Predicting trapped victims in debris using signal analysis ensemble classification

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Article Info	ABSTRACT
	One major difficulty in pervasive computing is trapped human detection in search and rescue (SAR) scenarios. Accurately identifying trapped individuals is challenging due to noisy data and the curse of dimensionality. When non-line-of-sight (NLOS) conditions are present during catastrophic occurrences, the curse of dimensionality can result in blind spots in detections because of noise and uncorrelated data. Because machine learning algorithms are incredibly accurate, this work focuses on using ultra-wideband (UWB) radar waves to detect individuals in NLOS scenarios and leveraging wireless communication to harmonize information. The paper uses ensemble methods to extract features using independent component analysis (ICA) and evaluate classification performance on both static and dynamic datasets. The testing results confirm the effectiveness of the proposed strategy, with classification accuracies of 87.20% for dynamic data and 88.00% for static data. Lastly, during SAR operations, our approach can assist engineers and scientists in making quick decisions. *This is an open access article under the CC BY-SA license.*

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1. INTRODUCTION

Around the globe, natural disasters such as earthquakes, inferno, hurricanes, tsunamis, and seismic, activity occur with alarming frequency, often leading to the collapse of infrastructure created by humans, such as buildings and bridges [1]. In such scenarios, survivors can become trapped within the debris, posing a significant challenge to search and recovery teams, who often lack precise information about the presence, location, and number of trapped individuals. Given that the life expectancy of patients in prison drops significantly after three days, a rescue operation is required in this situation [2], [3]. Over the past few decades, these catastrophic events have claimed millions of lives, underscoring the necessity for effective post-disaster rescue operations to minimize fatalities [4]. Developing reliable techniques for robotic navigation and monitoring in uncharted environments remains a critical research area in security and protection [5].

One promising technique for detecting human targets through barriers is ultra-wideband (UWB) radar. UWB radar offers numerous advantages, such as excellent penetrability, precise placement, low power consumption, high definition, and resilience to channel degradation [6], [7]. These features make it ideal for locating hidden targets beneath building materials, making it invaluable for law enforcement and emergency recovery efforts. UWB radar has proven effective in applications such as target identification, localization,

health monitoring, and through-wall human detection [8]. The quick development of machine learning, particularly deep learning, has revolutionized the ability to make optimal decisions quickly using high-performance computing systems that extract high-level features from large, multi-dimensional datasets [9]. This advancement is particularly relevant in disaster relief and humanitarian aid [10], [11]. Previous research proposed a downstream channel assessment network utilizing convolutional neural networks (CNNs) for feature extraction (FE) and recurrent networks for channel estimation [12]. However, these methods did not specifically address non-line-of-sight (NLOS) detection and often overlooked some data in the channel impulse response (CIR).

In this research, we employ an independent component analysis (ICA) approach for FE and an ensemble algorithm for the classification and identification of human targets buried beneath obstacles. Additionally, StandardScaler is introduced, a data normalization algorithm, and conduct stringent training and evaluation to classify and detect human targets in various scenarios. This will improve the ability to identify and detect both moving and stationary human targets behind walls. This will be accomplished by using an ensemble algorithm for classification and recognizing human victims concealed behind obstacles, as well as ICA for (fixed and dynamic) FE. To assess the efficiency of the two datasets (static and dynamic), a comparative study was also conducted.

The rest of the document is arranged as follows: the sections 2 and 3, respectively, focus on catastrophe management in search and rescue (SAR) as well as the guiding principles of the related activity. The section 4 discusses the resources and technical approaches, as well as the development and training of the data. The sections 5, 6, and 7, respectively, provide descriptions of the performance evaluation, application and testing methodology, and outcomes analysis. In section 8, the comparison analysis is presented. Section 9 presents the conclusion.

2. NLOS DETECTION FOR HUMAN SAR OPERATIONS IN CATACLYSM MANAGEMENT

It is feasible to prevent, prepare for, respond to, recover from, and lessen the effects of disasters through disaster management. Preventing disasters before they occur, reacting quickly to disasters, and helping to rebuild societies after a disaster are all parts of emergency management. Everybody's security depends on emergency management, which should be considered in all daily decisions rather than just in the case of a tragedy, which is becoming all too common [13]. Effective emergency management operations after a natural or man-made disaster depend on strong communication networks. Unfortunately, large-scale disasters have the potential to disrupt SAR operations and destroy telecommunications networks [14].

Resolving the issues now existing on the ground is crucial due to the growth of humanitarian activities and needs. Issues like traffic, delays, unaccountability, and inadequate connectivity could serve as test sites for the alleged advantages of new technological advancements [15]. The current reliance on centralized physical infrastructure methods poses a severe threat to the management system as a whole. Furthermore, current protocols for communication during system outages mostly depend on using temporary facilities, including telecom towers. Handling aid requests based on current disaster information and efficiently responding to such requests by distributing the management's available limited resources is the main goal of the entire process [16]. Blockchain-based technologies with sophisticated features can support SAR operations by leveraging advancements in information and communications technology (ICT), drones, the internet of things (IoT), cloud-based computing, image analysis, and autonomous aerial systems [17].

However, blockchain, IoT, and crowdsourcing methods can offer valuable insights that can facilitate the provisioning process. They might also be a means of fostering a dynamic mutual trust between people who provide, receive, and seek help to encourage this improvement. Furthermore, it can be used as a basis for incorporating technologies such as blockchain, three-dimensional printing, and artificial intelligence to improve the flow of information, products, and funds in humanitarian supply chains [15].

3. LITERATURE REVIEW

The use of machine learning techniques to identify and locate victims trapped behind collapsed structures has garnered a lot of attention during the last 20 years. However, obstacles in the line of sight (LOS) between the sending and the receiving device adversely impair basic measurements of radio signals. These measurements, like received signal strength indicator (RSSI) values, rendering them inappropriate for the conditions under investigation [18].

Yu *et al.* [19] proposed a technique that utilizes a higher-level cyclostationarity to detect human respiration and pulse to get beyond these restrictions. By employing the third-order cyclic cumulant, this technique effectively reduces harmonic intermodulation, random body motions, and clutter noise, allowing

radar sensors to detect weak signals with low signal-to-noise ratios (SNR). These developments are essential for target monitoring in military and emergency response operations.

By breaking down respiratory signals into distinct sub-signals, variational mode decomposition (VMD) has also been used to track a variety of objects behind walls. For microwave radar devices, this approach—which uses the Hilbert transform, distance bins, and traveling respiratory identification calculations—performed better than conventional fast Fourier transform (FFT) methods [20]. To increase generalization ability under a variety of NLOS circumstances, machine learning techniques have been created. For example, Khan *et al.* [21] used Wi-Fi sensors to create a CNN that classified and assessed human respiratory activity with a 94.85% accuracy rate.

The most recent developments in UWB through-wall radar research are covered in detail, with an emphasis on signal-processing methods for monitoring vital signs and identifying people. Three primary methods for human detection with NLOS sensors were determined. These are: i) multipath patterns of the radar reflected signal; ii) numerical characteristics of the received signal, such as skewness and kurtosis; and iii) constant false alarm rate (CFAR), which determines energy levels for target responses.

Park *et al.* [22] investigated a transfer learning-based UWB NLOS detection technique that achieved precision on par with deep learning methods developed with sparse data. Other designs and human detection tasks were not examined in their study, though. Similarly, two receiving antennas were utilized to measure vital signs in the investigation [23]. But they only decided to look at the strong signal. The mobile filter was subsequently fitted to the selected signal, which eliminated the quasi-static noise. Dual-frequency harmonic continuous wave (CW) radar sensing systems have been used in other studies to increase SNR and decrease flicker interference [24]. Despite these advancements, challenges such as the zero-point phenomenon, motion artifacts, and interference from multiple sources still affect the efficacy of microwave radar sensors in detecting vital signs [25], [26].

This research aims to address these challenges by examining radar and communication technologies for SAR operations. The review covers continuous CW UWB radar sensors, their operational principles, and their physical construction. The conclusion and future outlook are presented at the end of this paper.

4. MATERIALS AND METHOD

Both stationary and dynamic data were included in the datasets used for this investigation. Figure 1 provides a summary of the suggested framework. The phase of obtaining pertinent information from a given dataset changes the procedure when utilizing the ICA FE approaches for both stationary and fixed datasets. The results of the ensemble classification approach are contrasted with current approaches to evaluate the NLOS dataset's performance.
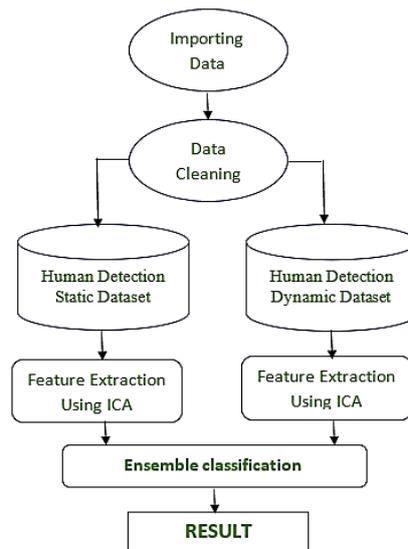

Figure 1. Proposed framework

The NLOS datasets used in this work included 17,408 (stationery) and 23,552 (dynamic) cases, with 256 samples per window. Standard scalar preprocessing or SC is typically used for data cleaning to make the

imputed primary data uniform for precise prediction. To identify the crucial discrepancy with fewer independent components and offer substantial evidence of more research, the ICA method was utilized to remove inactive elements from the UWB NLOS data. The ICA FE process isolates and removes conflicting variables. The data containing recovered ICA latent significant features is classified using the ensemble AdaBoost categorization technique. Ensemble classifiers are utilized to evaluate the efficacy of classification applications, employing seventy percent of the data for training and 30% for evaluating prediction accuracy.

To assess the data analysis learning enactment methodologies, the collected data was taken from the measurement data that is publicly available. The repository is located at 'https://github.com/disiunibo-nlu/uwb-nlos-human-detection". Many machine learning techniques have been replicated to analyze and predict NLOS human localization data of several complex materials. A conventional scaler was applied to human-detectable features, obstacles, objects with different angles, and objects at different distances from the collected dataset [27]. For better prediction, the output shows a more condensed and filtered collection of data.

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. First, consideration was given to the fixed measurement, which entails maintaining the radar motionless on a rolling wagon at a distance of about 130 cm from the earth. The targeted object (d), which was placed 20 cm after the obstructions, was 30, 60, and 90 cm from the radar (r). Another potential obstacle was the thickness of the material. Data collection explicitly considers the following materials: a crystal frame set at 2 cm, a brick wall set at 15 cm, wooden gates set at 3 and 5 cm, and double-glazing set at 10 cm. A more realistic scenario is presented in the second example, where the radar was handled at different heights, causing the acquisition to be dynamic via small motions [27]. Consequently, the following is a summary of the research strategy:

Make a dataset of UWB NLOS using the materials of different barriers and the body orientations of different victims.

i) Describe how data normalization impacts the dataset's accuracy.
ii) Use ICA FE techniques to identify the latent component in the dataset.
iii) Describe a classifier training approach that increases prediction accuracy by leveraging ensemble classification.
iv) Making categorization suggestions using the ensemble classifier.
v) Using pertinent literature to compare the outcomes to alternative approaches.

4.1. Methods

MATLAB was utilized to examine the information gathered from [27] experimentally, and ICA was used to extract features. Retrievable characteristics were used for classification utilizing an ensemble algorithmic technique. To homogenize collected data, eliminate noisy values and outliers, transform the data, and regularize it, the study employs SC. The goal of SC is to transform different eigenvalues into a preset range of zeros and ones. By using item scaling, this method makes sure that features are about the same size, which makes them more manageable for machine learning algorithms. The SC normalizes elements, by removing the median and normalizing the variance to one, achieving unit variance by dividing every parameter by the standard deviation. In the case of Gaussian-distributed data, this standardization—also known as normalization—is especially helpful since it makes machine learning techniques easier to handle. Standardization may have an impact on data outliers since it doesn't have a boundary range, unlike normalization. Normalizing data, however, might not always be necessary [28].

While learning the feature representation, the ensemble is utilized to animatedly optimize both the features and the classifiers. The suggested system consists of modules for FE, classification, result extraction, and dataset loading. After normalizing the dataset in the person detection module, the FE unit imports it and runs the ICA algorithm on it. The FE module receives the output module and applies FE on its own. The response is shown in the outcome module once the classification process using Ensemble has correctly classified it. SC feature selection in NLOS data analysis is combined with the FE techniques "ICA" and "ensemble."

These techniques will be combined and used to develop a model of evaluation measures. The article's methodology is as follows. We assessed our results in terms of accuracy, precision, F1-score, and sensitivity among others by utilizing ensemble classification, SC data standardization, and ICA FE to enhance the effectiveness of classification.

4.2. Materials

To enhance the effectiveness of the human presence detection dataset, this study explores the application of ensemble classification and ICA for dimensionality reduction of multifaceted NLOS 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 a particular of the following scenarios. To drastically lower the dimensionality of human detection data, this study considers ICA and ensemble classification algorithms. An I-J matrix M is used to display two datasets. There is a total of 23,552 instances in the static situation and 17,408 in the dynamic case. 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) [27], [29]. Data from the Cesena Campus School of Engineering at the University of Bologna. Table 1 give a thorough overview of the dataset, including feature sample occurrences and sampling characteristics. The specific characteristics of the dataset utilized in this research are shown in Table 1.

Table 1. Features of the dataset

Dataset features	Description
Moving radar	23,552
Stationery radar	17,408
Observation	256
Source	University of Bologna's Cesena Campus
Characteristics	Human body alignment, construction materials, rubbles, and sensor distances
Accessibility	Publicly available dataset [27]

4.2.1. Dimensionality reduction

Regarding computational intricacy, machine learning, and statistical evaluation, dimensionality reduction techniques are essential methods for overcoming the difficulties presented by large-scale data files. To lessen the curse of dimensionality, these methods seek to decrease the number of key variables being examined. Dimension reduction is frequently used as a preprocessing step before using unsupervised techniques such as clustering algorithms [30]. By removing multicollinearities, dimensionality reduction makes it easier to understand how machine learning algorithms read input information, which lowers the computing time and space needed, and permits display of data in lower-dimensional environments, like 2D or 3D.

FE and feature selection are the two primary steps in dimensionality reduction in machine learning [31]. To produce a smaller collection of meaningful features, FE entails locating and removing related characteristics from high-dimensional data. This procedure eliminates noise and redundancy while improving the data's interpretability. In contrast, feature selection entails eliminating superfluous or redundant features while selecting a subset of features that best capture the data [32].

4.2.2. Feature extraction

Huge volumes of unprocessed data are separated into categories that are easier to manage utilizing a dimensionality reduction technique termed FE. The fact that these massive data sets have numerous parts that require a significant amount of computing power makes them comparable. The phrase "FE" describes methods that choose pertinent variables and/or combine them to produce features, which minimizes the volume of data that needs to be processed while accurately and fully characterizing the original dataset [33]. FE is a creative substitute for feature selection when dealing with diminishing sizes of large-scale data. In a lower-dimensional domain, it is referred to as "feature translation or creation." The FE method portrays problems in a more usable and discriminating space by changing the starting variable in a space with fewer dimensions, which increases the efficiency of further analysis. Linear and non-linear approaches are the two main categories of FE algorithms. Linear processes are generally faster, more dependable, and simpler to comprehend than non-linear procedures. Complex data structures, or embedments, that linear algorithms cannot recognize are detected by non-linear approaches [34].

FE is the process of converting a dataset into a more basic form of characteristics so that more latent ideal component features can be inferred from it. It offers an open data representation of the associated variable for combining linear variables into feature subsets. Moreover, FE is a flexible method that may be used in various contexts [35]. This study utilizes ICA to match connected parameters in the system because it necessitates an orthogonal transformation with representations of uninterruptedly indistinguishable features.

4.2.3. Independent component analysis

When ICA was first introduced in the 1980s, it suggested a reinforced instantaneous method. There was no theoretical explanation included in that book, and the proposed method was irrelevant in several circumstances. But until 1994, when the word "ICA" first appeared and was marketed as a new concept, the ICA algorithm was typically unknown [36].

The goal of ICA is to extract pertinent information or fundamental signals—a collection of measured mixture signals—from the data. Source signals were recovered using ICA. When ICA can preserve or remove a specific source, it is sometimes seen as a dimensionality reduction procedure. Certain information can be eliminated or filtered using this process, which is also known as a filtering operation.

ICA can identify independent components and improve higher-order metrics like kurtosis. Several ICA algorithms exist, such as a FastICA projection pursuit and Infomax [37]. The main goals of using these techniques to identify distinct components are to apply the maximum likelihood (ML) estimate approach, maximize non-Gaussianity, or minimize mutual information [38]. The steps required to run the ICA program from beginning to conclusion are displayed in Algorithm 1.

Algorithm 1. ICA starts
1: Firstly, K is set to zero.
2: Ascertaining the distance among the training instances and the input example.
3: In the third stage, sort the division.
4: In step four, choose the highest-ranking k-nearest neighbors (KNN).
5: In step five, use the simple majority.
6: Use additional neighbors for identifying the loaded sample's subclass label.
Stop

4.2.4. Classification

Contemporary advances in data investigation emphasize the state-of-the-art utilization of ranking probabilistic models derived from both LOS and NLOS data to classification issues. According to Rayavarapu and Mahapatro [39], this method entails improving these representations through the use of an integrated framework, which makes it possible to develop efficient classification algorithms. Meanwhile, as described by Moro *et al.* [27] developments in machine learning have sparked the creation of ensemble decision tree classification techniques, including boosting, bagging, and random forests. Classification algorithms are essential for anticipating obstacles based on patterns of body position in the field of "victim detection" studies [40].

According to Ayyad *et al.* [41], machine learning is a scientific approach that seeks to improve computer learning through experience. In this framework, classification entails creating decision criteria according to body orientation and environmental features, which are essential for jobs such as rescue operations. This field frequently employs a variety of classifiers, such as decision trees, neural networks, artificial bee colonies, bat algorithms, particle swarm optimization, support vector machines (SVM), and KNN.

4.2.5. Ensemble

To produce incredibly accurate results, ensemble classifiers—like models of random subspaces—combine disparate sections of training data or different classifier variables. These classifiers are frequently used in machine learning, especially in situations where humans must identify themselves behind obstacles in both LOS and NLOS domains. Ensemble classifiers make classification judgments efficiently by combining the output from various classifiers [41].

By merging the results of several classifiers, ensemble techniques—sometimes referred to as ensemble methodologies—improve classification performance. In ensemble classification, boosting and bootstrap aggregating (bagging) are common techniques. While boosting modifies the weights of training instances according to their impact on classifier performance, bagging entails randomly changing the training data to produce substitute training cycles. The final classifier is derived from the weighted decisions of separate classifiers.

AdaBoost was developed as a result of the technique shown in [42], which demonstrates the use of ensemble learning to apply boosting algorithms in datasets. This iterative method demonstrates improvements in ensemble techniques by adjusting weights to enhance classifier performance. Assume that, given δt, anything can be made so that:

$$Z1(i) = \frac{1}{m}: \text{given } Zt \text{ and } \delta t: \tag{1}$$

$$Z_{i+i}(i) = \frac{Z_t(i)}{Z_t} \times \begin{cases} e^{-\alpha t} if\, y_i = \delta_t(x_i) \\ e^{\alpha t} if\, y_i \neq \delta_t(x_i) \end{cases} \tag{2}$$

$$Z_{i+i}(i) = \frac{Z_t(i)}{A_t} exp\left(-\alpha y_i \delta_t(x_i)\right) \tag{3}$$

Z_t is the normalization variable in this case, where:

$$\alpha t = \frac{1}{2} in \left(\frac{1-\rho_t}{\rho_t}\right) \tag{4}$$

5.   PERFORMANCE EVALUATION

To assess the machine learning model's efficacy, a few validation procedures are required. Confusion matrices are commonly used in categorization models to examine the four standards true positive (TP), true negative (TN), false positive (FP), and false negative (FN). The model dataset supplied to evaluate the model identifies the images that were correctly and incorrectly identified. Performance measures and their calculation methods are described as follows, whereas Figure 2 shows the data sample containing the features of the loaded raw dataset.

	Max	min	Mean	Std. deviation	Skewness	Kurtosis	Energy	Max / min	Max - min	SD / mean	Max - min sqrd
0	0.652988	-0.478481	-39.062063	0.098293	1.126915	17.370630	2.473360	-1.364710	1.131468	-0.002516	1.280221
1	0.680325	-0.520884	0.000047	0.104437	1.184565	16.914978	2.792200	-1.306096	1.201208	2201.734642	1.442902
2	0.654511	-0.521990	-78.124979	0.104355	0.918378	15.918480	2.787837	-1.253875	1.176501	-0.001336	1.384155
3	0.634057	-0.541421	-273.437461	0.103709	0.991626	16.377148	2.753444	-1.171099	1.175478	-0.000379	1.381749
4	0.606181	-0.552172	39.062362	0.105350	0.845794	15.462336	2.841272	-1.097813	1.158352	0.002697	1.341780

Figure 2. Data sample showing contents of the original unprocessed dataset

The four metrics that determine the condition in which a model is present are used to evaluate its accuracy. Because of this, FP finds the state when it isn't there. The TN product cannot be found whenever the state is not present. The FN product does not detect the state if it exists.

$$Accuracy = \frac{TP + TN}{TP+TN+FP+FN} \tag{5}$$

The percentage of accurately identified instances with positive positives is known as sensitivity. The definition of sensitivity is as follows.

$$Sensitivity\ (Recall) = \frac{TP}{TP+FN} \tag{6}$$

The quantity of properly identified events with negatives is determined by specificity.

$$Specificity = \frac{TN}{TN+FP} \tag{7}$$

$$Precision = \frac{TP}{TP+FP} \tag{8}$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{9}$$

6.   APPLICATION

Human unearthing and finding victims hidden beneath the wreckage is made easier with NLOS data processing. The need to locate relevant data is beneficial to the development of several technologies, such as the armed forces, intrusion detection, and automated detection, to name a few. Contradictory facts and designs can be found by using machine learning technologies. It has good algorithms, which are tools utilized in many different industries. Because of its user-friendliness and advantageous programming platform for engineers, architects, scholars, and academia, among others, MATLAB is used for experimentation. MATLAB is a computer language and multi-worldview mathematical computational environment developed by MathWorks.

It enables the development of user interfaces within several languages, including C, C++, C#, Java, Fortran, and Python, as well as the implementation of algorithms, function and data charting, and conceptual

model controls. The main focus of this study is the use of collapse structural technology, which makes utilize of the MATLAB program and the NLOS database, to anticipate the number of people entrapped underneath debris. An iCore3 CPU, 8 GB of RAM, a 64-bit operating system, and MATLAB 2015b as its execution tools make up the computer configuration utilized for this study.

7. RESULTS AND DISCUSSION

Both the findings and a commentary on the work are included in this section. The results of the tests and their implications for further research will be discussed in this section. The findings not only demonstrate the importance of our strategy but also pave the way for additional research in the area. The confusion matrix, performance metric table, and bar chart representation are the outcomes.

7.1. Results

The experiment is trained, assessed, and evaluated using an ensemble learning technique to categorize data and verify its effectiveness in reducing errors in the dataset. The outcomes are assessed using performance metrics and computational outcomes. The models are classified using an AdaBoost ensemble classifier, which achieves a performance accuracy of 88.00% for static models and 87.20% for dynamic models. The outcomes and processes of the results obtained for the two datasets are presented in Figure 3, while Figure 4 contains their graphical performance comparison. The ICA FE algorithm is employed to retrieve the concealed characteristics from the NLOS data in Table 1. The outcomes are shown in Table 2, which creates an output for the performance indicators in Figure 3(a) for static and Figure 3(b) for dynamic using the confusion matrix. The gathered attributes are categorized using the ensemble method.

(a)   (b)
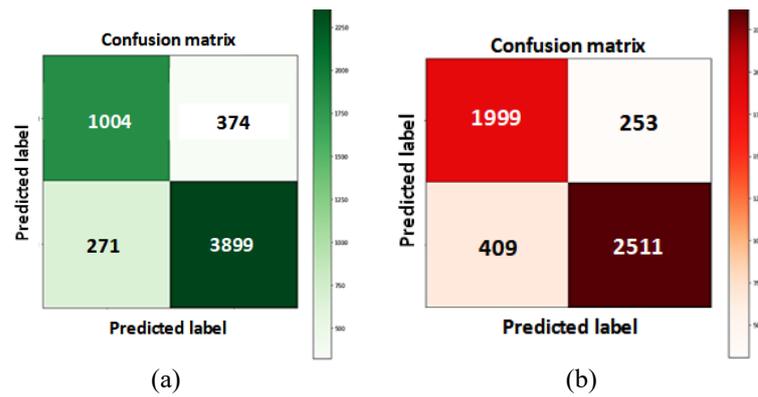
Figure 3. The resultant confusion matrix for the (a) static and (b) dynamic dataset ensemble classifications
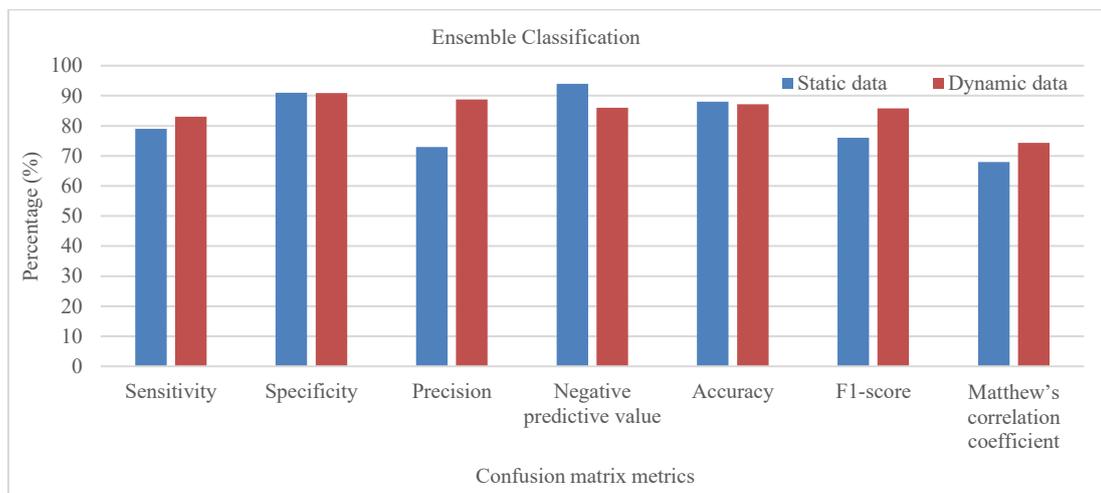

Figure 4. Performance indicator graph

Figure 4 shows the performance metrics for correctly and erroneously classified values, while Figure 3 show the datasets that were successfully classified. Numbers and graphs that act as measures for particular points of data are used to represent the variables' values. The relationships among the variables that have been categorized are displayed in this graph. Figure 3 display the confusion matrix for the boosted ensemble classifier predictions employed in the study. The confusion matrix table, which shows the true, false, true negative, and false negative figures, is then utilized to explain how well the prediction approach performs given sets of experimental data with verified true values.

Ensemble classification is utilized to predict performance. The results established the effectiveness of data processing when measured data is used. The performance outcomes for the recommended approach are shown and related in Table 2. Consequently, the accuracy and other performance metrics of ensemble categorization are significantly improved.

Figure 4 illustrates how ICA FE techniques in conjunction with an SC noise reduction model can enhance ensemble classification results. Figure 4 depicts the performance curve for contrasted output products. As previously said, Figure 3 and Table 2 presented the investigation and performance assessment of the research results. Researchers have suggested several improvements using the performance metrics in Figure 4, and the outcomes have demonstrated that using ICA FE techniques and a typical SC dimensionality reduction strategy can increase ensemble classifier accuracy.

Table 2. Performance metrics of the confusion matrix

Measurement metrics	Static data (%)	Dynamic data (%)
Sensitivity	79.00	83.01
Specificity	91.00	90.85
Precision	73.00	88.77
Negative predictive value	94.00	85.99
Accuracy	88.00	87.20
F1-score	76.00	85.79
Matthew's correlation coefficient	68.00	74.31

7.2. Discussion

In this study, the classification of NLOS signal data is examined more comprehensively. Even though scientists have proposed a lot of effort, the curse of dimensionality and data noise, especially in NLOS settings, make it difficult to accurately identify trapped persons. The curse of dimensionality leads blind areas as a result of noise and unconnected values in detections, and this issue has not been fully addressed in previous research. This study proposes an enhanced prediction and detection model for trapped human victims during disasters, using ICA dimensionality reduction and ensemble classification data mining procedures. The information in the figures and tables has validated that dimensionality reduction models with ICA FE methods can greatly enhance the results of ensemble classification. Table 2 displays the performance metrics graph for comparing the yielded results, revealing that preprocessing techniques can enhance the classifiers' predictive abilities.

Several researchers have studied UWB NLOS signal data classification for human detection using machine learning algorithms, aiming to offer a trustworthy method of detection and prediction for trapped human victims during disasters. Our study builds on this foundation, showing that the proposed method with ICA FE achieves higher accuracy and precision compared to previous methods. Static data evaluation outperformed dynamic data evaluation, with static data achieving 88.00% accuracy compared to 87.20% for dynamic data. This difference is attributed to the relative simplicity of NLOS detection when the sensor is stationary, as opposed to the increased complexity when the sensor is in motion.

This study suggests that higher dimensionality reduction through ICA does not hinder performance; instead, it enhances the classification results by mitigating the effects of noisy and uncorrelated data. This is in line with findings from similar studies that highlight the importance of preprocessing techniques in improving model performance. However, unlike some previous works, our approach demonstrates a lower reliance on extensive training sets, which can be beneficial in real-world disaster scenarios where immediate data collection is critical.

Despite the promising results, this study acknowledges certain limitations. The effectiveness of the proposed method in highly dynamic and cluttered environments needs further investigation. Additionally, the model's performance in different types of disasters and varying environmental conditions should be explored to ensure robustness and generalizability.

The findings indicate that ICA-based dimensionality reduction and ensemble classification methods are more resilient and effective in NLOS signal data classification [43]. Future research could explore the integration of real-time adaptive algorithms that adjust to changing environmental conditions, enhancing the

model's applicability in diverse disaster scenarios. Additionally, expanding the dataset with more varied NLOS conditions and including data from multiple types of sensors could provide a more comprehensive evaluation of the model's performance [44], [45].

This study demonstrates that the proposed ICA-based dimensionality reduction and ensemble classification method significantly improves the prediction and detection of trapped human victims during disasters. The findings provide conclusive evidence that this approach enhances accuracy and precision, particularly in static sensor conditions, and reduces the reliance on extensive training data. This contributes to a more effective and efficient SAR operation, ultimately aiding in saving lives during critical disaster situations.

8.   VALIDATION

Comparing this work with other related studies, as shown in Table 3, this approach demonstrates superior application and accuracy in human localization under NLOS scenarios. Unlike other methods, this approach effectively handles both static and dynamic data, leading to better overall performance. Table 2 encapsulates the performance enhancements achieved by this proposed model across all datasets. The model outperforms other approaches specifically, the accuracy for static data improved to 88.00%, surpassing the best-performing baselines.

This significant improvement is attributed to the effective integration of dimensionality reduction and hybridization techniques, which refine localization relevance and accuracy. By leveraging ensemble learning and noise reduction, this model demonstrates a robust ability to handle complex NLOS conditions. The ensemble learning approach, combined with noise reduction techniques, ensures that this model not only achieves higher accuracy but also maintains consistency across various datasets, both static and dynamic.

Table 3. Comparative approaches

Methods	Accuracy (%)
KNN [46]	85.00
SVM+autoencoder [47]	86.98
CNN+stacked-LSTM [48]	82.14
Proposed method	88.00

9.   CONCLUSION

This study analyzed and improved the classification of the NLOS human detection dataset. Data analysis in this research provides substantial and worthwhile advantages to the scientists and engineers, and the development of technology has greatly aided in the evolution of the issues of SAR operations. Human detection dataset prediction and reduction of dimensionality and classification techniques are examples of comparable technologies. These technological advancements have significantly contributed to the evolution of the problems of related applications, including the reduction of dimensionality and classification approaches. It is a serious issue because of the data's curse of dimensionality bound. A number of approaches have been put out to advance the technology and anticipate and identify trapped victims that are taken from samples; these difficulties have been resolved by reducing dimensionality. However, additional research must be done. Recently, several techniques have also been employed to categorize and predict UWB NLOS human detection signal data expression results. Nevertheless, the static ICA ensemble (88.00%) outperformed the dynamic ICA ensemble (87.20%) based approach by utilizing SC with ICA to carry out a dimensionality reduction approach with ICA for static and SC with ICA for dynamic datasets. The algorithms were applied discretely, and their performance on the ensemble classification model was evaluated. This work aims to provide a way to reduce the number of variables while maintaining informative ones for improved prediction, which engineers can use to make decisions. This work used NLOS human detection data to suggest a phased increase in dimensionality and prediction technique. A superior performance measure was obtained by retrieving relevant features. In order to determine the appropriate categorization of the NLOS's human-detecting expression data, future research suggests applying hybrid dimensionality reduction techniques to other classifiers, such as deep learning.

AUTHOR CONTRIBUTIONS STATEMENT

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

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis

I : **I**nvestigation
R : **R**esources
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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 GitHub at https://github.com/disiunibo-nlu/uwb-nlos-human-detection.

REFERENCES

[1] J. A. Enoch, I. B. Oluwafemi, and P. K. Olulope, "Survey of sensors and techniques in microwave imaging for through-wall imaging for detecting trapped humans under rubble," in *Social Media and Crowdsourcing*, Auerbach Publications, 2020, pp. 150–177.

[2] F. S. Hutabarat, I. M. D. Sitanggang, J. A. I. Damanik, G. P. B. Knight, and A. Sagala, "Unmanned aerial vehicle design for disaster victim search and rescue operation using wireless sensor network localization," *IAES International Journal of Robotics and Automation*, vol. 11, no. 4, pp. 288-303, 2022, doi: 10.11591/ijra.v11i4.pp288-303.

[3] A. Anyfantis and S. Blionas, "An analysis on the performance of a mobile platform with gas sensors for real time victim localization," *Sensors*, vol. 21, no. 6, pp. 1–30, 2021, doi: 10.3390/s21062018.

[4] R. Vyas, V. Agrawal, D. R. Verma, and P. Patel, "AI to the rescue: revolutionizing post-disaster recovery systems," in *Proc. Int. Conf. on Artificial Intelligence for Innovations in Healthcare Industries (ICSHIT 2024)*, 2025, pp. 235-245, doi: 10.2991/978-94-6463-528-9_24.

[5] U. Aparna, B. Athira, M. V. Anuja, A. Ramakrishnan, and R. Divya, "SPOTTER: detection of human beings under collapsed environment," *International Journal of Innovative Science and Research Technology*, vol. 5, no. 8. pp. 677–680, 2020, doi: 10.38124/ijisrt20aug459.

[6] X. Cui, Y. Sun, X. Tang, and Y. Fang, "NoA dynamic adaptive iterative greedy algorithm for collaborative helicopter rescue in post-disaster contexts with finite survival time constraints," *Expert Systems with Applications*, vol. 304, 2026, doi: 10.1016/j.eswa.2024.130771.

[7] M. R. Barusu, N. G. Rani, Y. V. S. Reddy, and G. P. R. Reddy, "A non-invasive technique for monitoring supply voltage variation to single phase induction motor using doppler UWB radar signal analysis," *International Journal of Power Electronics and Drive Systems*, vol. 15, no. 1, pp. 35–44, 2024, doi: 10.11591/ijpeds.v15.i1.pp35-44.

[8] J. Wang, M. Wang, D. Yang, F. Liu, and Z. Wen, "UWB positioning algorithm and accuracy evaluation for different indoor scenes," *International Journal of Image and Data Fusion*, vol. 12, no. 3, pp. 203–225, 2021, doi: 10.1080/19479832.2020.1864788.

[9] P. Mavaie, L. Holder, and M. K. Skinner, "Hybrid deep learning approach to improve classification of low-volume high-dimensional data," *BMC Bioinformatics*, vol. 24, no. 1, 2023, doi: 10.1186/s12859-023-05557-w.

[10] M. O. Adebiyi, A. A. Adebiyi, O. Okesola, and M. O. Arowolo, "ICA learning approach for predicting RNA-Seq data using KNN and decision tree classifiers," *International Journal of Advanced Science and Technology*, vol. 29, no. 3, pp. 12273–12282, 2020.

[11] N. Terranova, K. Venkatakrishnan, and L. J. Benincosa, "Application of machine learning in translational medicine: current status and future opportunities," *AAPS Journal*, vol. 23, no. 4, pp. 1–10, 2021, doi: 10.1208/s12248-021-00593-x.

[12] L. Zhan, Y. Liu, W. Yao, J. Zhao, and Y. Liu, "Utilization of chip-scale atomic clock for Synchrophasor measurements," *IEEE Transactions on Power Delivery*, vol. 31, no. 5, pp. 2299–2300, 2016, doi: 10.1109/TPWRD.2016.2521318.

[13] F. S. A. Pour, "Application of a blockchain enabled model in disaster aids supply network resilience," Ph.D. dissertation, Department of Engineering Management & Systems Engineering, Old Dominion University, Norfolk, Virginia, 2021.

[14] M. Ilbeigi, A. Morteza, and R. Ehsani, "An infrastructure-less emergency communication system: a blockchain-based framework," *Journal of Computing in Civil Engineering*, vol. 36, no. 2, 2022.

[15] O. R.-Espíndola, S. Chowdhury, A. Beltagui, and P. Albores, "The potential of emergent disruptive technologies for humanitarian supply chains: the integration of blockchain, artificial intelligence and 3D printing," *International Journal of Production Research*, vol. 58, no. 15, pp. 4610–4630, 2020, doi: 10.1080/00207543.2020.1761565.

[16] E. Samir, M. Azab, and Y. Jung, "Blockchain guided trustworthy interactions for distributed disaster management," in *2019 IEEE 10th Annual Information Technology, Electronics and Mobile Communication Conference, IEMCON 2019*, 2019, pp. 241–245, doi: 10.1109/IEMCON.2019.8936147.

[17] T. Nguyen, R. Katila, and T. N. Gia, "A novel internet-of-drones and blockchain-based system architecture for search and rescue," in *2021 IEEE 18th International Conference on Mobile Ad Hoc and Smart Systems, MASS 2021*, 2021, pp. 278–288, doi: 10.1109/MASS52906.2021.00044.

[18] R. Li, H. Hu, and Q. Ye, "RFTrack: stealthy location inference and tracking attack on Wi-Fi devices," *IEEE Transactions on Information Forensics and Security*, vol. 19, pp. 5925–5939, 2024, doi: 10.1109/TIFS.2024.3404810.

[19] Z. Yu, D. Zhao, and Z. Zhang, "Doppler radar vital signs detection method based on higher order cyclostationary," *Sensors*, vol. 18, no. 1, 2018, doi: 10.3390/s18010047.

[20] J. Yan, H. Hong, H. Zhao, Y. Li, C. Gu, and X. Zhu, "Through-wall multiple targets vital signs tracking based on VMD algorithm," *Sensors*, vol. 16, no. 8, 2016, doi: 10.3390/s16081293.

[21] U. M. Khan, Z. Kabir, S. A. Hassan, and S. H. Ahmed, "A deep learning framework using passive WiFi sensing for respiration monitoring," in *IEEE Global Communications Conference, GLOBECOM*, 2017, pp. 1–6, doi: 10.1109/GLOCOM.2017.8255027.

[22] J. Park, S. Nam, H. Choi, Y. Ko, and Y. B. Ko, "Improving deep learning-based UWB LOS/NLOS identification with transfer learning: an empirical approach," *Electronics*, vol. 9, no. 10, pp. 1–13, 2020, doi: 10.3390/electronics9101714.

[23] A. Lazaro, D. Girbau, and R. Villarino, "Techniques for clutter suppression in the presence of body movements during the detection of respiratory activity through UWB radars," *Sensors*, vol. 14, no. 2, 2014, doi: 10.3390/s140202595.

[24] L. Chioukh, H. Boutayeb, D. Deslandes, and K. Wu, "Noise and sensitivity of harmonic radar architecture for remote sensing and detection of vital signs," *IEEE Transactions on Microwave Theory and Techniques*, vol. 62, no. 9, pp. 1847–1855, 2014, doi: 10.1109/TMTT.2014.2343934.

[25] C. Li, V. M. Lubecke, O. B.-Lubecke, and J. Lin, "Sensing of life activities at the human-microwave frontier," *IEEE Journal of Microwaves*, vol. 1, no. 1, pp. 66–78, Jan. 2021, doi: 10.1109/JMW.2020.3030722.

[26] Z. Peng *et al.*, "A portable FMCW interferometry radar with programmable low-IF architecture for localization, ISAR Imaging, and vital sign tracking," *IEEE Transactions on Microwave Theory and Techniques*, vol. 65, no. 4, pp. 1334–1344, 2017, doi: 10.1109/TMTT.2016.2633352.

[27] 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, 2022, doi: 10.3390/s22041656.

[28] R. R. Sarra, A. M. Dinar, M. A. Mohammed, and K. H. Abdulkareem, "Enhanced heart disease prediction based on machine learning and χ2 statistical optimal feature selection model," *Designs*, vol. 6, no. 5, 2022, doi: 10.3390/designs6050087.

[29] B. Salah *et al.*, "A qualitative and quantitative analysis of remanufacturing research," *Processes*, vol. 9, no. 10, Oct. 2021, doi: 10.3390/pr9101766.

[30] J. Imperial, "The multidimensional scaling (MDS) algorithm for dimensionality reduction," *Medium-Data Driven Investor*. 2019. [Online]. Available: https://medium.datadriveninvestor.com/the-multidimensional-scaling-mds-algorithm-for-dimensionality-reduction-9211f7fa5345

[31] R. S. P. Lakshme and S. G. Kumar, "A review based on machine learning for feature selection and feature extraction," *Advancements in Smart Computing and Information Security (ASCIS 2022)*, 2022, pp. 144–157, doi: 10.1007/978-3-031-23092-9_12.

[32] S. Chakraborty, S. H. Islam, and D. Samanta, "Data mining-based variant subset features," in *EAI/Springer Innovations in Communication and Computing*, Springer, 2022, pp. 177–193, doi: 10.1007/978-3-030-93088-2_8.

[33] Y. E. Karabacak and N. G. Özmen, "Common spatial pattern-based feature extraction and worm gear fault detection through vibration and acoustic measurements," *Measurement: Journal of the International Measurement Confederation*, vol. 187, 2022, doi: 10.1016/j.measurement.2021.110366.

[34] B. Salman, "Infrastructure management and deterioration risk assessment of wastewater collection systems," *Doctoral dissertation*, Department of Engineering and Applied Science: Civil Engineering, University of Cincinnati, Cincinnati, Ohio, 2010.

[35] H. S.-Moghadam, "Fully component selection: an efficient combination of feature selection and principal component analysis to increase model performance," *Expert Systems with Applications*, vol. 186, 2021, doi: 10.1016/j.eswa.2021.115678.

[36] A. Tharwat, "Independent component analysis: an introduction," *Applied Computing and Informatics*, vol. 17, no. 2, pp. 222–249, 2018, doi: 10.1016/j.aci.2018.08.006.

[37] H. Liu, Q. Zhang, C. Xu, and Z. Ye, "A novel FastICA algorithm based on improved secant method for Intelligent drive," *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 1, pp. 165–178, 2021, doi: 10.3233/JIFS-190469.

[38] J. Agrawal, M. Gupta, and H. Garg, "Blind source separation in perspective of ICA algorithms: a review," in *International Conference on Computational Intelligence and Sustainable Engineering Solution, CISES 2022*, 2022, pp. 78–85, doi: 10.1109/CISES54857.2022.9844373.

[39] V. C. S. R. Rayavarapu and A. Mahapatro, "NLOS identification and mitigation in UWB positioning with bagging-based ensembled classifiers," *Annales des Telecommunications/Annals of Telecommunications*, vol. 77, no. 5–6, pp. 267–280, 2022, doi: 10.1007/s12243-021-00884-6.

[40] M. L. Tham, Y. J. Wong, B. H. Kwan, Y. Owada, M. M. Sein, and Y. C. Chang, "Joint disaster classification and victim detection using multi-task learning," in *2021 IEEE 12th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference, UEMCON 2021*, 2021, pp. 407–412, doi: 10.1109/UEMCON53757.2021.9666576.

[41] S. M. Ayyad, A. I. Saleh, and L. M. Labib, "Classification techniques in gene expression microarray data," *International Journal of Computer Science and Mobile Computing*, vol. 7, no. 11, pp. 52–56, 2018.

[42] K. Kowsari, K. J. Meimandi, M. Heidarysafa, S. Mendu, L. Barnes, and D. Brown, "Text classification algorithms: a survey," *Information*, vol. 10, no. 4, 2019, doi: 10.3390/info10040150.

[43] A. Benouakta, F. Ferrero, L. Lizzi, and R. Staraj, "Antenna characteristics contributions to the improvement of UWB real-time locating systems' reading range and multipath mitigation," *IEEE Access*, vol. 11, pp. 71449–71458, 2023, doi: 10.1109/ACCESS.2023.3294622.

[44] D. Ghosh, V. Honkote, and K. Narayanan, "Dynamic adaption of noise covariance for accurate indoor localization of mobile robots in non-line-of-sight environments," in *IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems*, 2020, pp. 387–393, doi: 10.1109/MFI49285.2020.9235245.

[45] Y. Wang, K. C. Ho, and Z. Wang, "Robust localization under NLOS environment in the presence of isolated outliers by full-Set TDOA measurements," *Signal Processing*, vol. 212, 2023, doi: 10.1016/j.sigpro.2023.109159.

[46] J. A. Enoch, I. B. Oluwafemi, O. K. Paul, F. A. Ibikunle, O. Emmanuel, and A. F. Olamide, "A comparative performance study of support vector machine, KNN, and ensemble classifiers on through-wall human detection dataset," in *2023 International Conference on Science, Engineering and Business for Sustainable Development Goals, SEB-SDG 2023*, 2023, vol. 1, pp. 1–9, doi: 10.1109/SEB-SDG57117.2023.10124476.

[47] D. H. Tran, B. Chung, and Y. M. Jang, "GAN-based data augmentation for UWB NLOS identification using machine learning," in *4th International Conference on Artificial Intelligence in Information and Communication, ICAIIC 2022*, 2022, pp. 417–420, doi: 10.1109/ICAIIC54071.2022.9722667.

[48] 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, 2020, doi: 10.1109/LCOMM.2020.2999904.

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