding results and benefits of the hybrid strategy for resolving dimension issues that hinder categorization have demonstrated its importance. For the classification of NLOS data signals and expression data analysis, it is critical to develop effective models that are quick to compute and simple to use [20]. Commonly used traditional target location and classification (TLC) methods overly rely on an understanding of signal propagation and environmental details, even if they work well in controlled conditions. They are quite labor-intensive to calibrate by hand, which is not appropriate for erratic extreme situations like seismic debris. Furthermore, TLC modes perform worse, particularly in low-reflective or stationary target separation, since they lack the sophisticated interference rejection methods needed to manage the greater occlusion levels present in non-line-of-sight situations. To imitate material produced by humans more accurately, it needs to create some changes that can boost complexity and variance.

Other challenges with the existing systems include reliance on manual calibration and prior knowledge of signal environments of propagation. This limits their adaptability in real-world disaster scenarios. Consequently, their performance cannot be ascertained when it comes to real-time post-disaster challenging environments with complicated debris. Their usability in real-world NLOS cases is limited due to dependence on manual calibration, lack of robust interference rejection, and limited performance in low-reflectivity environments.

This research proposes a GA and ICA hybridized approach for dimensionality reduction and an integrated system for optimizing SAR signal data. This technique dynamically selects relevant feature subsets while also extracting independent components to enhance classification accuracy and adaptability. This approach will overcome the computational limitations of standalone GA FS, and ICA for FE approaches to improve robustness in NLOS conditions, reducing noise and redundant features while maintaining high classification performance.

This research develops an adaptive human presence detection (AHPD) framework based on two optimized feature engineering strategies: GA and ICA where each is used in a separate pipeline and classified by k-nearest neighbors (KNN) for NLOS datasets. The proposed framework can provide noise filtering, adaptive feature optimization, and intelligent classification, which can lower the complexity of the algorithm

and provide better human detection. The study in this paper compares the GA-based feature selection with ICA-based feature extraction in the same AHPD and KNN architecture and shows that which one is more effective to optimize in under-rubble human detection for SAR applications.

The Hybridized systems consistently outperformed conventional methods that depended on scenario-specific parameterization. Enhanced flexibility across conditions will be achieved by dynamic noise filtering, automatic parameter calibration, and continuous feature optimization. When compared to other systems, the hybrid strategy presented here has significant advantages over traditional tracked localization settings. On the other hand, the suggested AHPD method lessens the requirement for intricate mathematical analyses or parameter searches by integrating GA and ICA separately to dynamically adapt to changing environmental conditions. This is in line with findings from the last few years of research, which highlight the necessity of machine learning-infused adaptive models for better generalization in various contexts.

An AHPD pseudocode is utilized by the methodologies to extract pertinent data subsets that filter noise and allow for automatic amplitude updates to extract latent components from the subset of data; GA and ICA are applied. KNN is used to classify AHPD with GA and AHPD with ICA. This approach operates on a variable parameter in complex scenarios (non-reliant). To help engineers and SAR teams make better decisions, this study aims to reduce prediction complications, including processing costs, obtaining pertinent subsets of data, and correlations between variables. This paper's remaining sections include the methodology section (materials and methods), algorithm development, results and discussion, as well as comparative analysis, and conclusions.

2. MATERIALS AND METHODS

Static data were used in this investigation. The overall proposed framework is shown in Figure 1. The AHPD method is primarily used for data pre-processing and pre-processing for data cleaning to make sure that the imputed primary data is consistent and appropriate for accurate predictions. A next step is to determine the most prominent differences and to simplify the number of separate components to get relevant evidence for further analysis. For the stationary dataset, the process of relevant information extraction from the dataset is carried out by using ICA-based feature extraction (FE) and genetic algorithm-based feature selection (GA-FS). Finally, the performance of the proposed approach is tested on the NLOS dataset, and the results are compared with those obtained by the existing approaches, using the KNN classification method.

In this study, the NLOS dataset has 17,408 static cases and 256 samples per window. The collected data was taken from publicly available measurement data to check the performance of the proposed data analysis and machine learning methods. The data used in this study to support the findings of this study is openly available at the following repository: “https://github.com/disiunibo-nlu/uwb-nlos-human-detection”.

The machine learning techniques employed analyze and predict NLOS human localization data of several complex materials and various orientations. An enhanced pre-processing technique was applied to human-detectable features, obstacles, objects with different angles, and objects at different distances from the collected dataset [20]. For better prediction, the output shows a more condensed and filtered collection of data. The proposed architecture of NLOS data human detection for anticipating victims trapped behind debris utilizing the NLOS signal dataset is depicted in Figure 1.

Experiments were conducted in a variety of indoor locations on the first floor of the University of Bologna's School of Engineering's Cesena Campus. Consideration the fixed measurement, which entails maintaining the radar motionless on a rolling wagon at a distance of about one-hundred and thirty centimeters from the earth. The targeted object, which was placed twenty centimeters after the obstructions, was thirty, sixty, and ninety centimeters from the radar. Another potential obstacle was the thickness of the material. Data collection explicitly considers the following materials: a crystal frame set at 2cm, a brick wall set at fifteen centimeters, wooden gates set at three and five centimeters, and double-glazing set at 10cm [20]. This then makes a dataset of ultra-wideband (UWB) NLOS using the materials of different barriers and the body orientations of different victims. Consequently, the following is a summary of the research strategy:

a) Obtain raw dataset of the experiment from the site.
b) Apply data normalization through AHPD and its impacts on the dataset's accuracy.
c) Use both GA and ICA for FS and FE techniques, respectively, to identify the significant components in the dataset.
d) Describe a classifier training approach that increases prediction accuracy by leveraging KNN classification.
e) Making categorization suggestions using the KNN classifier.
f) Using pertinent literature to compare the outcomes to alternative approaches.

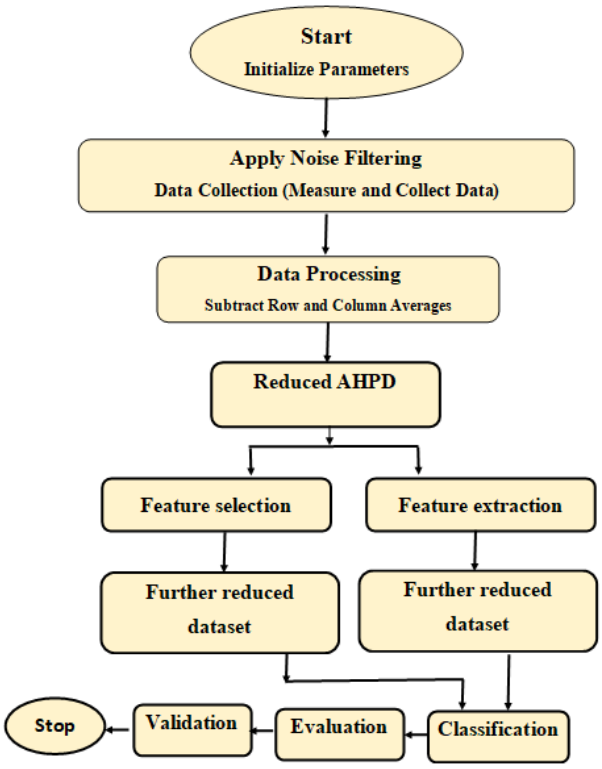

Figure 1. Work flow of the entire implementation process

Table 1 consists of the dataset used in this research. It gives a thorough overview of the dataset, including feature sample occurrences and sampling characteristics. The publicly available NLOS signal dataset collection for human detection through debris was used for the analysis. It consists of debris made of wood and glass, among other materials, and a human body in orientation, comprising 256 samples and 17,408occurrences [20]. The specific characteristics of the dataset utilised in this research are shown in Table 1.

Table 1. Features of the dataset

Dataset structures	Description
Static radar	17,408
Observation	256
Source	University of Bologna's Cesena Campus
Characteristics	Human body alignment, construction materials, rubble, and sensor distances
Accessibility	Openly obtainable dataset [20]

3. METHOD

A popular technique for localizing victims, including those hidden by debris, is through-wall human detection SAR. It identifies several facets of hidden data, which is a key feature of current high-throughput genetic factor technology. It reacts to various surroundings and other training solutions, creating sufficient quantities of sequencing data [21] and finding secret alterations occurring in the conditions of buried victims, providing greater insight for imprisoned individuals, rescue, and improved detection [22]. Classifying and evaluating persons behind walls has been made possible by the human detection prediction of NLOS signal data [23].

To enhance the effectiveness of the human presence detection dataset, this study explores the application of KNN classification and GA used side by side with ICA for dimensionality reduction of multifaceted no-line-of-sight data. The training processes used, supervised learning techniques that adhere to the training dataset's organization, which normally take designated instances as input. Consequently, for every instance, the class of concern will be determined. This is done by labeling waveform instances as either "Person Present" or "Person Absent." This allows the last model to categorize further preprocessed harmonics into one of the following scenarios. To drastically lower the dimensionality of human detection data, this study considers ICA and GA with KNN classification algorithms. An I-J matrix M is used to

display two datasets. There are a total of 17,408instances in the static situation. Both situations apply: J = 256 (K). To determine the overall number of rows generated by combining each pulse set from the data collection inquiry, a qualitative analysis was utilized to remove the inaccurate parts (i.e., those with significant displacement and low data content).

For UWB data signals obtained from sensors, the issue of detection is a major one that produces unsatisfactory findings because of the high-dimensional dataset. An NLOS signal dataset is used in this investigation. The Python tool is used to examine the data samples. The advanced human presence detector receives the samples. After that, a smaller sample is obtained and fed into the ICA and GA independently. Training and testing sets are created from the further reduced data. Using KNN, classification is done.

These techniques will be combined and used to develop a model for evaluation measures. The article's methodology is as follows: Assessing the results in terms of accuracy, precision, F1-score, and sensitivity, among others, by utilizing KNN classification. While learning the feature representation, the KNN is utilized to dynamically optimize both the features and the classifiers. Noise filtering and elimination through data standardization. After normalizing the dataset in the person detection module, the dimensionality reduction unit imports it and runs both GA and ICA algorithms on it. The response is shown in the outcome module once the classification process using KNN has correctly classified it. An Intel Core 5 processor with 16 GB of RAM and a 64-bit operating system are used for the study's experiments. The algorithm was written using the Python environment.

To train the KNN classifier, a 70:30 ratio of training data to testing data was used, with 70% of the data utilized for training, and 30% was set aside for independent testing. The GA and ICA were used to optimize the value of k (number of neighbors). The optimized k value of 12 was used for classification using KNN in the dynamic dataset. The model performance was then tested with an independent test set of 30% of the data.

3.1. Dimensionality reduction

Dimensionality reduction is a well-known method for removing extraneous features and undesirable noise. The NLOS dataset has high-dimensional features that are computationally heavy, which hinders classification model performance. Dimensionality reduction procedures are crucial for removing redundancy and collecting unnecessary characteristics that disrupt efficiency with activity by reducing the sample-to-feature ratios. This technique aids in lessening the likelihood of overfitting. One important technique called feature extraction and collection is reducing the dimensionality [24], [25].

3.2. Feature selection

Training and testing models depend on technologies like NLOS signals data, which creates pertinent, unique feature IDs for transcript sequences. To improve classification performance, feature selection is crucial. The selection of features minimizes the curse of dimensionality by eliminating unnecessary and duplicate characteristics, allowing one to select appropriate elements for classification model performance [26], [27]. It improves the success of the model and contributes to the success of the classification phase learning process.

For example, supervised and unsupervised decision-making learning is involved in the vast information feature selection procedure using wall and SAR data. The prediction model's performance will be improved by choosing the optimal rank attributes that convey importance for classification tasks. One effective method known as a filter, wrapper, or embedded type is the collection of feature selection [28], [29].

3.3. Genetic algorithm

A genetic algorithm is a wrapper-based evolutionary method for picking pertinent features, employed in the analysis of engine optimization issues. In the survival of the fittest paradigm, genetic algorithms depend on real-world behaviors linked to human genetic determinants. Genetic algorithms consist of initial population development, fitness evaluation, parent selection, crossover, and mutation [30], [31].

The GA is an exploratory discovery technique characterized by a straightforward procedure, utilizing a sample of randomly generated outcomes (entities) to yield an acceptable value for the primary objective of calculating advantageous results. Debris or rubble generally consists of property sets represented as binary strings of 0s and 1s [32]. Although genetic algorithms are highly sensitive to the initial population, they exhibit a deficiency regarding optimality. Their result quality drops as problem dimensions rise; however, it has been found to produce reasonable quality solutions to boost it for NLOS sampling [33], [34].

3.4. Feature extraction

The process of identifying key traits, attributes, or features that are present in data is known as feature extraction. Finding patterns and finding public occurrences in a set of identifications are two examples of feature extraction approaches [35]. Feature extraction is used with data that has dimensional loads to produce an explanation of characteristics that is more detailed. The curse of dimensionality can be lessened by using feature extraction to isolate relevant feature variables. In particular, there are two general categories of feature extraction methods: linear (assumes a low-dimensional subspace characterized by a high-dimensional feature, like ICA) for a non-linear relation between features, and non-linear (assumes data on a low-dimensional subspace, like PCA) [19], [36]

3.5. Independent component analysis

The ICA method was utilized to remove inactive elements from the UWB NLOS data. The independent component analysis FE process isolates and removes conflicting variables. The data containing recovered ICA latent significant features is classified using the KNN AdaBoost categorisation technique. For statistically independent components, disintegrating multivariate signals into separate non-Gaussian signals allows ICA to facilitate the extraction of hidden features from multidimensional information. By altering or reducing the relevant data, ICA decorrelates the data in an attempt to find a relationship between the pieces of information [37]. As a straight-line combination of the separate components I: Opinion X is adopted by ICA. Define the independent weighted matrix R, the basic feature vectors of observation X, if B refers to the columns of B:

$$I = RtoX, X = BtoS \quad (1)$$

ICA has been widely utilized for NLOS SAR and through-wall applications for information, recognition, and other purposes [38], [39]. GA is a non-linear alteration method that reduces the number and dimension of features. It is a "non-linear" algorithm, but ICA performs better and is "linear" if data is preprocessed [40].

3.6. Classification

Classification, a supervised learning approach used in data mining methods. It is typical helpful activity in this research by assigning and forecasting class labels based on the predefined class label (person present, person absent) and the available data. Two processes are involved in constructing a categorization [41]. The learning procedure involves creating a classification model with a class label that is provided with a set of training data. The model calculates the KNN classifier's accuracy and predicts class labels for hidden data.

3.7. K-nearest neighbor

KNN is a benefit of creative application, and event assessment that enables neighborhood classification to be carried out using supervised learning. Kth closest neighbor classification technique for NLOS signal datasets. Dataset values after refinement are classified by the KNN algorithm using training/test models, attributes, and examples. KNN classifiers are retention-based rather than fitting models during training, which makes them suitable for this research. The chosen features serve as segment inputs. The neighbor with the Kth value closest to the query spot is chosen. The detachment between query instances and training models is considered and ranked based on the minimal determined distance of the Kth. The outcome is selected from the nearest neighbors. The approximate number of incidents in question is determined by looking at the unassuming predominance of groupings of nearest neighbors. Bonds may spontaneously break [42].

3.8. Enhancing high-dimensional dataset through hybridization

Increasing the dimensionality of NLOS signal data poses a serious challenge to straightforward, dependable research techniques. When learning complex strategies on multiple levels, moved by morphological processes that are interested in processing, it is vital to employ traditional methods. Most common processes used to handle high-dimensional data, like the NLOS signal data, contain several complications. In essence, the combination of several dimensionality reduction techniques will benefit from special advantages when subset data from one operation is supported as an input to another. Generally speaking, feature extraction methods effectively enable feature selection, either by utilizing redundant signal data elimination or by employing feature selection to select the original subset of data. It can be helpful to extract primary subset features and combine several feature extraction techniques [36], [43].

This research proposed an efficient dimension reduction technique for NLOS signal data classification. This method has enormous promise for locating, identifying, and tracking down victims who

are concealed beneath the ground. Nevertheless, the structures are easier to see when the dimensionality is reduced. However, data continues to be difficult, and existing algorithms require the right development to show the right features. The fusion strategy is a beneficial one, but it needs positive modelling techniques. The stages suggested classification technique, are as follows:

- Data acquisition.
- AHPD cipher text.
- Features were chosen.
- Features were taken out.
- Class of class.

The overall proposed architecture of NLOS data human detection for anticipating victims trapped behind debris utilizing the NLOS signal dataset is depicted in Figure 2, which shows the predicted hybrid system. The subsystems make up the framework: one for feature collecting, one for AHDP pseudo code, one for feature extraction based on classes, and one for classification. The function selection sub-system makes use of AHPD pseudocode, by using the first method to filter noise and GA to determine an optimal subset by evaluating the fitness. Because of its impertinent ordering and data projection of efficiency invariance, ICA is used by the function extraction subsystem. KNN is used to classify research standards.

The dynamic nature of the algorithm's features, which aids several search spots that independently and concurrently investigate the ideal result to yield a good result, is the significance of human detection algorithm optimization. In order to reduce the number of features and preserve discriminant features, genetic algorithm features were used in this study. The features are extracted in an ideal way, converting reduced data into latent components. However, this reduces productivity and suffers from both of the dimensionality reduction techniques used to classify the dataset.

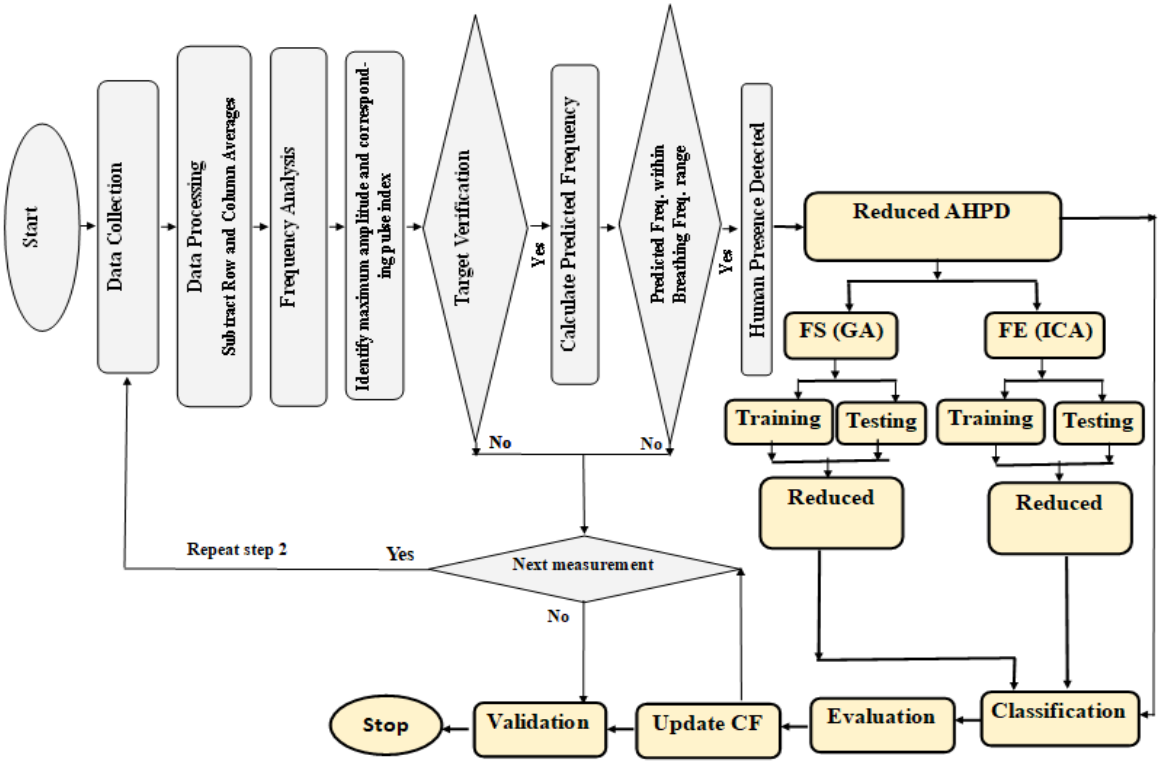

Figure 2. Overview of the Complete Architectural frameworks for NLOS data human detection

4. ADVANCED HUMAN PRESENCE DETECTOR ALGORITHM

The transmitted UWB pulse is significantly attenuated, distorted, and reflected several times due to the nature of rubble. Due to these difficulties, radar has trouble picking up little details in the chaos. In order to remove these barriers, the first step is to preprocess the raw data that is obtained from the environment using processing methods. For the proposed investigation, Algorithm 1 shows a dynamic, adaptive human presence detector.

Algorithm 1. Proposed flexible adaptive human presence detector

```
Initialize parameters:
n pulses = 512,n samples = 256,dtpulse = 0.014,breath freq = [0.2,0.7]
amp thresh = 0.5,noise thresh = 0.3,NF F T = 1024,n measures = 10
CF ← zero-initialized 2x2 confusion matrix
actual targets ← Random binary vector of length n measures
function FILTER_NOISE(data,noise thresh)
if noise thresh > max(data) then
f iltered data ← data - median(data)
return f iltered data
else
return data
end if
end function
function VERIFY HUMAN PRESENCE(measure)
Subtract row/column means: Mdif f ← measure - meanrow/col
Filter noise on each column to get Mf iltered
for i = 1 to n samples do
Mf iltered[:,i] ← filter noise(Mdif f [:,i],noise thresh)
end for
Mf f t ← |FFT(Mf iltered,NF F T)|
max amp,idx ← max(Mf f t),arg max(Mf f t)
i,← unravel index(idx)
if max amp > amp thresh then
pred freq =  (i-1)/(n_pulse+dtpulse)
if breath freq[0] ≤ pred freq ≤ breath freq[1] then
return True
end if
end if
return False
end function
function UPDATE CF(predicted,actual,CF)
if actual then
if predicted then
CF[0,0]+ = 1
else
CF[1,0]+ = 1
end if
else
if predicted then
CF[0,1]+ = 1
else
CF[1,1]+ = 1
end if
end if
return CF
end function
for k = 1 to n measures do
measure ← rand(n pulses,n samples)
actual ← actual targets[k]
predicted ← verify human presence(measure)
CF ← update cf(predicted,actual,CF)
end for
Output: Confusion Matrix CF
```

The suggested method determines the likelihood of human activity through a multi-step process that finds human presence. The algorithm analyses each measurement in detail to ascertain the probability of human activity after noise filtering. This thorough analysis guarantees the detection system's resilience and efficacy in a range of situations and uses.

5. RESULT AND DISCUSSION

Results from the use of AHPD-GA and AHP-ICA with KNN classifier dataset analysis are presented in this section, along with thorough remarks and discussion highlighting the conclusions and their ramifications. They establish the foundation for future studies in this area and show how successful the recommended approach is. Section 5.1 has the outcome, while Section 5.2 contains the commentary.

5.1. Result

This paper presents a Python-tool-based NLOS signal dataset categorization utilizing a publicly available dataset of 17,408samples and 256 occurrences Moro *et. al.* [20]. During the investigation, we used an AHPD method to filter out noise and relevant features from the dataset. The breath frequency was

set to [0.2, 0.7] using 0.5 thresholds. The state-of-the-art classifier ability was applied to the mandatory evaluations. The ideal number of neighbours (n_neighbours) producing the highest performance based on the fitness function for the dynamic dataset was found to be 12 for KNN after applying GA and ICA on the AHPD for feature selection.

The KNN classification algorithm with validation is used to classify the extracted feature results. This technique is essential for evaluating predictive models because it divides the given sample into training and testing sets for assessment. The performance metrics study was then used to assess the KNN confusion matrix. Additionally, the filtered AHPD features were subjected to the GA method and the ICA variables. After using cross-validation to classify the latent features on KNN, the confusion matrix is assessed. The NLOS signal dataset is used to test the AHPD + GA + KNN and AHPD + ICA + KNN algorithms. The results of the experiments' performance assessments are listed in Table 2.

Table 2. Performance metrics table for the AHPD + GA + KNN and AHPD + ICA + KNN classification

Performance Metric	AHPD + GA + KNN	AHPD + ICA + KNN
Accuracy (%)	77.25	83.40
Sensitivity (%)	71.29	75.84
Specificity (%)	82.45	91.04
Precision (%)	78.02	89.55
Recall (%)	71.29	75.84
F1-Score (%)	74.50	82.13

This research makes many important recommendations for data analysis in crises. This experiment has the potential to provide pertinent understanding into technical and physical discussions that can elucidate structures that have been revealed and provide data interpretations suitable for analyses, predictions, identification of impacted victims buried beneath the earth, localization, and rescue plans (Figure 3). This study achieved dependable performance with practical algorithms, as indicated in Table 2.

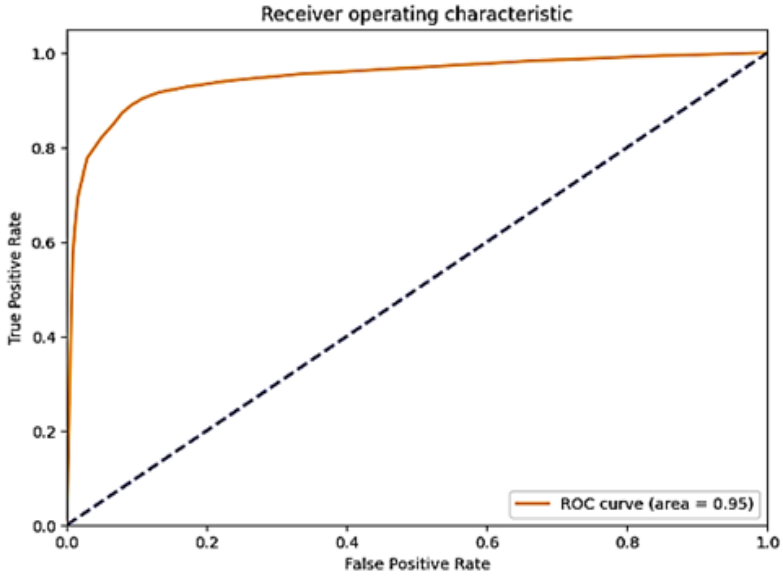

Figure 3. A ROC curve of the KNN attributes with ICA

5.2. Discussion

The classification results demonstrate the effectiveness of combining GA feature selection with KNN for high-dimensional dynamic datasets. In the GA-KNN experiment (Figure 4), starting from 17,408features, GA reduced the dataset by extracting the most relevant features, improving both computational efficiency and predictive accuracy. The model achieved a true positive rate (TPR) of 71.29% (1,157 correctly predicted positives) and a true negative rate (TNR) of 82.45% (1,532 correctly predicted negatives). These results indicate good sensitivity in detecting concealed human subjects and reliable specificity in rejecting irrelevant or non-human signals. However, 326 false positives (17.55%) and 466 false

negatives (28.71%) highlight the trade-off between sensitivity and specificity. The missed detections may be attributed to signal attenuation or scattering from dense debris, overlapping feature patterns between human and non-human signals, or GA's potential limitations in preserving minority class features.

In the AHPD–ICA experiment (Figure 5), the model correctly identified 1,328 positives (TPR = 75.84%) and 1,575 negatives (TNR = 91.04%), again showing good sensitivity and specificity. Feature reduction through ICA likely contributed to this performance by eliminating redundancy and enhancing relevant signal patterns. Nonetheless, 155 false positives (8.96%) and 423 false negatives (24.16%) indicate that almost one in ten non-human instances were falsely flagged and approximately one in four human instances were entirely missed. The higher false negative rate is particularly concerning in post-disaster rescue contexts, as undetected victims could lead to loss of life. Such errors may stem from environmental interference, occlusion, imbalanced class distributions, or overfitting during training.

A comparative analysis of AHPD–GA and AHPD–ICA datasets (Figure 5) underscores that while both approaches produce strong predictive models, reducing false negatives remains critical for life-saving applications in complex NLOS environments.

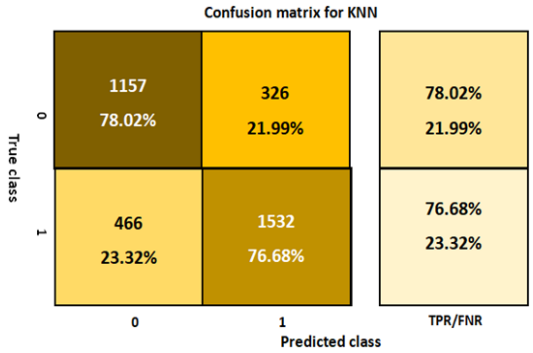

Figure 4. Confusion matrix for AHPD + GA + KNN TP=1157; TN=1532; FP=326; FN=466

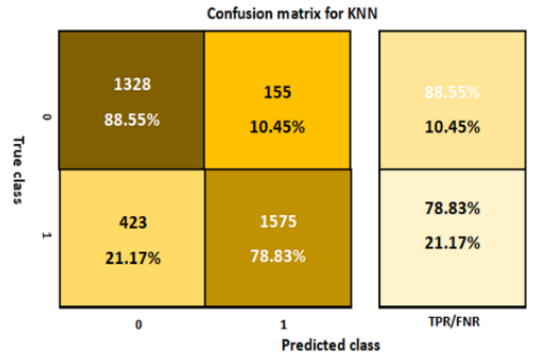

Figure 5. Confusion matrix for AHPD + ICA + KNN TP=1328; TN=1575; FP=155; FN=423

The AHPD + GA + KNN model achieved an accuracy of 77.25%. 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 71.29%. 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 (82.45%) 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.

The precision of 78.02% indicates that 78.02% 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 (71.29%) indicates 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 74.50% 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 + KNN model demonstrated higher performance, achieving an accuracy of 83.40%. This suggests that while ICA is effective in extracting meaningful features, it may retain fewer redundant or noisy components, leading to improved classification accuracy. The 75.84% sensitivity indicates that the model is more effective than the GA-based model in detecting human presence, which could reduce the likelihood of false negatives. The model has a strong capability (91.04%) in correctly identifying non-human signals as non-human presence (specificity), potentially leading to fewer false alarms. The precision of 89.55% suggests that when the model does classify human presence, it is highly confident in its prediction. However, the recall (75.84%) indicates that the model is less effective at capturing all instances of human presence. The F1-score of 82.13% suggests a stronger overall balance between precision and recall.

The performance of AHPD + ICA + KNN suggests that ICA is more effective than GA in feature extraction for human detection in NLOS environments. However, the superior performance of AHPD + ICA + KNN indicates that using Independent Component Analysis for feature extraction 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 ICA-KNN hybrid increased significantly (by 6.15%) from 77.25% to 83.40% in a complex and dynamic scenario compared to GA. Sensitivity rose from 71.29% to 75.84%, demonstrating ICA's ability to extract relevant signal features. Additionally, the F1-score (82.13) improved, indicating a better balance between precision and recall. These results emphasize the importance of feature extraction in dealing with complex scenarios where irrelevant features could obscure important patterns.

The AHPD with ICA and KNN 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 ICA-enhanced KNN 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 SAR operations. Table 3 shows the comparison with other state-of-the-art results. Table 3 shows how our study compares to other approaches that have been reported in the literature.

Table 3. Comparative approach table

Methods employed	Accuracy (%)
CNN + Stacked- LSTM [44]	82.14%
SVM + Ensemble [45]	81.00%
AHPD + ICA + Bagged Ensemble [38]	82.13%
AHPD + ICA + KNN (proposed model)	83.40%

7. CONCLUSION

The objective of this study is to develop an AHPD system for human presence detection (HPD) in a NLOS scenario for SAR missions. It overcomes some drawbacks of traditional through-wall localization and classification (TWL) methods by introducing signal noise filtering and two other feature optimization methods – GA and ICA – and applying KNN classification. The pipelines of AHPD + GA + KNN and AHPD + ICA + KNN were tested separately. The results proved that the classification accuracy of AHPD + ICA + KNN is 83.40%, whereas AHPD + GA + KNN is 77.25%, which shows the superiority of AHPD + ICA + KNN over AHPD + GA + KNN.

The results show that feature extraction based on ICA yielded a more effective representation of the signal characteristics evaluated in the NLOS signals and could be used in SAR operations for under-rubble human detection. The study is, however, limited to computational evaluation, based on the available NLOS dataset, and has not yet been validated in real-world disaster environments. To this end, further research and studies are required with larger and more diverse datasets, real-world UWB radar deployments, alternative

machine learning and feature optimization approaches, and real-time implementation, including integration with victim localization and evacuation decision-support systems.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Enoch Adama Jiya	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	
Ilesanmi B. Oluwafemi	✓	✓			✓	✓	✓	✓	✓	✓	✓	✓		
Kazeem Oyebode		✓			✓		✓			✓	✓	✓	✓	
Oluwafemi Emmanuel Oni		✓			✓		✓			✓	✓			✓

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 competing interests.

DATA AVAILABILITY

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

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BIOGRAPHIES OF AUTHORS



Enoch Adama Jiya holds a Bachelor of Engineering (B.Eng.) in Electrical and Electronics Engineering from Kwara State University, a Master of Science (M.Sc.) in Electronics System Design Engineering from Universiti Sains Malaysia (USM), and holds a Ph.D from Landmark University, Omu-Aran, Kwara State, Nigeria. He is currently lecturing in the Department of Electrical and Electronic Engineering at Niger State Polytechnic, Niger State, Nigeria. He is a member of the Nigeria Society of Engineers (NSE), the Council for the Regulation of Engineering in Nigeria (COREN), and the International Association of Engineers (IAEng). His research areas of interest include Artificial Intelligence, Digital images, and Signal Processing. He can be contacted at email: jiya.adama@lmu.edu.ng.



Prof. Ilesanmi B. Oluwafemi received a B.Eng. degree in Electrical and Electronic Engineering from the University of Ado Ekiti, Nigeria, in 2000. He obtained a Master of Engineering degree in Electronic and Telecommunication from the University of Benin, Nigeria in 2005 and a PhD in Electronic Engineering from the University of KwaZulu-Natal, Durban, South Africa in 2012. He is currently an Associate Professor in the Department of Electrical and Electronic Engineering at Ekiti State University, Nigeria. He is also the Leader of the Center for Research in Electrical Communication (CRECO), at Ekiti State University, Ado-Ekiti, Nigeria. His research interests are in the area of wireless communication, including space-time coding, channel coding, MIMO and OFDM systems, and signal propagation, IoT, WSN, and Indoor broadband PLC. He can be contacted at email: ilesanmi.oluwafemi@eksu.edu.ng.



Kazeem O. Oyebode holds a Bachelor of Engineering (B.Eng.) in Electrical and Electronic Engineering from the University of Ado-Ekiti, Nigeria, obtained in 2009, a Master of Science (M.Sc.) in Software Engineering from the University of the West of England, United Kingdom, obtained in 2012, and a Ph.D. in Computer Engineering from the University of KwaZulu-Natal, South Africa, obtained in 2017. He is currently lecturing in the Department of Electrical and Computer Engineering at the University of Zululand, South Africa. His research areas of interest include Artificial Intelligence, Computer Vision, Machine Learning, and Digital Image Processing. He can be contacted at email: oyebodek@unizulu.ac.za.



Oluwafemi Emmanuel Oni received his B.Sc. (Honours) degree in Electrical and Electronic Engineering from Ekiti State University, Nigeria, in 2013, and his M.Sc. and Ph.D. degrees in Electrical Engineering from the University of KwaZulu-Natal, South Africa, in 2017 and 2021, respectively. He previously worked in the power industry before commencing his postgraduate studies and later served as a lecturer at the Durban University of Technology, South Africa. He is currently a Senior Lecturer and Programme Convener for the Electrical and Computer Engineering Programme at the University of Zululand, South Africa. His research interests include Artificial Intelligence applications in power systems, renewable energy integration, multiterminal HVDC (MTDC) systems, and smart grid technologies using FACTS devices. He can be contacted at email: onio@unizulu.ac.za.