Journal of Physics: Conference Series

PAPER • **OPEN ACCESS**

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To cite this article: L. Antognoli *et al* 2024 *J. Phys.: Conf. Ser.* **2698** 012025

Laser Doppler Vibrometry for detecting survivors in hard-to-reach environments

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Abstract. Search and Rescue (SAR) operations in remote and hazardous environments are crucial for the rapid and accurate location of survivors, with a timely response being essential during the "golden hours" following a disaster. Recent technological advancements offer innovative solutions to enhance SAR efforts. This study aims to investigate the use of Laser Doppler Vibrometry (LDV) as a tool for remote vital sign assessment and explore its integration with Machine Learning (ML) techniques for accurate individual identification in challenging SAR scenarios. Various scenarios, such as different distances, difficult angles, and non-ideal body placements, are explored in the study to faithfully recreate hard-to-reach environments. Two models, the OS-Model trained with data acquired under optimal conditions and the AS-Model trained with data acquired including all the different conditions studied, were compared to evaluate classification performance. Results indicate that the LDV-assisted ML approach, particularly the AS-Model, exhibits promising outcomes with a higher median prediction accuracy of 0.93, emphasizing the importance of diverse and comprehensive datasets. However, limitations regarding accuracy at greater distances, smaller angles, and lower-body laser targeting must be considered for practical implementation.

1. Introduction

Locating survivors in remote and difficult-to-reach areas presents significant obstacles for search and rescue (SAR) teams. Environments that are difficult to reach include mountain cliffs, radiation-contaminated sites, combat zones [1], and areas impacted by natural disasters like avalanches, earthquakes, and floods [2]. A SAR operation aims to locate a lost or injured person by searching the largest area of the territory in the shortest time possible [3]. The immediate aftermath of such events is a pivotal period when a well-coordinated and prompt response can significantly minimize the loss of life [4]. The time frame immediately after a disaster is crucial and referred to as the "golden hours". This period, lasting up to 72 hours, presents the highest chances of saving lives and minimizing suffering [5].

Rapidly locating individuals in distress is crucial for prompt action, enabling quicker rescue efforts and reducing the time between requesting help and the actual rescue. This is particularly important in situations with limited air supply or risk of hypothermia, as it allows for timely localization of individuals and optimization of resources. Concentrating search efforts in the right area minimizes unnecessary search operations and reduces strain on personnel, equipment, and aircraft.

The evolution of technology has brought in a new era of possibilities, offering innovative tools to enhance the efficiency and effectiveness of SAR operations [6]. These innovative solutions have played a crucial role in minimizing the risks faced by rescuers while also accelerating the entire operation [2]. Unmanned search and rescue vehicles are essential in locating victims during rescue missions. They are advantageous to both rear rescue commanders and forward aid workers. Collecting real-time vital signs like the heart rate (HR) and the respiration rate (RR) of discovered victims is crucial [7]. Obtaining the real-time physiological parameters of injured individuals with precision and speed is essential for understanding their physical status and facilitating subsequent medical interventions [8]. Among these technologies, robots, drones, radar systems, and laser technologies have revolutionized the way search and rescue operations are conducted. Rescue robots equipped with sensors and thermal cameras can detect vital signs and locate survivors in challenging conditions, relaying that information to rescuers [9]. These mobile rescue robots are specifically designed to navigate disaster-stricken areas that humans cannot access, assisting in the search and tracking of victims who might otherwise be difficult to locate [10], [11]. Unmanned aerial vehicles, also called drones, are compact aircraft operated by a ground-based controller. These vehicles can reduce search durations and speed up subsequent actions [12]. These drones are equipped with advanced cameras, thermal imaging capabilities, and sensors that aid in identifying survivors and assessing their well-being, all without putting rescuers at risk [13]. Radar sensor-based vital signs monitoring systems have found extensive utility across various domains, including SAR missions. This innovation allows for non-invasive tracking of a person's vital indicators by studying the radar signals they reflect [14]. By analyzing subtle vibrations of the human body, it can estimate heart and respiration rates and detect movements that indicate signs of life [15]. Laser Doppler Vibrometry (LDV) emerges as a promising contactless technique for remote assessment of vital signs, effectively capturing physiological parameters through non-contact methods [16], [17], [18]. Through the emission of a laser beam toward the subject, this innovative technology can sense vibrations induced by vital activities like breathing and heartbeat [19].

On another hand, in recent times there have been significant developments in the field of artificial intelligence (AI), which has proven to be a valuable tool in supporting critical decision-making during emergencies, particularly in disaster scenarios [20]. These advancements, particularly in machine learning (ML) and deep learning (DL), have further amplified the potential of these SAR technologies [21]. ML algorithms are instrumental in processing the vast amounts of data generated (among others) by robots, drones, radar systems, and laser technologies. They enable intelligent decision-making and enhance the overall efficiency of SAR operations. Convolutional Neural Networks (CNN) are versatile tools capable of not only locating survivors, but also detecting damage to buildings, flooded areas, and debris in disaster scenarios [22]. AI plays a significant role in the analysis of biomedical signals like electrocardiogram (ECG) and respiratory data. For example, Bassiouni et al. [23] have developed hybrid methods for identifying individuals based on their ECG signals. Their results are notable, demonstrating substantial accuracy rates: 95% for Artificial Neural Networks (ANN), 98% for K-Nearest Neighbors (kNN), and 99% for Support Vector Machine (SVM) when applied to an ECG database.

In the context of advancing SAR technologies, this paper aims to investigate the utilization of LDV as a means of remotely assessing vital signs. Additionally, it explores the integration of ML techniques to distinguish human vital signs and accurately identify individuals. Scenarios involving varying distances, difficult angles, and non-ideal body positions are the focus of the study. The objective is to propose a measurement method to detect a human being in a faithfully recreated hard-to-reach environment, exploiting LDV and ML techniques.

2. Materials and methods

2.1. Experimental campaign

A total of 17 individuals (12 male and 5 female), with an average age of 24 ± 2 years (mean ± standard deviation) and body mass indices (BMIs) ranging from 18.2 to 24.9 kg/m², constituted the test population. Using the Fitzpatrick scale [24], participants were categorized into distinct groups based on their skin tone. Out of the total participants, ten were categorized as type I, representing individuals with light pale skin, five as type V, indicating individuals with brown skin, and two as type VI, representing individuals with black skin. Before the execution of the tests, a comprehensive explanation of the data acquisition process and the study objectives were provided to all participants. Then, they were asked to sign an informed consent module. The study followed the ethical guidelines of the World Medical Association (WMA) in the Declaration of Helsinki [25] for research involving human subjects and the principles outlined by the Ethical Committee of Università Politecnica delle Marche.

2.2. Acquisition methodologies

A single-point direct beam LDV (PDV-100, Polytec, Germany) [26] was used to acquire the signals. The laser utilized is eye-safe and falls under the category of Class II visible HeNe lasers, with a wavelength specifically at 632.8 nm. The subject's skin was not subjected to any specific treatment before conducting the signal acquisition. The experimental setup used to acquire the signal is shown in Figure 1. The LDV was placed on a tripod with the laser beam directed over different anatomical sites of each participant, varying distances, angles, and tightness of clothing. Various anatomical sites, such as head, chest, stomach, arm, leg, and foot, were chosen to encompass a wide range of vital sign vibrations. It is important to highlight that no specific focal point was targeted within these sites, opting instead for a generalized approach.

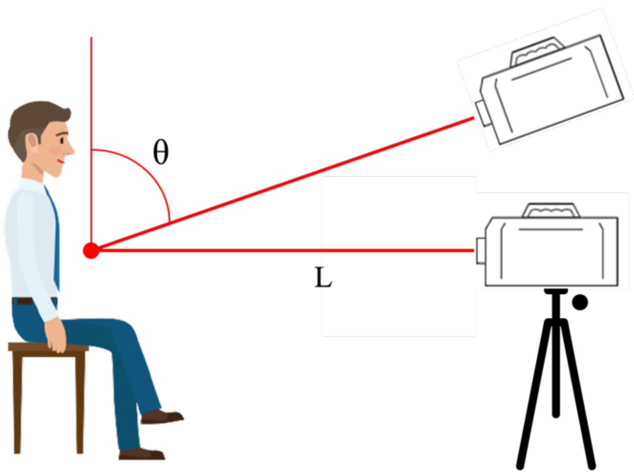

Figure 1. Experimental setup for signal acquisition.

Table 1 shows the acquisition protocol for each subject; for each variable, a 1-min LDV signal was acquired with a sampling frequency of 1 kHz. Aside from human subjects, a 1-min signal dataset was gathered by directing the LDV at inanimate objects to represent lifeless subjects. These objects included a resuscitation baby mannequin and various environmental elements such as trees, stones, building walls, metals, and glass. The total number of signals acquired was 213 obtained from human participants, 21 from a resuscitation baby mannequin, and 30 from environmental objects.

Table 1. Parameters of the acquisition protocol.

	Distance (m)	Angle (°)	Clothing tightness
Head	0.5	90	N/A
Chest	0.5, 1, 2, 3, 5	90, 80, 70, 60, 50, 40, 30, 20, 10	Loose, tight
Stomach	0.5	90	N/A
Arm	0.5	90	N/A
Leg	0.5	90	N/A
Foot	0.5	90	N/A

2.3. Data processing

As mentioned above, a total of 264 signals were acquired, with 213 obtained from human participants, 21 from a resuscitation baby mannequin, and an additional 30 from environmental objects. From each of these raw signals, 100 portions of 50 samples were randomly taken and labelled as either the presence or the absence of the human subject. Then, two different datasets were created. The first, called the Optimal Signals (OS) Dataset, included 20 signals acquired from human subjects wearing tight-fitting clothes, with the laser beam pointed to the chest area with a length (L) of 0.5 m and an angle (θ) of 90°. To balance the dataset, it included 5 signals collected from the resuscitation baby mannequin and 15 signals from various environmental objects. In total, this dataset consisted of 4000 samples. The second dataset was called the All Signals (AS) Dataset and it included all signals from human subjects, from the resuscitation baby mannequin, and from different environmental objects. The AS dataset contained a total of 55370 samples. Both datasets were used as inputs for building a decision tree classifier, which aimed to discriminate between human and non-human related LDV signals. The validation process involved splitting the dataset into training and testing data, with a ratio of 70:30. From the training of the classifiers the OS-Model and the AS-Model were created from the OS-Datasets and AS-Dataset, respectively. In the evaluation of the decision tree classifier performance, key metrics were computed from the test set. These metrics, including precision (1), recall (2), and the F1-score (3), offer a comprehensive assessment of the classifier performance.

$$\text{Precision} = \frac{\text{True Postive}}{\text{True Positive} + \text{False Positive}} \tag{1}$$

$$\text{Recall} = \frac{\text{True Postive}}{\text{True Positive} + \text{False Negatives}} \tag{2}$$

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

A comparative analysis was conducted between the two models to evaluate their prediction considering variations in distances, angles, body regions, clothing fit, and skin color. The goal of this evaluation was to assess the classification performance and to determine whether training on a dataset with greater diversity would yield better performance than a model trained only on signals acquired under optimal conditions.

3. Results and discussion

The macro average (Macro avg) performance metrics are reported for both the OS-Model and AS-Model in Table 2. These metrics include precision, recall, and F1-score. The AS-Model performed slightly better in terms of precision, recall, and F1-score, with values of 0.91 for each metric. This indicates that the AS-Model, which considers a broader range of signals and conditions, achieves slightly better classification results compared to the OS-Model.

Table 2. Macro Average Performance Metrics for OS-Model and AS-Model.

	Macro avg	
	OS-Model	AS-Model
Precision	0.90	0.91
Recall	0.89	0.91
F1-score	0.89	0.91

The predictive outcomes for each variable in both the OS-Model and AS-Model are reported in the following figures, including the 50th percentile, 90th percentile, and 10th percentile, in conjunction with the respective fitting curves for the data.

Figure 2 presents the results of the study on how distance affects the model performance. The OS-Model has an average prediction accuracy of 0.86, while the AS-Model performs slightly better with an average prediction accuracy of 0.89. Importantly, the AS-Model shows a significant 4% improvement in prediction accuracy compared to the OS-Model. They follow similar trends, indicating that performance decreases as distance increases. However, the OS-Model has more variation in its predictions compared to the AS-Model in this context.

In Figure 3, the influence of different angles on the predictive outcomes of the two models is presented. The AS-Model achieves a higher average prediction accuracy (0.89), whereas the OS-Model yields a lower average prediction accuracy (0.86). The AS-Model demonstrates an improvement of approximately 4% as it approaches a 90° angle, corresponding to the orientation where the laser is directed perpendicularly towards the subject. The OS-Model exhibits greater variability in predictive performance across different angles.

Figure 4 represents the analysis of the predictive performance of the OS-Model and AS-Model across various anatomical positions. The average prediction of the OS-Model is 0.69 ± 0.22, whereas of the AS-Model is 0.82 ± 0.17. Differences in predictive effectiveness are observed when these models are applied to different anatomical regions. Specifically, both models show better predictive performance when applied to the chest, stomach, and head (0.88 for OS-Model and 0.93 for AS-Model). However, their predictive accuracy decreases when they are applied to the lower limbs, with a higher degree of variability evident (0.49 for OS-Model and 0.62 for AS-Model).

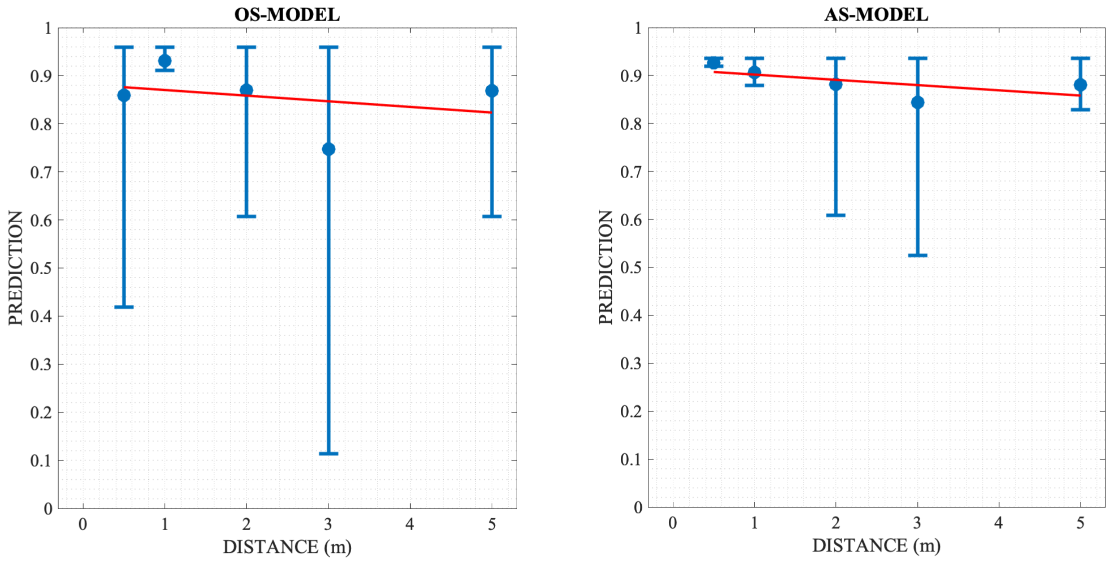

Figure 2. Predictive outcomes and fitting curves illustrating the effects of varying distances in the OS-Model (left) and AS-Model (right), including 50th, 90th, and 10th percentiles.

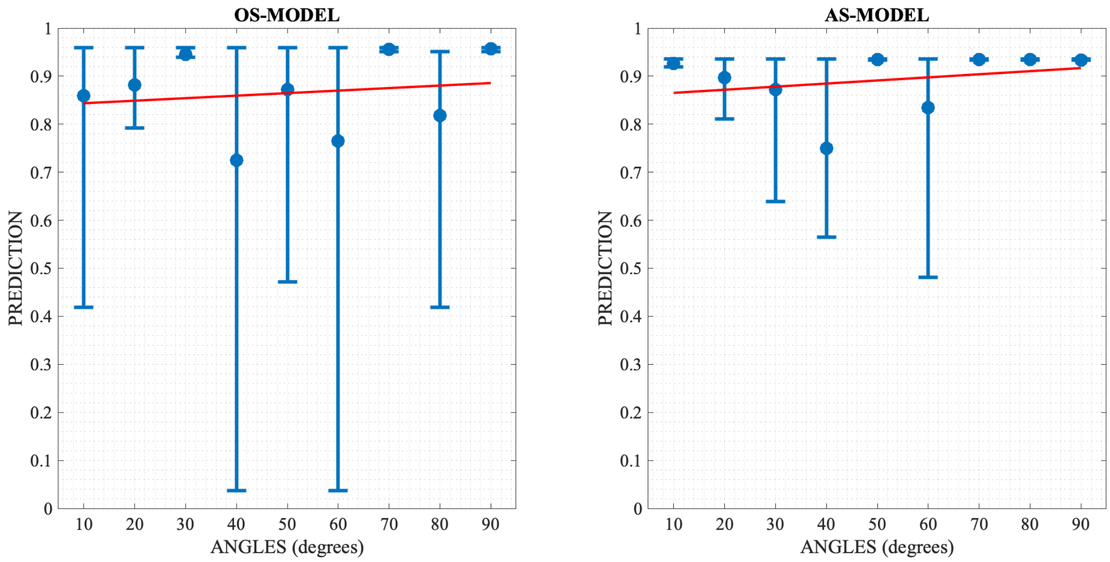

Figure 3. Predictive outcomes and fitting curves illustrating the effects of varying angles in the OS-Model (left) and AS-Model (right), including 50th, 90th, and 10th percentiles.

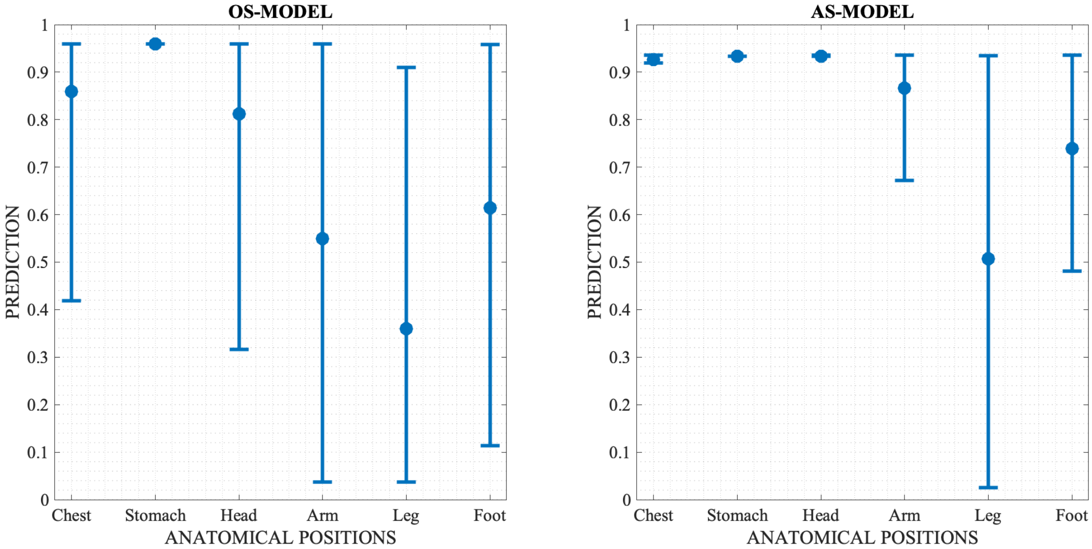

Figure 4. Predictive outcomes illustrating the effects of varying anatomical positions in the OS-Model (left) and AS-Model (right), including 50th, 90th, and 10th percentiles.

In Figure 5, the performance comparison of the two models is depicted in terms of predictive accuracy, considering tight and loose clothing fit. The OS-Model shows an average predictive accuracy of 0.83. In particular, moving to loose clothes shows a decrease in the predictive accuracy of 25.4%, indicating its sensitivity to clothing variations. In contrast, the AS-Model shows superior predictive performance, with an average accuracy of 0.93, and is not affected by clothing variations. The improvement in predictive accuracy is 12% in the AS-Model compared with the OS-Model.

Figure 6 represents the performance of the two models in their response to changes in skin color. The OS-Model shows an average predictive accuracy of 0.88, with a significant improvement of 4.6% in predictive accuracy when changing from skin color type I to type IV. In contrast, the AS-Model has a higher mean predictive accuracy of 0.93, with a minimal improvement in predictive accuracy, less than 1%, when moving from skin color type I to type IV. This difference emphasizes the substantial impact of skin color as a parameter on OS-Model performance, resulting in inherent variability among different skin tones. The laser has a wavelength of 632.8 nm, in the visible red region of the electromagnetic spectrum. Darker skin tones inherently exhibit greater light absorption than lighter skin tones. Consequently, the use of a red wavelength laser facilitates more effective penetration in darker skin, potentially leading to better predictive accuracy in this specific subgroup of individuals.

A real-world validation of the AS-MODEL was undertaken by directing the LDV towards a human subject and various objects. The LDV signals recorded in proximity to the human subject yield a classification score of 0.93, indicating a strong probability of accurately detecting vital signs. Conversely, LDV signals from all other environmental elements achieve a classification score below 0.10, thus proving the model ability to effectively discriminate between vibrations associated with humans and non-humans.

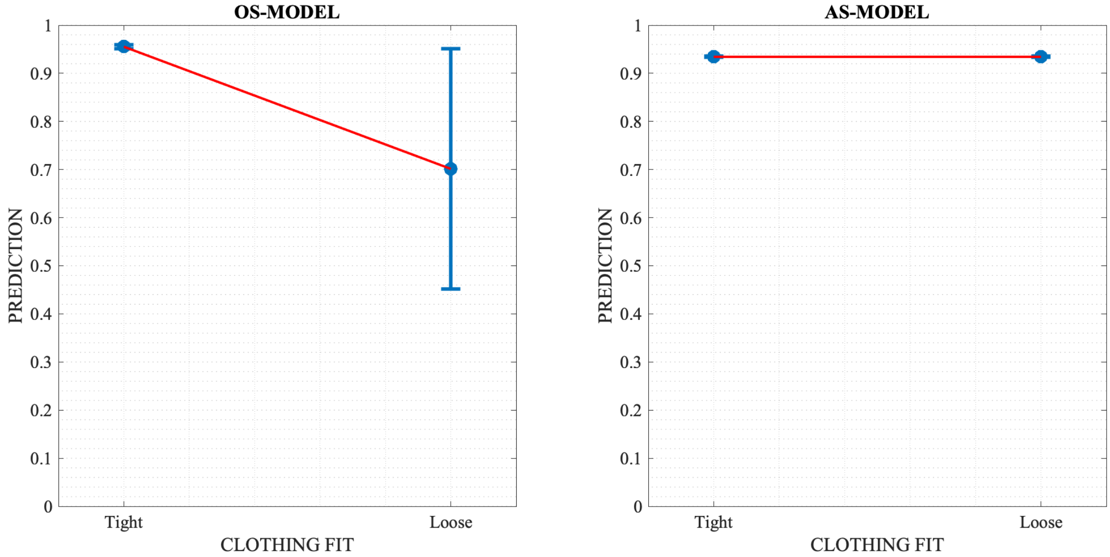

Figure 5. Predictive outcomes and fitting curves illustrating the effects of varying clothing fit in the OS-Model (left) and AS-Model (right), including 50th, 90th, and 10th percentiles.

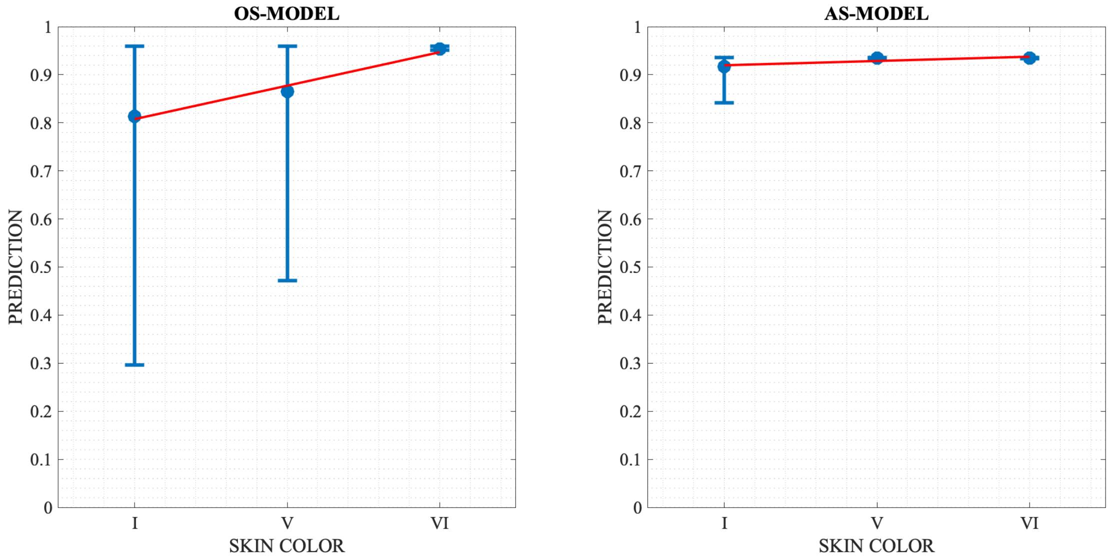

Figure 6. Predictive outcomes and fitting curves illustrating the effects of varying skin color in the OS-Model (left) and AS-Model (right), including 50th, 90th, and 10th percentiles.

4. Conclusion

The main aim of this work was to define a measurement procedure to detect human beings in hard-to-reach environments exploiting non-contact techniques, in particular using LDV as a tool for remote vital sign assessment and exploring its integration with ML techniques for accurate individual identification in challenging SAR scenarios. A comparative analysis was conducted between two different models: the OS-Model, which was trained using signals acquired exclusively under optimal conditions, and the AS-Model, which utilized a broader range of signals acquired under various conditions. Hence, the classification performance of different solutions was evaluated, and the authors analysed whether training on a dataset exhibiting greater diversity would result in enhanced performance compared to a model trained exclusively on signals acquired under ideal conditions.

The results demonstrate that the LDV-assisted ML approach exhibits favorable outcomes in the classification of vital signs within challenging environments. The AS-Model displays a higher median prediction accuracy of 0.93 in contrast to the 0.82 accuracy achieved by the OS-Model, demonstrating its superior performance in human beings' detection. This result emphasizes the significance of employing a larger and more comprehensive database over a restricted dataset of optimal signals. This approach consistently outperforms in terms of classification accuracy, underscoring the importance of dataset diversity and size in the model development process. It is important to acknowledge certain limitations identified in our research that affect the accuracy of classification. Specifically, errors tend to escalate as the distance increases, when dealing with smaller angles, and when pointing the laser at the lower part of the body. These limitations should be considered when implementing LDV-assisted ML systems in practical applications and may necessitate further research and technological advancements for mitigation.

Further developments should focus on the assessment of diverse ML algorithms to enhance performance evaluation, leading to even more accurate and robust results, thereby expanding the capabilities of ML in vital sign classification. Moreover, the validation of this approach needs to be conducted on a larger test population, including greater physiological variability. It is critical to ensure that the LDV-assisted ML system can effectively adapt to the unique physiological characteristics of a diverse population, improving its applicability and reliability in real-world scenarios.

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