Fusion of Unobtrusive Sensing Solutions for Sprained Ankle Rehabilitation Exercises Monitoring in Home Environments

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Abstract: The ability to monitor Sprained Ankle Rehabilitation Exercises (SPAREs) in home environments can help therapists to ascertain if exercises have been performed as prescribed. Whilst wearable devices have been shown to provide advantages such as high accuracy and precision during monitoring activities, disadvantages such as limited battery life, users’ inability to remember to charge and wear the devices are often the challenges for their usage. Also, video cameras, which are notable for high frame rates and granularity, are not privacy-friendly. This paper, therefore, proposes the use and fusion of unobtrusive and privacy-friendly sensing solutions for data collection and processing during SPAREs in home environments. Two Infrared Thermopile Array (ITA-32) thermal sensors and two Frequency Modulated Continuous Wave (FMCW) Radar sensors were used to simultaneously monitor 15 healthy participants during SPAREs which involved twisting their ankle in 4-fundamental movement patterns namely (i) extension, (ii) flexion, (iii) eversion and (iv) inversion. Experimental results indicated the ability to identify thermal blobs of participants performing the 4 fundamental movement patterns of the human ankle. Cluster-based analysis of data gleaned from the ITA-32 sensors and the FMCW Radar sensors indicated average classification accuracy of 96.9% with K-Nearest Neighbours, Neural Network, AdaBoost, Decision Tree, Stochastic Gradient Descent and Support Vector Machine, amongst others.

Keywords: Unobtrusive Sensing; Data Fusion; Data Mining; Radar Sensing; Thermal Sensing; Sprained Ankle; Infrared Thermopile Array; Home Environment.

1. Introduction

Sprained ankles are injuries sustained due to inappropriate movement of the ankle. Although they are generally regarded as common injuries, they can degenerate into lifelong problems if not properly treated. Common causes of a sprained ankle include ankle twists during a fall, awkward landing during sports activities and stepping on uneven surfaces during walking or exercising. Sprained Ankle Rehabilitation Exercises (SPAREs) include a range of exercises aimed at helping recovery from these injuries [1]. Whilst some of these exercises can be performed using common devices such as elastic bands and deformable plastic materials, sophisticated instruments, such as gyroscopes, accelerometers, and actuators, can also be used.

1.1. Related Work

Azizi et al. [1] proposed the use of a gyro-based system that included WiFi and microcontroller modules to determine ankle inclination and orientation. This study was noted to have provided significant improvement to the patients though it failed to estimate the percentage at which the participants recovered from the ailment. A further study by [2] proposed a video game-based approach to SPAREs. The approach, which was measured against traditional exercises, was said to be effective in restoring the ankle functions based on indexes such as mood, pain perception and readiness to return to active sports, amongst others. Furthermore, a game-based solution by [3] was compared...
with physical therapy and a controlled group. The study, which suggested six weeks of treatment, noted significant improvements in pain reduction. Work in [4] proposed the use of augmented reality to help patients and physiotherapists in SPAREs. The study focused on the importance of using autonomous devices during SPAREs. In all the studies, monitoring processes were either performed using human observation or a video camera. While the former is prone to optical illusion and error, the latter requires higher storage space. Also, video recordings can intrude into the privacy of the users of these technologies.

A privacy-friendly Sensing Solution (SS) was proposed by [5]. The work involved the use of a thermal imaging camera to study temperature variations in human ankles by comparing blood flow on paretic and non-paretic ankles. Although the thermal camera offered a privacy-friendly solution, parameters such as range, velocity and angle of the movement were not considered in the study. Also, the extent of recovery was through human observation. Therefore, to ensure the effectiveness of these rehabilitation approaches and processes, Data Mining (DM) and Machine Learning (ML) algorithms should be used for their data analysis for pattern assessment and clustering.

Research evidence has suggested that most SPAREs that are monitored through face-to-face interaction and supervision of a physiotherapist can be monitored remotely [6], [7]. Performing SPAREs in a remote environment, such as the home setting, can include following a set of instructional guides provided by a therapist [8]–[10]. The home-based approach can help address problems related to insufficient therapists and cost [11]. Unlike other rehabilitation exercises, monitoring SPAREs can be difficult owing to smaller angular movements of the ankle and the possibility of occlusion. Whilst video cameras pose privacy issues, Wearable Sensing Solutions (WeSSs) such as gyroscopes and accelerometers pose battery life and wearability problems. On the other hand, human observation can be prone to optical illusions and errors [12].

This study, therefore, proposes the use of unobtrusive and privacy-friendly SSs in the form of thermal and Radar sensors to monitor SPAREs in a home environment. It also considers the use of DM and ML algorithms to perform Classification by Clustering (CbyC) of thermal images and blobs and other parameters such as range, speed and the Angle of Approach or Retreat (AAR).

2. Materials and Methods

The experimental setup involved the use of multiple sensors to record SPAREs in a laboratory living room that mimics a real-world living room. They included (i) one Frequency Modulated Continuous Wave (FMCW) Radar sensor, (ii) one Multi-Chirp Frequency Modulated Continuous Wave Mono-pulse (MC-FMCW-M) Radar sensor, (iii) two Infrared Thermopile Array (ITA-32) sensors, and (iv) two Shimmer-3 accelerometer (S3BA) SSs. The S3BAs were used for ground truth measurement of velocity. While the Radar and Thermal sensors were mounted on tripod stands and placed for side and frontal views of the ankles, the two S3BA were attached to the metatarsal to record the acceleration of each foot in the X, Y and Z directions. The rationale for taking measurements from the front and side views was to avoid the effects of occlusion. The rationale for using multiple sensors was to allow for complementary monitoring, redundancy and cross-validation of measurements. The setting of the study, including the Living Lab that the study was conducted, the physical location of the participants and the SSs are presented in Figure 1.
Figure 1. Sprained Ankle Rehabilitation Exercise Setting: (a) the Living Lab where the study was conducted, and (b) the Sensing Solutions (SSs) used during the study. In Figure 1(a), the red, white and yellow spots indicted the locations of the side-facing SSs, the front-facing SSs and the participants, respectively, during the study.

In an upright sitting position, 20 directional movements were performed by 15 participants for 20 seconds on each leg. These included twisting the ankle in 4 fundamental directions of human ankle movement: (i) flexion, (ii) extension, (iii) eversion and (iv) inversion. These movements were recorded simultaneously by all the sensors. The parameters measured included the angular orientation of the ankles and postures. Other parameters included their ranges and velocities at instances of flexion, extension, eversion, and inversion. Data from the wearable sensors (S3As) were, however, not considered in the data analysis. The rationale for not considering the S3BA data is that data analysis involving the S3BA and the FMWC Radar (aimed at comparing their velocity values) was considered in our previous study [13]. Data obtained by the thermal sensors were stored in a bespoke time series database (SensorCentral) [14].

Data collected during this study were analysed using a sensor data fusion architecture referred to as Modified Distributed Sensor Data Fusion and Evaluation Architecture (MDSFEA) [15] as presented in Figure 2. The MDSFEA is an architecture suitable for data analysis ranging from homogeneous to heterogeneous datasets.

Figure 2. The Sensor Data Fusion and Evaluation Architecture.

In Figure 2, data from thermal and Radar SSs are imported to the architecture with the help of the image and data import toolkits, respectively [16]. While the Radar sensors data are stored in a CSV file, the thermal sensors data are stored as PNG files. Information such as the range of participants, speed and the AAR from the Radar SS were
fused to the corresponding thermal images with the help of their timestamps using the
data merging system. After the preliminary feature extraction which took place at the da-
ta merging system, Definitive Feature Extraction (DFE) began automatically. The DFE
took the data embedding toolkit to extract up to 1,000 features from the datasets
and represented them as vectors (n₀ to n₉⁹₉) [17]. Although the MDSFEA description (in
Figure 2) suits heterogeneous datasets such as those from thermal and Radar SSs, it
should be noted that the same architecture was used for the single and homogeneous da-
tasets analysis.

Two main algorithms were used to further process the sensors datasets after the
DFE stage namely, the Hierarchical Clustering Algorithm (HCA) and the K-Means++
Algorithm (KMA). While the HCA used the Distance Toolbox (DT) to access the data em-
bedder, the K-Means toolkit dissected the datasets (from the embedder) into clusters and
conveyed them directly to the Test and Evaluation Toolkit (TET) (see Figure 2). DM
models such as K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Stochastic
Gradient Descent (SGD), Random Forest (RF), and Neural Network (NN), amongst oth-
ers, were used to evaluate the performance of the architecture.

Thermal blobs from the ITA-32 thermal sensors were automatically binarised using
a sequence of codes in MATLAB. Also, to remove excess blobs from heating and
electrical devices, a blob-based background subtraction algorithm was used [18]–[20].
Hence, the clear and distinct thermal blobs that are presented in Figure 3 (a) and (b). The
RGB equivalents demonstrating similar actions by the ITA thermal SS are shown in
Figure 4.

3. Results

Data gleaned from the thermal SS indicated instances of the four directional
movements on the right leg, as presented in Figure 3. To aid description, the last two
digits of the thermal images' timestamps are used for the analysis in this work. For
example, thermal images code-named 20200311T145144_145211 and
20200311T145144_145222 (Figure 3(a)) are represented as T-11 and T-22, respectively.

![Figure 3](example.png)

**Figure 3.** Instances of right-ankle and foot flexion, extension, eversion, and inversion as recorded by ITA-32 thermal sensors: (a) Thermal blobs from the front-facing camera, and (b) thermal blobs from the side-facing camera.
In Figure 3, T-11 and T-49 indicated instances of eversion; T-12, T-22 and T-48 presented instances of inversion. Furthermore, extension is observed in T-37, T-38 and T-49, while flexion is indicated in T-23 and T-24. Background subtraction and image binarisation algorithms utilised in this study enhanced the granularity of the images, thus helping to clarify the direction of the ankle and foot by eliminating heat blobs from other individuals and devices [18], [20]. A comparison of instances of eversion and inversion of the ankle as recorded by an RGB and the ITA (thermal) sensors are presented in Figure 5.

![RGB Equivalents of Thermal Blobs obtained during Sprained Ankle Rehabilitation Exercises](image)

**Figure 4.** RGB equivalents of the thermal images recorded during sprained ankle rehabilitation exercise. Shimmer-3 accelerometer is worn on metatarsals (on both legs) for ground-truth velocity measurements.

3.1. Single Dataset Analysis

On a single dataset analysis such as data from the front-facing ITA-32 thermal sensor, image embedding took place automatically after data import. This was followed by data distancing using the Inception-v3 Architecture (IV3A). The rationale for using IV3A included low computational requirements [20], and high performance in image analysis [21]. KMA and HCA were used simultaneously to perform CbyC on the datasets, and their results were evaluated using separate TETs. Moreover, while the K-Means toolbox was initialised with KMA to a maximum of 300 iterations, the hierarchical clustering toolkit used a 10-fold cross-validation function based on a 66% training set. The results of these analyses are presented in Tables 1 and 2.

![Instance of eversion and inversion of the ankle as presented by RGB and ITA-32 thermal sensors](image)

**Figure 5.** Instances of eversion and inversion of the ankle as presented by RGB and ITA-32 thermal sensors. (a) An instance of eversion by an ITA-32 thermal sensor, (b) an instance of eversion by an RGB camera, (c) an instance of inversion by an ITA-32 thermal sensor, and (d) an instance of inversion by an RGB camera.

| Model          | AUC (%) | CA (%) | F1 (%) | Precision (%) | Recall (%) |
|----------------|---------|--------|--------|--------------|-----------|
| KNN            | 98.2    | 93.0   | 93.0   | 93.1         | 93.0      |
| Decision Tree  | 91.4    | 90.1   | 90.1   | 90.1         | 90.1      |

Table 1. Evaluation results showing the accuracies of data mining models during Classification-by-Clustering of a set of sprained ankle rehabilitation exercises data using K-Means++ Algorithm (KMA).
Table 2. Evaluation results showing the accuracies of data mining models during Classification-by-Clustering of a set of sprained ankle rehabilitation exercises data using the Hierarchical Clustering Algorithm (HCA).

| Model           | AUC (%) | CA (%) | F1 (%) | Precision (%) | Recall (%) |
|-----------------|---------|--------|--------|---------------|------------|
| KNN             | 99.5    | 95.6   | 95.6   | 95.7          | 95.6       |
| Decision Tree   | 90.6    | 89.7   | 89.7   | 89.7          | 89.7       |
| SVM             | 99.6    | 95.1   | 95.2   | 95.5          | 95.1       |
| SGD             | 99.2    | 98.9   | 98.9   | 98.9          | 98.9       |
| RF              | 99.3    | 94.9   | 94.9   | 94.9          | 94.9       |
| NN              | 99.4    | 98.1   | 98.1   | 98.1          | 98.1       |
| LR              | 100     | 99.6   | 99.6   | 99.6          | 99.6       |
| CN2 Rule Inducer| 84.8    | 71.4   | 71.4   | 71.4          | 71.4       |
| AdaBoost        | 91.9    | 89.2   | 89.2   | 89.2          | 89.2       |
| Average         | 96.0    | 92.5   | 92.5   | 92.6          | 92.5       |

Legend: KNN = K-Near Neighbours, LR = Logistic Regression, NN = Neural Network, RF = Random Forest, SGD = Stochastic Gradient Descent, SVM = Support Vector Machine, CA = Classification Accuracy, and AUC = Area under the Curve.

A close comparison of Tables 1 and 2 indicated that best average accuracies of the metrics were obtained using the HCA. Although KMA with four models: NN, SVM, SGD, and LR, obtained an accuracy of more than 98% for Area Under the Curve (AUC), Classification Accuracy (CA), F1, Precision and Recall, the accuracies obtained in CN2 inducer and AdaBoost affected the overall accuracy of KMA. CN2 rule inducer had the least accuracy values for all the metrics in both KMA and HCA, as presented in Tables 1 and 2.

3.2. Homogeneous Sensor Data Fusion

On homogeneous data fusion involving the front-facing and side-facing thermal sensors, data from the sensors were fused using a Matching Pairs of Rows Method (MPoRM). The rationale for using the MPoRM is that it allows for the proper fusion of homogenous data without information mismatch [16], [22]. With the help of the image-embedding toolkit and its SqueezeNet architecture, a lightweight convolutional neural network model for image recognition [15], the merged data was routed to the Louvain Clustering Toolbox (LCT). The LCT automatically discovered 8 clusters from the fused
dataset by performing Euclidean distancing and Principal Component Analysis (PCA). The rationale for using the Euclidean Distance Metric (EDM) includes the ability to perform distancing on raw data without previous analysis being affected by the addition of new data [23]. On the other hand, using PCA helps to improve the clustering of the dataset. It differs from Linear Discriminant Analysis (LDA) because it is a variance-based algorithm, whereas LDA is based on class information [24]. Moreover, PCA is best suited for unsupervised data clustering, such as that used in this analysis [15].

The KMA involving up to 8 clusters and 300 iterations was used for clustering the unified data. The rationale for using K-means included simplicity and the ability to increase similarities within clusters and reduce the same outside the group [25] [26]. This includes defining and associating k centroids for each cluster. Therefore, with the help of the KMA, the DM models related to the TET were capable of computing the accuracies of the processes based on a 10-fold cross-validation and average over classes as presented in Table 3.

Table 3. Evaluation results of the front and side facing ITA-32 thermal sensor data using a-10-fold cross-validation and the average of classes. The fused data were obtained during sprained ankle rehabilitation exercises.

| Data Fusion of Side-Facing and Front-Facing ITA-32 Sensors (SF-Fusion) |
|--------------------------|----------------|----------------|----------------|----------------|----------------|
| **Model**                | **AUC (%)**   | **CA (%)**    | **F1 (%)**    | **Precision (%)** | **Recall (%)** |
| KNN                      | 98.2          | 93.0          | 93.0          | 93.1            | 93.0           |
| Decision Tree            | 91.4          | 90.1          | 90.1          | 90.1            | 90.1           |
| SVM                      | 99.9          | 98.2          | 98.2          | 98.2            | 98.2           |
| SGD                      | 99.3          | 99.1          | 99.1          | 99.1            | 99.1           |
| RF                       | 98.0          | 91.5          | 91.5          | 91.5            | 89.5           |
| NN                       | 99.7          | 98.6          | 98.6          | 98.6            | 98.6           |
| NaïveBayes               | 92.9          | 80.5          | 80.7          | 81.4            | 80.5           |
| LR                       | 99.9          | 98.9          | 98.9          | 98.9            | 98.9           |
| CN2 Rule Inducer         | 85.6          | 71.8          | 71.9          | 72.3            | 71.8           |
| AdaBoost                 | 90.4          | 87.3          | 87.3          | 87.3            | 87.3           |
| **Average**              | **95.5**      | **90.9**      | **90.9**      | **91.1**        | **90.7**       |

Legend: KNN = K-Near Neighbors, LR = Logistic Regression, NN = Neural Network, RF = Random Forest, SGD = Stochastic Gradient Descent, SVM = Support Vector Machine, CA = Classification Accuracy, and AUC = Area under the Curve.

From Table 3, it can be observed that SGD and NN scored more than 98% in all the parameters such as AUC, CA, F1, Precision and Recall. An accuracy of more than 90% was obtained in KNN, Decision Tree, SVM, SGD, RF, NN, and LR in all their parameters presented in Table 3. While SGD had the highest accuracy of 99% in all the parameters, CN2 rule inducer scored the least. A further breakdown of the latter indicated the least accuracy of 85% for AUC and approximately 72% in CA, F1, Precision and Recall. Average accuracies for all parameters were more than 90%.

3.3. Heterogeneous Sensor Data Fusion

Heterogeneous sensor data such as those from the side-facing ITA-32 thermal and Radar sensors were also fused using the data merging toolkit. These data were first uploaded and processed using the import toolkits before being merged using the matching row appending rule. The fusion outcome was trained using the VGG-19, a-19-layer im-
age recognition algorithm [27]. The merged data were normalised and distanced using the Manhattan Distance Metric (MDM). The rationale for using the MDM instead of others such as the cosine rule, included the grid-like behaviour of the former, which is a useful characteristic when dealing with heterogeneous data [28]. The accuracies of the CbyC with respect to heterogeneous data fusion are presented in Table 4.

Table 4. Evaluation results of ITA-32 thermal and FMCW Radar sensor data using a-stratified-10-fold cross-validation and the average of classes. The fused data were obtained during sprained ankle rehabilitation exercises.

| Data Fusion of ITA-32 Thermal and Radar Sensors |
|-----------------------------------------------|
| Model | AUC (%) | CA (%) | F1 (%) | Precision (%) | Recall (%) |
|-------|---------|--------|--------|---------------|------------|
| KNN   | 99.5    | 99.3   | 99.3   | 99.3          | 99.3       |
| Decision Tree | 99.7 | 99.5 | 99.5 | 99.5 | 99.5 |
| SVM   | 99.6    | 95.1   | 95.1   | 95.5          | 95.1       |
| SGD   | 99.1    | 98.8   | 98.8   | 98.8          | 98.8       |
| RF    | 99.0    | 94.4   | 94.4   | 94.4          | 94.4       |
| NN    | 99.7    | 97.4   | 97.4   | 97.4          | 97.4       |
| NaiveBayes | 98.9 | 95.6 | 95.7 | 95.8 | 95.6 |
| CN2 Rule Inducer | 99.6 | 99.5 | 99.5 | 99.5 | 99.5 |
| AdaBoost | 90.8 | 87.8 | 87.8 | 87.8 | 87.8 |
| Average | 98.4 | 96.4 | 96.4 | 96.4 | 96.4 |

Legend: KNN = K-Nearest Neighbors, NN = Neural Network, RF = Random Forest, SGD = Stochastic Gradient Descent, SVM = Support Vector Machine, CA = Classification Accuracy, and AUC = Area under the Curve.

As presented in Table 4, Stratified Cross-Validation (SCV) involved dividing the data into smaller sub-groups (strata). The rationale for using the SCV includes their ability to identify shared attributes in a dataset [28]–[30]. Moreover, all the metrics returned an average accuracy of more than 96%.

A further test on the averages of the models from Tables 1, 2, 3 and 4 represented as KMA-A, HCA-A, SF-Fusion and Rad-T Fusion, respectively, is presented in Table 5. The models considered were KNN, Decision Tree, SVM, SGD, RF, NN, NaiveBayes and AdaBoost. Models that were not common to the tested models in a column were, however, excluded from the test. The rationale for excluding them was to achieve a balanced and unbiased dataset at each instance. Considering the averages presented in Table 5, the highest average accuracy value was obtained in Rad-T Fusion as 96.9%. The row containing NaiveBayes was not included in the computation of the averages because of the non-availability of a value for HCA-A.

Table 5. Model averages from KMA (Table 1), HCA (Table 2), SF Fusion (Table 3) and Rad-T (Table 4).

| Model | KMA-A (%) | HCA-A (%) | SF-Fusion (%) | Rad-T Fusion (%) |
|-------|-----------|-----------|---------------|-----------------|
| KNN   | 94.1      | 96.4      | 94.1          | 99.3            |
| Tree  | 90.1      | 89.9      | 90.4          | 99.5            |
| SVM   | 98.5      | 96.1      | 98.5          | 96.1            |
| SGD   | 99.3      | 99.0      | 99.1          | 98.9            |
| RF    | 91.2      | 95.8      | 92.4          | 95.3            |
A 2-Sample T-Test of the KMA-A values and the HCA-A values at 95% confidence interval indicated that there was no significant difference ($p = 0.553$) between the samples. This implied that the accuracy values obtained in Tables 1 and 2 were within a close range. On the other hand, a 2-Sample T-Test of the KMA-A and the Rad-T Fusion values (Table 5) indicated a significant difference between the values ($p = 0.037$). Similarly, a 2-Sample T-Test between SF-Fusion and Rad-T values also showed a significant difference between the values ($p = 0.040$). The significant differences ($p = 0.037$ and $p = 0.04$) obtained in the two instances involving Rad-T indicated that the accuracy values of the heterogeneous sensor fusion datasets (in Table 4) were distinct and different from those obtained from the homogenous and single datasets. A descriptive analysis of the parameters in Table 5 (KMA-A, HCA-A, SF-Fusion and Rad-T Fusion) based on one way ANOVA is presented in Table 6.

**Table 6.** Descriptive analysis of KMA-A, HCA-A, SF-Fusion and Rad-T Fusion average values.

| Parameters       | N | Mean | StDev | 95% CI         |
|------------------|---|------|-------|----------------|
| KMA-A            | 9 | 91.9 | 8.2   | (86.6, 97.2)   |
| HCA-A            | 9 | 92.4 | 8.2   | (87.1, 97.7)   |
| SF Fusion        | 9 | 92.0 | 8.1   | (86.7, 97.3)   |
| Rad-T Fusion     | 9 | 96.9 | 3.9   | (91.6, 102.2)  |

Legend: N = total number of rows used for the analysis, CI = Confidence Interval, StDev = Standard Deviation.

In Table 6, one way ANOVA involving KMA-A, HCA-A, SF-Fusion and Rad-T Fusion indicated the latter (Rad-T Fusion) as the parameter with the highest range of values at 95% confidence interval. From the result, Rad-T Fusion still maintained its highest average value. It also has the least standard deviation of 3.9, which further indicated the proximity of its values.

**4. Discussion**

SPAREs using USSs such as the MC-FMCW-M Radar and ITA-32 thermal SSs offers the ability to visualise the movement of the ankle in the four fundamental movements of the human ankle. The level of details such as the direct computation of the speed and range of motion of the ankle presents the FMCW Radar variants as better alternatives to wearables such as the S3BAs, which are not capable of direct computation of speed. Also, the privacy-friendly images obtained from the ITA-32 thermal SS are best suited for home-based monitoring compared with the RGB images produced by video cameras, which can negatively affect their users’ privacy.
Furthermore, the data gleaned from the USSs required less storage space, lesser computational time and resources compared with RGB data. Hence, the proposed USSs are better candidates for home-based monitoring of SPAREs compared with wearables such as the gyro-based systems. Additionally, the MDSFEA offered added advantages in feature extraction and model evaluation. Instead of processing each model separately, which can be time consuming, the models all learnt from the TETs and simultaneously produced comprehensive results on the TETs. The fusion of data from the SSs gives useful and additional information such as the speed and the AAR of the ankle at every second during the exercise. Information such as posture, speed, range and the AAR related to the ankle movement during SPARE can help physiotherapists to ascertain if exercises have been performed as prescribed.

One of the limitations of this study is that homogeneous data fusion involving the front-facing and the side-facing ITA-32 thermal sensors did not produce evaluation results with HCA when the datasets were fused with MPoRM. This issue was resolved by using the "instance ids" of the datasets for results scoring and evaluation. Another limitation is that ML models such as LR and NaiveBayes were not computed for all datasets types. The rationale for this exclusion included their incompatibility with the datasets and the data fusion algorithms.

Comparing the average results in Tables 5 and 6 indicated that the highest average percentage accuracy was obtained in the heterogeneous datasets involving thermal and Radar SS as 96.9%. Hence, it can be suggested that complementary monitoring involving heterogeneous SSs, such as the approach demonstrated in this study, yields higher accuracy compared with a single or homogeneous monitoring solution. Therefore, the fusion of USSs for SPAREs monitoring is recommended in home environments.

Funding: Research is funded by the EU’s INTERREG VA program, managed by the Special EU Program Body (SEUPB).

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