Radar based Fall Detection with Imbalance Data Handling and Data Augmentation

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***Abstract*—Radar-based fall detection is helping seniors to live independently. In this paper, a new method for fall detection from human activities is proposed using data augmentation and class imbalance handling. Data collected from a radar signal is processed and a time series is obtained by aggregating the individual time series in the fast-time of the radar returns. This time series is used as input to several classifiers to distinguish fall from non-fall activities. To this end, we augment the radar time series data using a Mu-Sigma method. To handle the imbalanced data, we apply the synthetic minority over-sampling technique and class weighting strategy. A comprehensive study is performed to build a supervised learning method with or without data augmentation and imbalanced data handling. The performance of the proposed method is compared with some of the other existing methods using different classifiers including k-nearest neighbors, decision trees, naive Bayes, support vector machine and multi-layer perceptron. The results demonstrate that the proposed fall detection method outperforms the other methods in terms of providing higher accuracy, precision, sensitivity and specificity values.**

***Index Terms*—Smart home care, pervasive healthcare, fall detection, ultra-wide band radar.**

I. Introduction

Fall detection is an important area of research and development for healthcare and assistive technology industries, aimed at improving the safety and independence of elderly and vulnerable populations. One promising approach for fall detection is through the use of radar technology, which can capture high-resolution data of a person's movement and detect falls through the analysis of specific patterns and features [1]–[3]. In recent years, fall detection algorithms using radar have gained increasing attention and have shown great potential for accurately detecting falls in real-world scenarios. This technology has the advantage of being non-invasive and can operate in various environmental conditions, making it suitable for both indoor and outdoor settings while preserving the privacy of users [4], [5].

Current fall detection methods that use radar data typically rely on extracting certain features from the data in either the time, frequency, or time-frequency domains [6]. These features may include low/high order moments, cepstrum coefficients [7], and peak frequency [8], among others. However, this approach has limitations as it requires expert knowledge to manually engineer the features. To address this issue, researchers have proposed automated feature extraction methods from radar data. For instance, a deep restricted Boltzmann machine was proposed in [9] for radar signal recognition, while [4] and [10] presented deep neural network approaches to reduce feature dimensionality extracted from radar signals. Additionally, [11] utilized an acoustic sensor and deep neural network for gait-based human identification. These approaches offer more automated and potentially more accurate feature extraction methods compared to traditional feature engineering techniques.

In this work, a fall detection method is proposed by incorporating time series derived from ultra wideband radar (UWB) returns. The radar time series is augmented using a Mu-Sigma method to increase data samples during training. Since the collected radar data for fall detection is highly imbalanced, we apply the synthetic minority over-sampling technique and class weighting strategy. A comprehensive study was performed to build a supervised learning method with or without data augmentation and imbalanced data handling. The proposed method was compared against some of the existing methods including Naive Bayes, support vector machine, K-nearest neighbors, decision trees. Figure 1 shows the complete pipeline of the proposed method starting from raw data-collection using the UWB radar to fall/non-fall binary classification.

II. Experimental Setup

For our experiments, we utilized UWB radar to collect data. This radar operates within the frequency ranges of 5.9-10.3 GHz, and provides several benefits, such as high spatial resolution and unobtrusive, privacy-preserving monitoring capabilities. The radar works by transmitting short pulses at high frequencies, resulting in a high range resolution. We positioned the radar 1.5 meters above the floor in a cluttered room. The static clutter was filtered out by removing the mean from the radar scattering matrix before further processing. Each scan is repeated for 15 seconds, digitized at a rate of 200 samples per second, and summed up to form a time series over scans. The dataset consists of various fall and non-fall activities,

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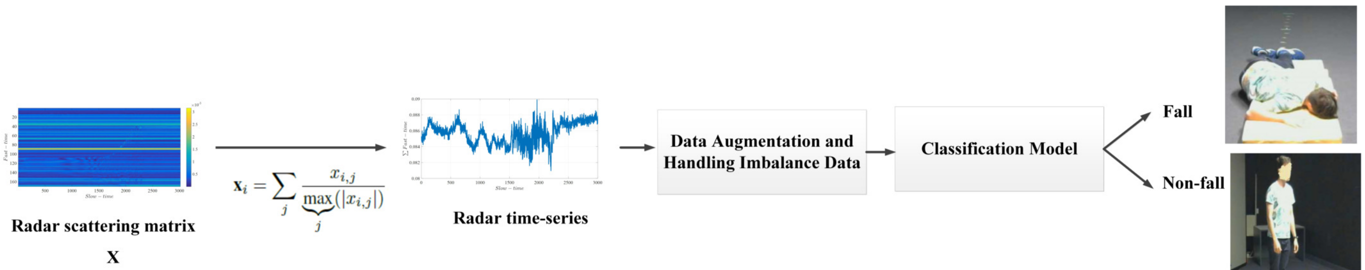

Fig. 1. Schematic of the proposed method from collecting data using the UWB radar to fall/non-fall classification.

performed by five healthy male subjects aged 20 to 25. These activities included walking towards the radar and falling down, standing in front of the radar and falling down, standing and falling down perpendicular to the radar line of sight, lying down and standing up in front of the radar, and lying down and standing up perpendicular to the radar line of sight.

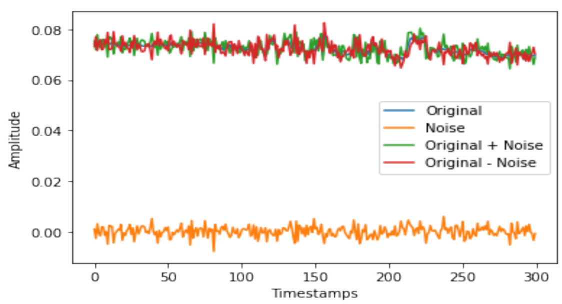

Fig. 2. Mu-Sigma data augmentation method applied to a sample radar time series data.

III. Proposed Methods

It is known that collecting large number of samples for fall detection tasks is tedious and expensive since high interactions with human subjects are required. In our experiments, we have collected a total number of 336 samples including 149 fall and 187 non-fall samples. In view of the fact that low number of samples makes a machine learning model to either underfit or overfit over the single class in such an imbalanced dataset, in this work, we increase our data samples during training by using a Mu-Sigma augmentation method [12]. This is realized by creating a minimal noise of the same dimension as the sample signal with zero mean and standard deviation of sample signal. From this noise signal, two more signal can be created as $X_{synthetic} = X \pm Noise$. Figure 2 illustrates the generation of two additional signals by adding and subtracting minimal noise from the original signal. It is evident from the figure that both the generated signals closely follow the original signal since the noise is generated based on the standard deviation of the original signal.

$$Noise \sim \mathcal{N}(0, \sigma^2) \tag{1}$$

where, $\sigma = \sqrt{\frac{\sum(x_i-\mu)^2}{N}}$ and $N = 3000$.

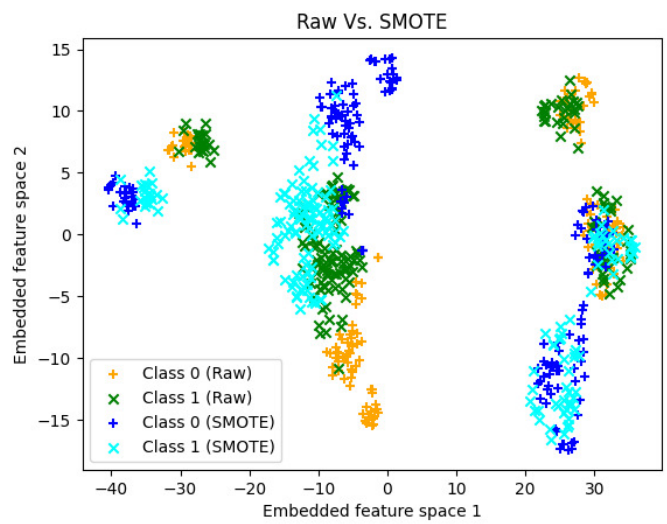

Fig. 3. Radar time series and its corresponding SMOTE synthetic data.

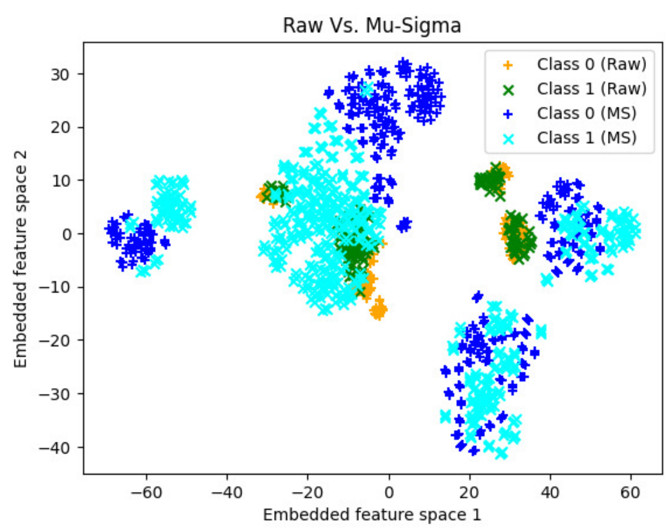

Fig. 4. Radar time series and its corresponding Mu-Sigma generated data.

TABLE I
DIFFERENT COMBINATION OF THE RADAR TIME SERIES WITH/WITHOUT MU-SIGMA DATA AUGMENTATION, SMOTE AND CLASS WEIGHT IMBALANCED DATA HANDLING METHODS.

Mu-Sigma	SMOTE	Train set				Validation set		Test set	
		Class 1	Class 0	Class 1 Weight	Class 0 Weight	Class 1	Class 0	Class 1	Class 0
False	False	112	89	0.44	0.56	37	30	38	30
True	False	336	267	0.44	0.56	37	30	38	30
False	True	112	112	0.50	0.50	37	30	38	30
True	True	336	336	0.50	0.50	37	30	38	30

TABLE II
EXPERIMENTAL RESULTS ACHIEVED ON ALL FOUR DATASET USING VARIOUS CLASSIFIERS

Model	Mu-Sigma	SMOTE	Accuracy	Precision	Recall	Specificity	F1
NB	False	False	57.35	56.72	100	03.33	72.38
	True	False	55.88	55.88	100	0	71.70
	False	True	55.88	55.88	100	0	71.70
	True	**True**	**61.76**	**59.38**	**100**	**13.33**	**74.51**
SVM	False	False	94.12	90.48	100	86.67	95
	True	False	95.59	92.68	100	90	96.2
	False	True	94.12	90.48	100	86.67	95
	True	**True**	**95.59**	**92.68**	**100**	**90**	**96.2**
KNN	False	False	92.65	88.37	100	83.33	93.83
	True	False	88.24	91.67	86.84	90	89.19
	False	True	92.65	88.37	100	83.33	93.83
	True	**True**	**97.06**	**95**	**100**	**93.33**	**97.44**
DT	False	False	82.35	80.95	89.47	73.33	85
	True	False	91.18	86.36	100	80	92.68
	False	True	82.35	77.08	97.37	63.33	86.05
	True	**True**	**94.12**	**90.48**	**100**	**86.67**	**95**
MLP	False	False	94.12	97.22	92.11	96.67	94.59
	True	False	97.06	95	100	93.33	97.44
	False	True	94.12	90.48	100	86.67	95
	True	**True**	**98.53**	**97.44**	**100**	**96.67**	**98.7**

At this stage, to handle an imbalanced dataset, two methods are considered. The synthetic minority over-sampling technique (SMOTE) [13] is used to create more samples from under-represented class to match the over-sampled class.

We also use weighted loss strategy [14] by calculating the class-weights from the input data. The class weight information is determined by taking the inverse proportion of the number of samples in a specific class within the input data. In other words, the class-weight information helps models to fit better on under-sampled class by penalizing more if it is wrongly predicted. Table I shows different scenarios from the training set by applying combinations of the Mu-Sigma and SMOTE methods. The number of samples for the training, validation and test dataset for each combination is also presented in this table. Figures 3 and 4 illustrate the high dimensional data visualizing in 2-dimensional embedded feature space using t-SNE [15]. From Figure 4, it is seen that the Mu-Sigma method generates more number of samples that imitates the behaviour of raw dataset clusters.

IV. EXPERIMENTS

Experiments were conducted on a set of radar data collected in a realistic room environment to evaluate the performance of the proposed fall detection method. For comparison purposes, several approaches are considered which are based on K-nearest neighbours (KNN) [7], naive Bayes (NB) [16], support vector machines (SVM) [7], decision trees (DT) and multi-layer perceptron (MLP). In the proposed method, the radar returns are pre-processed to obtain the range-integrated time series data. The resulting time series are fed into different classifiers to test whether or not an specific time series represents a fall. The input of these models are the preprocessed radar time-series signals as well as their augmented versions.

All the models' hyper-parameters are optimized on raw training and validation set using random search optimization technique [17]. The performance of the classification models are assessed by obtaining the classification metrics such as sensitivity and F1-score.

In order to train the NB model, the class imbalance information is given as priors to the model while to train other models, namely, SVM, DT and MLP, class weight information, shown in Table I, is provided to handle imbalance among categories. It is noted that when using SMOTE method combined with the augmented dataset, since both classes have similar number of samples, class weights are equal to 0.5.

In order to train the MLP model, we optimized the model architecture and tuned the hyperparameters. The resulting MLP model includes a 3-layer architecture with 1024, 256, 32 neurons in each hidden layer, respectively. The sigmoid activation function and a binary cross-entropy loss function are used in this model. The model was trained using Adam optimizer with initial learning rate set to $2e^{-4}$ for 200 epochs.

The classification accuracy of each model is calculated and

TABLE III
CLASSIFICATION METRICS COMPARISON OF THE PROPOSED METHOD WITH OTHER EXISTING WORKS

	Accuracy	Precision	Recall	Specificity
Deep CNN [3]	95.83	92.31	100	91.67
TFA + CNN [1]	89.12	94.32	83.28	**95.04**
CS + LDA [18]	-	95.28	93.43	92.41
TL-Fall [19]	95.64	96.12	96.73	-
CapsFall [5]	94.22	95.66	93.99	94.55
ResNet [10]	93.07	**96.15**	90.91	-
MLP + Mu-Sigma	**97.06**	95	**100**	93.33
MLP + MS + SMOTE	**98.53**	**97.44**	**100**	**96.67**

listed in Table II. Accuracy, precision, recall, specificity, and F1-score for each model are given with various combination of augmented dataset. Since we are dealing with an imbalanced data problem, most of the models are over-fitted on the positive class with 100% recall. All the models are compared based on specificity and F1-socre. It is seen from this table that the MLP algorithm outperforms other conventional methods in terms of classification metrics. When using the raw dataset, the highest F1-score was achieved by SVM at 95%, with MLP coming in second with a score of 94.59%. However, after applying the Mu-Sigma augmentation, we observed an improvement of 2% and 1% in MLP and SVM, respectively, with MLP showing the best performance overall.

Without data augmentation, it is seen from this table that F1-score achieved for the NB, SVM, KNN, DT, and MLP is 72.38%, 95%, 93.83%, 85%, and 94.59%, respectively. After applying Mu-Sigma augmentation and SMOTE method, we observe a considerable improvement in F1-score for these methods. It is noted that in all experimental results a 100% recall was observed except for KNN and DT. This can be attributed to the addition of arbitrary noise causing some samples from one class to be closer to the opposite class, resulting in false positives. It is also seen from this table that the augmented dataset with Mu-Sigma combined with SMOTE give rise to higher classification metrics for all the method.

Table III shows the comparative results of the proposed method with other state-of-the-arts. The results demonstrate that the proposed using Mu-Sigma data augmentation with SMOTE performs significantly better than all the other methods, including [1], [3], [18]. On average, we obtained a 2% increase in all performance metrics with 100% sensitivity using only Mu-Sigma and MLP. However, better results were achieved with the combination of SMOTE and Mu-Sigma.

V. CONCLUSION

A new radar-based fall detection method was proposed using an and a supervised learning approach based on deep neural network. Radar data was collected using an ultra wideband radar in a room environment by considering the home healthcare setting. The data was processed by deriving a time series from the radar back-scattered matrix. Data augmentation using Mu-Sigma method and class imbalance handling using both SMOTE and Class Weighting methods were employed and the resulting data was fed into several classifiers to distinguish fall from non-fall activities. Experiments were conducted to assess the performance of the proposed method and to compare it with that of state-of-the-art. The results demonstrated that the proposed fall detection method using Mu-Sigma data augmentation and multi-layer perceptron outperforms the other methods by providing higher classification metrics. It has also been observed that utilizing the information present in imbalanced data to train models can lead to significant improvements in classification metrics without requiring the generation of more data samples through techniques like SMOTE.

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