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Empirical Mode Decomposition for Power Spectral Density Features in Radar-Based Fall Detection

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Abstract: In recent years, the increase in the number of older people and their tendency to live alone has made them more vulnerable to accidents. The most suffered situation in this regard is their falls. In this study, fall detection is carried out using radar. The proposed method classifies different falls and activities of daily living using radar-based measurements. The signals obtained by means of empirical mode decomposition (EMD) are separated into intrinsic mode functions (IMFs). The power spectral densities (PSD) of IMFs are calculated using the Welch method to provide features for classification. Thus, the effect of IMFs on classification is observed. In the study, conventional machine learning classes are employed, and the cubic Support Vector Machine (SVM) classifier detects the fall with 100% accuracy as a result of the PSDs calculated depending on the IMF 2-6 values. Furthermore, the classification results obtained based on other IMFs are almost error-free for some classifiers. Therefore, classification is also performed for seven different movements depending on IMFs. The cubic SVM algorithm performs above 90% in this case. The proposed method demonstrates that the effect of classical machine learning remains operative and efficacious.

Radar-Tabanlı Düşme Tespitinde Güç Spektral Yoğunluk Özellikleri için Ampirik Mod Ayrıştırması

Anahtar Kelimeler
Radar,
Düşme tespiti,
Sinyal işleme,
Makine öğrenmesi,
Sınıflandırma

Öz: Son dönemde yaşlı bireylerin artması ve yalnız yaşama eğilimleri onları kazalara açık hale getirmektedir. Bu hususta en fazla muzdarip olunan durum onların düşmesidir. Bu çalışmada radar kullanılarak düşmenin tespiti gerçekleştirilmektedir. Çeşitli düşme ve günlük aktiviteler radar tabanlı ölçümler yapılarak önerilen metot ile sınıflandırılmaktadır. Ampirik mod ayrıştırma (EMD) vasıtasıyla elde edilen sinyaller içsel mod fonksiyonlara (IMFs) ayrılmaktadır. IMF'lerin Welch yöntemiyle güç spektral yoğunlukları (PSD) hesaplanarak sınıflandırma için özellik olması sağlanmaktadır. Böylece IMF'lerin sınıflandırma üzerine etkisi gözlemlenmektedir. Geleneksel makine öğrenme sınıflarının kullanıldığı çalışmada IMF 2-6 değerlerine bağlı olarak hesaplanan PSD'ler sonucu Destek Vektör Makinesi (SVM) (kübik) sınıflandırıcısı düşmeyi %100 doğrulukla tespit etmektedir. Ayrıca diğer IMF'lere bağlı olarak elde edilen sınıflandırma sonuçları da bazı sınıflandırıcılar için neredeyse hatasızdır. Bundan dolayı yedi farklı hareket için de IMF'lere bağlı olarak sınıflandırma gerçekleştirilmektedir. SVM (kübik) algoritması bu durum içinde %90'ının üzerinde bir performans sergilemektedir. Önerilen yöntem ile geleneksel makine öğrenmesinin etkisinin hala aktif ve etkili olduğu sunulmaktadır.

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1. Introduction

It is expected that the world population growth will continue for about 60 years and will peak at about 10.3 billion. In parallel with this expectation, it is stated that the population will also age. In fact, it is predicted that the number of elderly individuals will reach 2.2 billion during this time period, exceeding the number of children [1]. From another point of view, people who socialize in the virtual environment day by day are getting lonelier both physically and spiritually in the real world. The most obvious indicator of this is the change in the old social structure and the intensification of individuals' desire to live alone. While it is obvious that this situation may be seen as appropriate and even fun for young and middle-aged individuals, the situation is the opposite for older individuals. This demographic and social change shows that health and social systems worldwide will need to be updated.

The elderly who become lonely can continue their lives comfortably at home if they have the ability to be self-sufficient. Similarly, individuals seeking a more social environment prefer elderly care homes. However, physically weakened elderly people become vulnerable to accidents and injuries both at home and in care homes. Here, one of the most dangerous accident types for the elderly is falls [2]-[3]. There is almost no one around us who has not heard that an elderly person has fallen and been injured. This determination is confirmed by the World Health Organization with the statement 'Falls are the second leading cause of unintentional death in the world'. Looking at the situation only in terms of death causes an underestimation of the magnitude of the problem. The injuries of an elderly person who falls and the subsequent treatment process cause both a financial and moral burden for individuals and a responsibility for the health infrastructure. Therefore, the timely detection of falls, especially for lonely elderly individuals, will pave the way for the rapid and effective implementation of treatment and subsequent services as well as preventing loss of life. Thus, individuals will be able to regain their health and participate in life again [4].

Two types of approaches come to the fore in the studies carried out by researchers for the detection of falls. The first of these is the use of contact or wearable devices. As the most basic, button types can be shown for these devices. The presence of a fall is determined by using the device in the event of a fall and danger [5]. Accelerometers and gyroscopes, which are essentially more advanced devices, have recently come to the fore in fall detection with a wearable approach [6]-[7]. The presence of a fall is determined by processing the velocity and orientation data of the devices due to movement. In addition to being attached directly to clothing, they can also be integrated into smartwatches or smartphones. Successful studies have been carried out with a wearable approach using small, lightweight, and accessible devices [8]-[9]. However, the fact that elderly individuals either do not want to carry the devices or forget to carry them pushes this approach to the back of the list of priorities. In addition, the battery problem of the devices is also stated as another negative factor.

Due to the disadvantages of the wearable approach, the other approach, the contactless approach, comes to the fore. Cameras, widely regarded as the most elementary method for a contactless approach, have been used for fall detection. [10]-[12]. They are placed in various parts of the house (living room, bedroom, bathroom, etc.), and the individual is followed. This situation disturbs the elderly based on privacy, especially in the context of interference in private life. In addition, the camera's occlusion and low light problems are among the factors that reduce its performance and preference. Within the scope of this approach, the use of a microphone for sound was used in fall detection [13]. However, ambient noise and dependence on environmental factors push it to the background. Lidar was another sensor investigated in fall detection [14]. Expensive and difficulties in controlling it are shown as disadvantages. The most remarkable and prominent studies of the non-contact approach to fall detection are carried out using radar. The fact that radar has proven itself in indoor applications makes it stand out [15]-[19].

The radar, which is not dependent on environmental conditions, does not have a problem such as privacy and is at very reasonable levels in terms of price, has been used extensively in fall detection research. Low power consumption and most importantly, the fact that its presence is not even felt is a reason for comfort for the elderly individuals observed. In the most basic expression, the fall is detected depending on the change in the signal reflected from the individual as a result of the application of the electromagnetic signal by the radar to the observed environment. In recent years, radar-based fall detection studies have been carried out by researchers using different hardware and algorithms.

In early studies, continuous wave radars and pulse radars were generally used [20]-[22]. In studies with one or two subjects, scenarios were set up to detect the presence of a fall. In studies carried out at home or in the laboratory, the presence of a fall or non-fall was detected by repetition of several movements, usually by creating a dataset of about a hundred movements. Due to the nature of the radar used, detection studies based on phase change were carried out. Using traditional machine learning, the presence of a fall was detected with considerable accuracy.

In the following period, with the increase in indoor radars, especially frequency-modulated radars, both range and speed can be detected. This situation has also accelerated the fall studies. The fall and non-fall (daily activities) movements obtained from the measurement results enable spectrograms to be obtained with time-frequency analysis approaches with such modulated radars. Thus, the modern approach of deep learning algorithms is used rather than traditional machine learning. The feature extraction process, which requires a long effort, has also been eliminated and the studies have gained new momentum and have positive effects on the detection results [23]-[25]. Recent fall studies have enabled Doppler-time, range-time, and even angle-time maps to be obtained with high-frequency multi-input multi-output radars due to the high number of receivers. In addition to this effect, point cloud studies also stand out. Hybrid approaches to deep learning are also encountered. As a result, fall detection studies, which started with one or two subjects, and non-fall detection, are a popular subject that is being studied with the use of multiple fall types and movements as well as a large number of subjects and advanced algorithms [26]-[29].

This study shows that the use of traditional machine learning, rather than deep learning, which is a popular approach in recent times, is still quite effective in fall studies. Intrinsic mode functions (IMFs) are calculated by applying empirical mode decomposition (EMD) to the data obtained in the measurement studies. The power spectrum densities for each of these functions are calculated and collected using the Welch method, which has been shown to be effective in our previous studies [33,40]. This situation was developed to reveal the effect of IMFs. Then, power spectral densities (PSDs) are used as features for traditional machine learning. Classifiers provide the detection of falls and other daily activities. So that, the effects of the intrinsic functions obtained by EMD on fall detection are analyzed in detail and presented. The present study, which combines EMD and PSD, makes a modest contribution to the existing literature on fall detection.

2. Material and Method

2.1. Measurement Setup

The measurement of falls and daily activities has been performed by the commercially available K-LD7 radar from RF-Beam. In addition to being a low-cost Doppler radar, the radar employs frequency shift keying (FSK) to detect the velocity, direction, distance and angle of moving objects. The radar, which comprises a transmitter and two receiver structures, utilizes frequencies of 24.05 and 24.25 GHz. In the measurement studies, the radar has been operated in continuous wave (CW) mode by using a receiver and a transmitter structure. Its small structure, low power consumption and the ability to detect people up to 15 m are among its remarkable features. Moreover, ease of use is another advantage [30]. Figure 1 shows the K-LD7 radar and its block diagram.

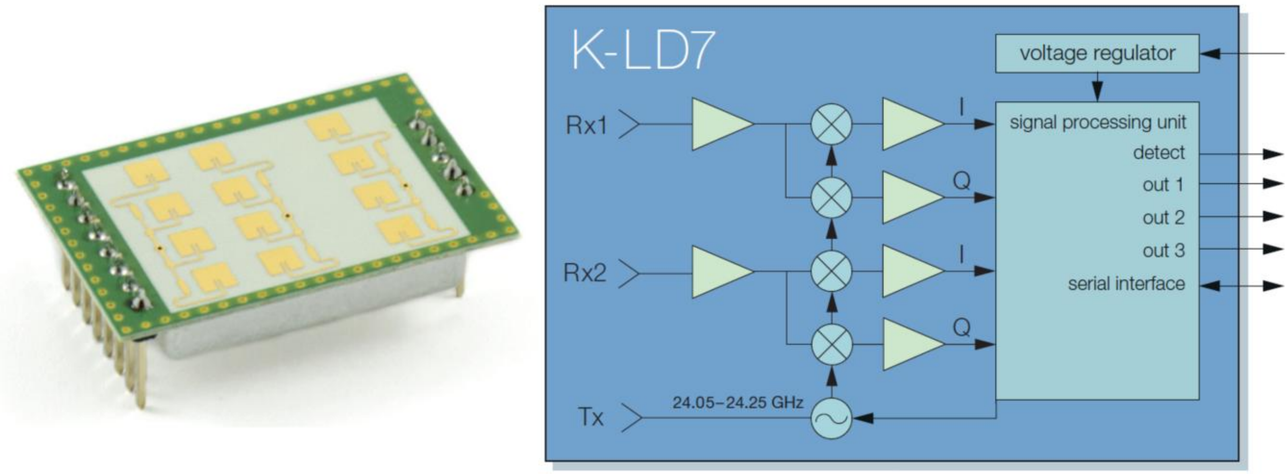

Figure 1. K-LD7 radar and block diagram [30]

2.1.1. Experimental Environment and Scenario

Falls and other activities are performed in the home environment in the context of being as close to reality as possible. The radar is placed 90 cm above the ground, in direct line of sight of the subject, after reviewing the literature. The basis of the measurement study is formed by a total of four falls and three daily activities. Falls have been performed in a variety of directions, including backward, forward, right, and left. Daily activities have been preferred as walking forward and backward, sit-stand and crawling. A total of six volunteer subjects participated in the experimental study. Participants are asked to do ten repetitions for each movement. Falls and sit-to-stand measurements have been achieved by placing a cushion at a distance of 3 meters from the direct field of view of the radar. Walking forward and backward and crawling measurements were made with the subjects' movements at a distance of 2-4 meters. The duration of each activity is approximately 11.5 seconds. The creation of 420 radar data sets has thus been achieved. The experimental environment is illustrated in Figure 2.

Figure 2. Experimental environment

2.2. Signal Processing

The I and Q signals, which are separated by a 90° phase difference due to the structure of the radar, have been recorded using a sampling frequency of 2200 Hz. These signals are then subjected to EMD separately.

2.2.1. Empirical Mode Decomposition

Huang et al. proposed the EMD method as a means of analyzing nonlinear and non-stationary data [31]. EMD is a technique that adaptively decomposes any data (signals) into a finite set of AM/FM modulated components. The basis of EMD is the shift process. The shift produces amplitude and frequency modulated signals called IMF. Indeed, EMD is the process of arbitrarily separating the signal into components called IMF and residual.

The IMF is characterized by two properties. Firstly, the number of zero crossings of the IMF and the number of extrema are equal or at most one difference. Secondly, the average of the envelope defined by local maxima and the envelope defined by local minima must be zero. Consequently, the IMFs are almost orthogonal to the original data and provide a complete basis [31]. In the context of EMD for a signal $s(t)$, the IMFs can be expressed as follows:

1. The local minimum and maximum values of the $s(t)$ signal are determined.
2. The lower envelope, $e_a(t)$, and the upper envelope, $e_u(t)$, are derived from the application of interpolation to the local maximum and minimum points of the signal.
3. The mean of the upper and lower envelope is calculated in order to obtain $m(t)$. This situation is given by expression (1).

$$m(t) = \frac{e_a(t) + e_u(t)}{2} \tag{1}$$

4. The detail signal $d(t)$ is found by subtracting the average of the envelope values from the initial signal $s(t)$. The detail signal is shown by (2).

$$d(t) = s(t) - m(t) \tag{2}$$

5. Then, for the detail signal $d(t)$, the IMF properties (mentioned above) are checked. If the properties are fulfilled, the signal $d(t)$ is accepted as IMF_1. If the properties are not satisfied, the first 4 steps are repeated by replacing the signal $s(t)$ with $d(t)$ until the IMF properties are satisfied.

6. After determining the IMF, this signal is subtracted from the original signal and the residual signal $r(t)$ is calculated. This expression is obtained with (3).

$$r(t) = s(t) - d(t) \tag{3}$$

7. Subsequent to this stage, the residual signal $r(t)$ is regarded as the initial signal $s(t)$, and the aforementioned six steps are reiterated. When the residual signal $r(t)$ cannot be obtained from the IMF component, when it is a monotonic signal, in other words, when the stopping criterion is met, the IMF acquisition, that is, the decomposition process, ends. IMFs and residual component are shown as in (4).

$$s(t) = \sum_{i=1}^{N} IMF_i + r(t) \tag{4}$$

where, N denotes the total number of IMFs, while $r(t)$ signifies the residual signal [31].

In this study, the eight IMF values obtained from the EMD for each I and Q signal are considered to be real and imaginary components, respectively. These components are then combined into a complex form, as illustrated in (5).

$$IMF_{combined} = IMF_{real}(I) + IMF_{imaginary}(jQ) \tag{5}$$

2.2.2. Welch Method

The Welch method is a non-parametric technique for estimating PSD. In this method, time series are primarily segmented into sub-segments, with a specific overlap ratio. Segments are multiplied by a window function and become the average of the modified periodograms. Since the method uses the PSD of different segments, the modified periodograms provide almost uncorrelated estimates of the true PSD [32]. Further details regarding the Welch method can be found in our preceding study [33]. The parameters employed in the Welch method are demonstrated in Table 1.

Table 1. Welch method parameters

Welch Method	
Parameters	***Values***
FFT	256
PSD Length	129
Noverlap	64
Hamming	128

The PSD of the complex IMF signals obtained is calculated using the Welch method. The PSDs calculated for the IMFs of each activity are then summed to obtain a single PSD value for each activity. The generation of PSDs is achieved by repeating the aforementioned process for 420 data, encompassing falls, and other activities.

Numerous studies have utilized PSDs as features for classification purposes [34]-[35]. Inspired by this situation, the use of PSDs as features for the classification of falls and activities is proposed.

2.3. Classification

2.3.1. Decision Tree (DT)

Decision tree is a nonparametric supervised learning method used for classification problems. DT, a popular approach, is effectively used in many areas. As its name suggests, it aims to reveal the results related to the target values of an element from the findings of an element using a tree as a classification model. The model, which consists of four types of nodes, has roots, branches, internal nodes, and leaves. A tree starts from the root node and ends at the last node, the leaves. Each leaf represents a classification and each branch represents the combination of features that reveal the target classifications. Classification can be done quickly and easily in decision trees [36].

2.3.2. Support Vector Machine (SVM)

Support vector machine is a supervised learning method that is utilized extensively in the context of classification. It can be preferred in the classification of linear or non-linear data. SVMs have the capacity to be trained with a variety of functions. The fundamental premise of the method is to ascertain the optimal decision boundary in two-dimensional space. In other words, classification is done by modeling complex non-linear decision boundaries with the appropriate training function. The optimal decision boundary is categorized into classes for the accurate allocation of new data. Hence, the best separating hyperplane is identified [37].

2.3.3. K-Nearest Neighbors (KNN)

K-Nearest Neighbors are a simple and widely used supervised learning method. KNN, a nonparametric method, also performs example-based learning. It does this by storing examples during the training process. In this method, data is divided into clusters during training. In the testing phase, the training data of k neighbors is compared with the test data in the variable space and classification is performed according to the class of the k nearest neighbors categorically. The determination of neighbors is found with the Euclidean distance metric between the investigated data point and k neighbors [38].

2.3.4. Ensemble Learning

Ensemble learning, which is frequently seen in classification studies, is essentially a method that tries to produce better classification performance by combining predictions obtained from multiple classifiers. It consists of three main classes. In the first of these, bagging, more than one model is created. This is done by training each on a subset of the training dataset. The second class is called boosting. Boosting is the class in which a series of models are created sequentially and each model learns from the errors of the previous model. The last class is stacking. It is defined as the class that trains by combining the outputs from different model sets [39].

Among the traditional machine learning methods, 4 basic classifiers and their derivatives are preferred in the study. The parameters used for the classifiers are presented in our previous study [33]. The number of IMF signals and their effect on the classification are revealed as stated below. The signal processing steps in the study are shown as a block diagram in Figure 3.

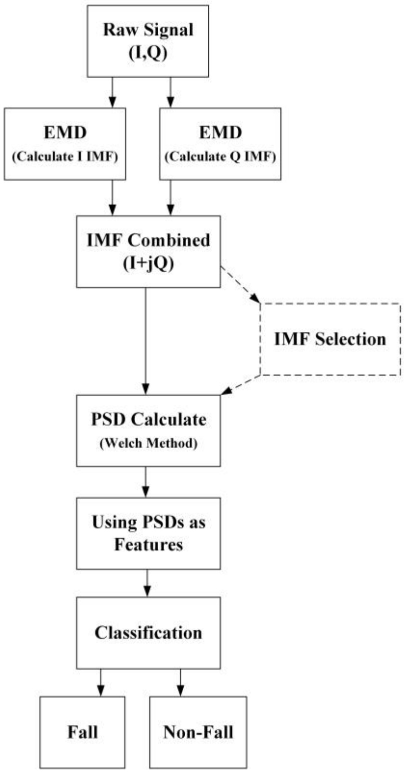

Figure 3. Signal processing block diagram

3. Experimental Results and Discussion

The classification of falls and daily activities using PSDs as features is achieved through the utilization of four fundamental classifiers and their respective derivatives. The ensuing classification results of fall and non-fall situations using IMF number 1, depending upon other IMFs, are displayed in Table 2.

Table 2. Classification accuracy rates of IMF number 1 based on the other IMFs

EMD Method	**Performance Comparison of Classifiers**			
	Classifiers and Accuracy Rate (%)			
IMF Values	**DT (fine)**	**SVM (cubic)**	**KNN (fine)**	**Ensemble (bagged tree)**
1-8	96	92,4	81,4	99,5
1-7	**96,2**	**92,6**	**81,4**	**99,5**
1-6	95,7	93,3	81,7	99,5
1-5	95,7	92,6	81,4	99,5
1-4	95,7	93,3	80,5	99,5
1-3	95,7	92,4	79	99,5
1-2	95,7	84	76,4	99,5

Upon analysis of the table, it is evident that the KNN classifier exhibits the lowest classification accuracy. Depending on the IMF values, it is stated that it provides a classification success of around 80%. The accuracy rates for both the DT and SVM classifiers exceed 90%, with the DT classifier demonstrating a higher rate of accuracy than the SVM. In the table presenting the analysis of the effect of IMF number 1 in conjunction with other IMFs, the Ensemble Bagged Tree algorithm demonstrates the highest level of accuracy, with a rate of 99.5%. It repeats its success with a constant accuracy rate in the comparison of all IMFs. The confusion matrix for this classifier can be seen in Figure 4. Additionally, precision, recall and F1-score values are presented in Table 3.

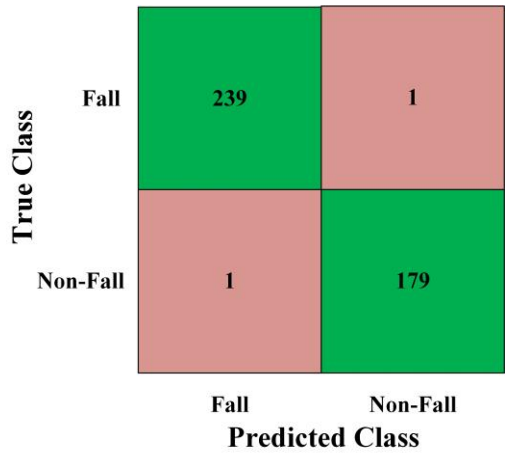

Figure 4. Confusion matrix for ensemble bagged tree algorithm to IMF 1-7

Table 3. Other classification metrics for the Ensemble Bagged Tree algorithm to IMF 1-7

Classification Metrics	Precision	Recall	F1-Score
Fall	99,6	99,6	99,6
Non-Fall	99,6	99,6	99,6

The classification of the fall is carried out based on IMFs numbered 2. The accuracy rate results obtained are shown in Table 4.

Table 4. Classification accuracy rates of IMF number 2 based on the other IMFs

EMD Method	Performance Comparison of Classifiers			
	Classifiers and Accuracy Rate (%)			
IMF Values	**DT (fine)**	**SVM (cubic)**	**KNN (fine)**	**Ensemble (bagged tree)**
2-8	97,9	99,8	99,3	99,8
2-7	97,9	99,8	99,3	99,8
2-6	**98,3**	**100**	**99,5**	**99,8**
2-5	98,3	100	99,5	99,8
2-4	98,1	100	99,5	99,8

Table 4, which presents the results of the effect of IMF number 2, demonstrates that each classifier is highly effective. It is noteworthy that even the DT classifier, which exhibits the lowest accuracy rate, attains a substantial result by attaining a rate of 98.3%. The KNN classifier, on the other hand, has achieved an accuracy rate of over 99% depending on each IMF value. Once more, the Ensemble bagged tree algorithm, which offers a very stable accuracy rate, reinforces its success with one incorrect classification in the table in which all 2 and other IMFs are compared. The classifier that provides an error-free classification for Table-4 is SVM. It reaches a rate of 100% for almost all 2 and other IMFs. The confusion matrix for the classification obtained with IMF values 2-6 is presented in Figure 5. In addition, other classification indicators are presented in Table 5 for IMF 2-6.

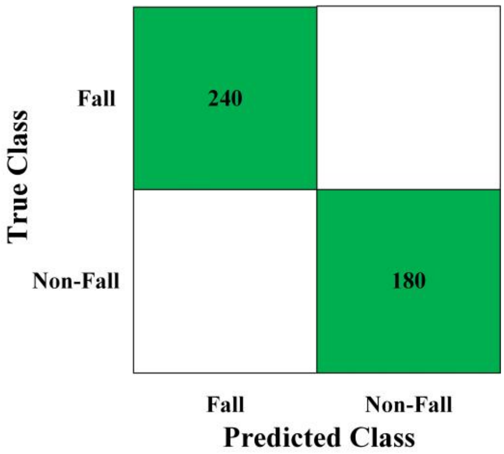

Figure 5. Confusion matrix for cubic SVM algorithm to IMF 2-6

Table 5. Other classification metrics for cubic SVM algorithm to IMF 2-6

Classification Metrics	Precision	Recall	F1-Score
Fall	100	100	100
Non-Fall	100	100	100

The classification of the fall is achieved through the calculation of the PSDs based on IMFs numbered 3. The performance of the classifiers is presented in Table 6.

Table 6. Classification accuracy rates of IMF number 3 based on the other IMFs

EMD Method	Performance Comparison of Classifiers			
	Classifiers and Accuracy Rate (%)			
IMF Values	DT (fine)	SVM (cubic)	KNN (fine)	Ensemble (bagged tree)
3-8	95,7	99,3	99,3	99
3-7	**96,2**	99,3	98,8	99
3-6	96	99,5	98,8	98,8
3-5	**95,7**	**99,5**	**98,8**	**99**

According to Table 6, it is evident that the decision tree algorithm once again exhibits a low accuracy rate in comparison to the other classifiers. However, it is still seen that the performance of this classifier is not negligible with a rate of 96.2%. Despite the fact that the ensemble bagged tree algorithm attains a 99% accuracy rate, it exhibits inferior performance in comparison to the other two classifiers and consistently generates a stable rate with almost all IMFs. The KNN classifier demonstrates a high level of accuracy, with a rate of 99.3%. In this table, where the effect of IMFs numbered 3 and other IMFs is examined, the SVM classifier reaches the best result with a classification accuracy of 99.5%. Figure 6 presents the confusion matrix for the SVM classifier. Other classification metrics obtained from the cubic SVM algorithm to IMF 3-5 are given in Table 7.

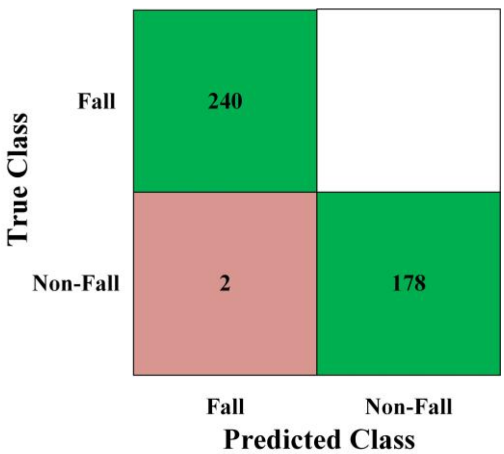

Figure 6. Confusion matrix for cubic SVM algorithm to IMF 3-5

Table 7. Other classification metrics for cubic SVM algorithm to IMF 3-5

Classification Metrics	Precision (%)	Recall (%)	F1-Score (%)
Fall	99,2	100	99,6
Non-Fall	100	98,9	99,4

The accuracy rate obtained as a result of classifying the fall based on IMF number 4 is presented in Table 8.

Table 8. Classification accuracy rates of IMF number 4 based on the other IMFs

EMD Method	Performance Comparison of Classifiers			
	Classifiers and Accuracy Rate (%)			
IMF Values	**DT (fine)**	**SVM (cubic)**	**KNN (fine)**	**Ensemble (bagged tree)**
4-8	**93,6**	**98,1**	**93,8**	**92,6**
4-7	92,9	98,1	93,1	92,9
4-6	93,3	97,6	95,5	93,6

When looking at Table 8, it is seen that the accuracy rates have decreased for other IMFs. However, these rates are still above 90%. Surprisingly, the lowest accuracy rate is obtained by the Ensemble bagged tree classifier, which gives quite high results under the influence of other IMFs. The decision tree classifier also shares the same result with the Ensemble bagged tree algorithm. In this case, where the effect of IMF number 4 and other IMFs is examined, the KNN classifier has shown an accuracy rate of 95.5%. SVM, on the other hand, has achieved the highest accuracy rate, as in the effects of IMF numbers 2 and 3. Although it achieved the highest accuracy rate with a rate of 98.1%, the accuracy rate has decreased compared to other IMF effects.

Following a thorough examination of the impact of IMF on classification accuracy, it has been determined that IMF number 2 exerts a more significant influence on the accuracy of classification. In light of the favorable outcomes, the classification situation performed as falling and not falling is expanded for seven different movements. As demonstrated in Table 9, the maximum results obtained for each IMF value are presented. Contrary to expectations, the highest accuracy rate for seven movements has been obtained for IMF values 1-4. This success has been achieved by the cubic SVM classifier. The confusion matrix of the cubic SVM classifier for seven movements is given in Figure 7. Table 10 presents a range of additional classification parameters calculated for these seven movements.

Table 9. The highest classification accuracy rates obtained based on seven movements for each IMF

EMD Method	Performance Comparison of Classifiers			
	Classifiers and Accuracy Rate (%)			
IMF Values	**DT (fine)**	**SVM (cubic)**	**KNN (fine)**	**Ensemble (bagged tree)**
1-4	**83,8**	**91,7**	**59,8**	**88**
2-4	83,3	90,2	**84**	86,9
3-6	83,6	8,5	83,6	86,7
4-8	75,5	78,3	75,2	76,4

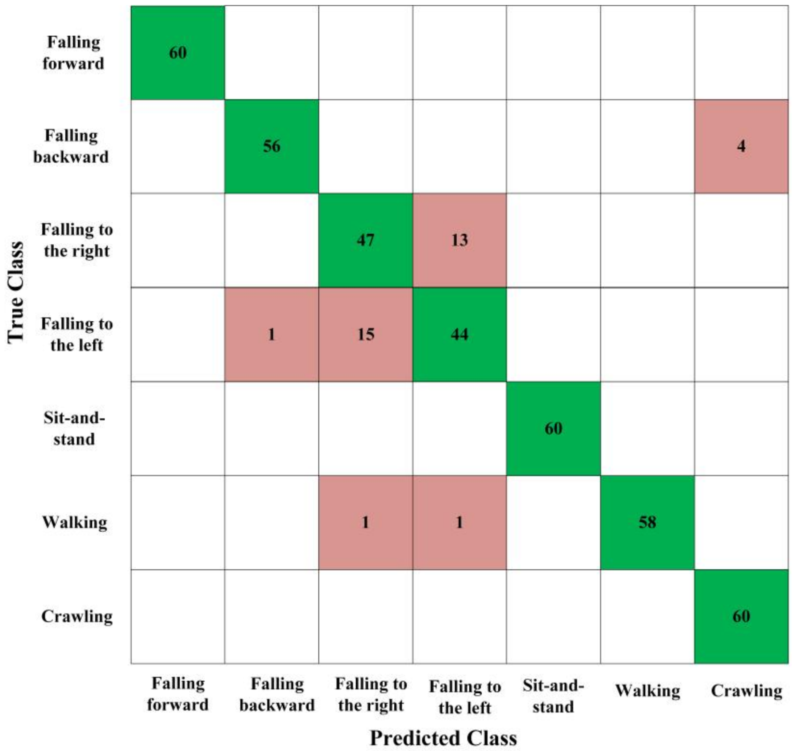

Figure 7. Confusion matrix for cubic SVM algorithm for seven movements

Table 10. Other classification metrics for cubic SVM algorithm to IMF 1-4

Classification Metrics	Precision (%)	Recall (%)	F1-Score (%)
Falling forward	100	100	100
Falling backward	96,6	93,3	94,9
Falling to the right	74,6	78,3	76,4
Falling to the left	77,2	73,3	75,2
Sit-and-stand	100	100	100
Walking	100	96,7	98,3
Crawling	93,8	100	96,8

As Figure 7 illustrates, the classification of 'falling forward', 'sit-and-stand', and crawling has been conducted without any errors. Conversely, the accuracy rate of the algorithm is diminished by the incorporation of falling to the right and falling to the left results for merely two data. In the case of backward falls, the algorithm has been misclassified in four data. The data about falling backward has been interpreted as crawling data. The main reason for the decrease in accuracy and other parameters is that falling to the right and falling to the left are confused with each other. It is thought that the main problem underlying this situation is due to the radar structure.

4. Conclusion

The number of individuals living alone, particularly the elderly, is increasing daily. In this context, the accident with the most serious consequences for the elderly is falling. In this study, radar-based fall detection is discussed. In the study carried out in a home environment, various fall and daily activity scenarios are considered and necessary measurement studies are carried out. The obtained data are decomposed into IMFs using the EMD method. Depending on the radar structure, the IMFs of I and Q signals are combined and complexities. Subsequently, PSDs are calculated using the Welch method. The PSDs, which are highly specific for each motion, are directly used as features in the classification of fall detection.

A range of derivatives of conventional machine learning methods have been favored for classification. In the study, the effect of IMFs in the context of fall classification is presented. In particular, the effect of IMFs numbered 2 and 3 on falling detection is revealed. The present study successfully achieves error-free fall classification. With this motivation, the classification of seven movements is also made and activities are classified with the proposed method with an accuracy rate of 91.7%. It is thought that the biggest disadvantage in achieving this rate is the difficulty of distinguishing right and left falls with the relevant equipment. It is revealed with the method we propose that traditional machine learning is still quite effective, practical and solution-oriented.

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