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Araştırma Makalesi / Research Article

Elderly Fall Detection Using Autoencoder Based Dimensionality Reduction and Smartwatch Based Wearable Motion Detectors

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Keywords
Autoencoder; Dimensionality reduction; Fall detection; Logistic regression; Smartwatch; Wearable devices.

Abstract

Falling is a serious health risk that can even result in death, especially for the elderly. For this reason, it is crucial to prevent falls and, in cases where prevention is not possible, to detect and intervene as soon as possible. Smartwatches are an ideal tool for fall detection due to their constant presence, rich sensor resources, and communication capabilities. The aim of this study is to detect falls in elderly people with high accuracy using motion sensor data obtained from smartwatches. To achieve this, a dataset was created consisting of falls and daily activities. Then, the feature vector was extracted which has provided successful results in signal processing studies. Afterward, the dimensionality of the dataset was reduced using an autoencoder-based approach in order to decrease the workload on smartwatches and ensure more accurate and faster classification. The dataset was classified using machine learning methods including naive Bayes, logistic regression, and C4.5 decision tree, and successful results were obtained. Their performances were then compared. It was observed that reducing the dimensionality had positive effects on both the classification accuracy and the computation time.

Otokodlayıcı Tabanlı Boyut Azaltma ve Akıllı Saat Tabanlı Giyilebilir Hareket Algılayıcıları Kullanarak Yaşlılarda Düşme Tespiti

Anahtar kelimeler
Otokodlayıcı; Boyut azaltma; Düşme tespiti; Lojistik regresyon; Akıllı saat; Giyilebilir cihazlar.

Öz

Düşme, özellikle yaşlılar için ölümle bile sonuçlanabilecek ciddi bir sağlık riskidir. Bu nedenle düşmelerin önlenmesi, engellenemeyen durumlarda ise en kısa sürede tespit edilerek müdahale edilmesi büyük önem taşımaktadır. Akıllı saatler, her zaman kişinin yanında bulunması, zengin algılayıcı kaynakları ve haberleşme imkânı sayesinde düşme tespiti için ideal bir araçtır. Bu çalışmanın amacı, akıllı saatlerden elde edilen hareket algılayıcısı verilerini kullanarak yaşlı bireylerde düşmeleri yüksek doğrulukla tespit etmektir. Bunun için düşme ve günlük aktivitelerden oluşan bir veri seti oluşturulmuştur. Daha sonra sinyal işleme çalışmalarında başarılı sonuçlar veren öznitelik vektörü çıkarılmıştır. Devamında akıllı saatlerin iş yükünü azaltmak, daha doğru ve hızlı sınıflandırma sağlamak için otokodlayıcı tabanlı bir yaklaşım kullanılarak veri setinin boyutu azaltılmıştır. Naive Bayes, lojistik regresyon ve C4.5 karar ağacı makine öğrenmesi yöntemleri kullanılarak veri seti sınıflandırılmış ve başarılı sonuçlar elde edilmiştir. Sonrasında performansları karşılaştırılmıştır. Boyutsallığın azaltılmasının hem sınıflandırma doğruluğu hem de hesaplama süresi üzerinde olumlu etkileri olduğu gözlemlenmiştir.

1. Introduction

Falling is a common occurrence among the elderly and tends to become more frequent with age. While half of the elderly who fall are able to stand up on their own, those who cannot get up require assistance and may remain on the ground for a long time. Muscle weakness, balance problems, gait disturbance, loss of consciousness, heart attack, trauma, epilepsy, visual impairment, stroke, advanced age, and dizziness are among the main risk factors for falls (Beyazova 2011). Furthermore, environmental factors such as wet and slippery floors, unevenly distributed rooms, poor lighting, high bed position, and wearing inappropriate or oversized shoes can also contribute to falls (Berke and Aslan 2010). As the number of risk factors increases, so does the likelihood of falling. Preventing falls is crucial because they can lead to severe medical issues for older individuals. However, prevention is not always feasible. In such cases, it is crucial to detect falls with high accuracy and intervene as soon as possible.

Wearable devices are electronic or computer technologies that can be worn as accessories or clothing comfortably on the body. These devices are capable of performing computations that are comparable to many computers and smartphones, and in some cases, they can provide superior results (Sağbaş *et al.* 2016). Smartwatches are a popular type of wearable device that is particularly suitable for health applications due to their rich sensors and ability to be worn throughout the day. Machine learning methods can be used to classify motion sensor data obtained from smartwatches (Ballı *et al.* 2019a). However, various data mining problems are encountered during this process. High-dimensional features require significant computational power and computation time, but there are various approaches to addressing the issue of dimensionality.

The literature contains numerous studies on fall detection, where machine learning methods are applied to process data obtained from smartphones, smartwatches, wearable sensors, and videos. Hakim *et al.* (2017) aimed to detect human falls with data obtained from smartphone motion sensors. With the obtained data, machine learning-based action recognition and threshold-based fall detection approaches are presented. Lu *et al.* (2018) combined 3D-CNN LSTM methods to detect drops on video kinematics data with high accuracy. Harrou *et al.* (2019) discussed the detection of human falls with machine learning methods, using relevant pixel-based features that reflect differences in body shape. Núñez-Marcos *et al.* (2017) proposed a vision-based solution that uses Convolutional Neural Networks to decide whether a set of frames contains a falling person. Khraief *et al.* (2020) proposed multi-stream deep convolutional networks using rich multimodal data provided by RGB-D cameras. The proposed method automatically detects fall events and sends a help request to the relevant people. De Miguel *et al.* (2017) presented a new low-cost fall detector for smart homes based on machine vision algorithms. Taramasco *et al.* (2018) used very low-resolution thermal sensors to classify fall and then alert maintenance personnel. As a result of the experiments, 93% successful classification accuracy was achieved with the Bi-LSTM method. Hussain *et al.* (2019) proposed a wearable sensor-based continuous fall monitoring system that can detect a fall and identify the fall pattern and activity associated with the fall event. The performance of the proposed structure has been tested with three machine learning methods: kNN, support vector machine, and random forest. Ballı *et al.* (2018, 2019b) presented a machine learning-based approach for fall detection using a smartphone and a smartwatch together. Kerdjdj *et al.* (2020) classified the falls with high accuracy with accelerometer and gyroscope sensors. According to Musci *et al.* (2020) investigated the design of software architecture based on iterative neural networks that could be effective for fall detection while operating on a fully wearable device. Khojasteh *et al.* (2018) analyzed alternative models for fall detection with a wrist-mounted sensor. Mauldin *et al.* (2018) presented an Android application that uses accelerometer data collected from a smartwatch to detect falls. Zurbuchen *et al.* (2021) investigated a multi-class classification approach for fall detection and the effect of the sampling rate of sensors on fall detection system performance. Ponce *et al.* (2020) proposed a methodological analysis to determine the minimum number of sensors required to develop an accurate fall detection system using the UP fall detection dataset. They analyzed two camera viewpoints and five wearable sensors separately.

The study's main contributions can be summarized as follows:

1. A machine learning approach was proposed to detect falls among the elderly with high accuracy and as quickly as possible, using only accelerometer and gyroscope sensor data from a smartwatch.
2. An untested feature vector was created for fall detection.
3. A hybrid structure was developed by applying autoencoder-based dimensionality reduction to reduce computational costs. The dimensionality-reduced dataset was tested using three different machine learning methods, and their performance was compared.
4. Autoencoder-based dimensionality reduction significantly reduced run time and improved classification accuracy.
5. A system was designed to detect falls and provide early intervention based on successful results.

The remainder of the work is organized as follows. Applied artificial intelligence methods to the dataset are briefly explained in the second section. The used dataset, the obtained experimental findings, and the developed fall detection system architecture are explained under the third section. Finally, the study is concluded in the fourth section.

2. Applied AI Methods

2.1 Autoencoder

Studies show that extracted features are not equally effective on every dataset. Therefore, it is more appropriate to extract features for the dataset (Ravi *et al.* 2016). Autoencoder is a neural network designed for this purpose. The structure is an unsupervised method that creates the same number of output vectors as the number of inputs shown in Figure 1, instead of assigning class labels. If the input data is high dimensional, a single hidden layer of an Autoencoder may not be sufficient to represent all the data. Alternatively, several Autoencoders can be stacked to form a deep Autoencoder architecture (Hinton and Salakhutdinov 2006).

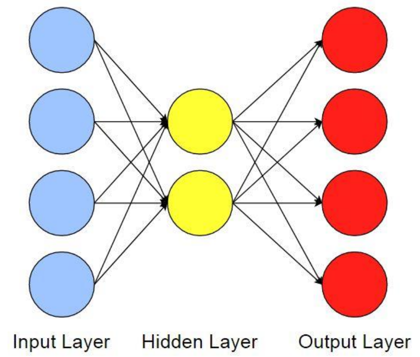

Figure 1. The simple neural network structure for autoencoder

After pre-training, standard backpropagation can be used to fine-tune the parameters. Many autoencoder variations have been proposed to make the learned representations more robust or stable (Ravi *et al.* 2016). In this study, a contractive autoencoder was implemented to the dataset. This method was presented by Rifai *et al.* (2011) and provides an alternative to weight decay. All attributes are standardized, including the class attribute. This method has several parameters. The lambda parameter is used to determine the penalty on the size of the weights. The number of hidden layers is also one of the parameters. To improve the speed, an approximate version of the logistic function is used as the activation function (Web Resource 1).

2.2 Classification Approaches

C4.5 Decision Tree (C4.5)

A divide-and-conquer approach for learning tasks from a set of self-directed examples is modeled using a decision tree. Decision tree nodes test attributes, with tests at nodes typically comparing an attribute value to a constant. In contrast, a collection of trees compares two properties to each other or implements a particular function with at least one property. Classification(s) or probability distribution is made according to each potential classification at leaf nodes. To classify the signals, the signal is propagated from top to bottom according to the values of the verified attributes in successive nodes. When the signal reaches the leaf, the classification process ends, and the signal is classified according to the leaf class (Alickovic and Subasi 2016).

Naive Bayes (NB)

The Naive Bayes classification algorithm is built on the Bayes theorem, assuming that the features are independent. This Bayesian classifier employs statistical analysis to forecast an upcoming feature and is well-suited for large datasets. During the learning process, the Naive Bayes Classifier trains on the test data and identifies the class with the highest sample (Venkatesh *et al.* 2019).

Logistic Regression (LR)

Logistic regression is a popular method for modeling binary data in biostatistics and health sciences. Unstable parameter estimates occur when the number of covariates is relatively large or there is a high correlation between covariates (Saleh abd Kibria 2013). The logistic regression model describes the binary interaction variable with a linear combination of a set of covariates.

3. Fall Detection System Design

3.1. Dataset

This study proposes a two-class machine learning approach for fall detection, using data obtained from the Moto 360 smartwatch shown in Figure 2. The smartwatch is configured to collect 50 data samples per second, providing the necessary data for classification.

The data used in this study were obtained from the accelerometer and gyroscope sensors, which return sensor information in three axes: x, y, and z (Sağbaş and Balli 2017). Figure 3 shows sample accelerometer and gyroscope data for the falling action.

Figure 2. The smartwatch used for data collection

When examining the sensor signals of a fall, it is observed that the action occurs within approximately 0.7 seconds. Therefore, the dataset was adjusted to have classifications at 0.7-second intervals. Falls were classified as falling from a chair, falling while walking, falling back, and falling to the right or left, resulting in a total of 104 fall class patterns. For the not_fall class, sensor data from 7 different daily activities were collected. This aimed to detect falls between daily activities. An unbalanced dataset was created by labeling a total of 728 patterns, with 104 for each of the daily activities, as the not_fall class. Next, 10 statistical formulas used in signal processing studies, such as Şen *et al.* (2014) and Sağbaş *et al.* (2020), were applied to each axis of each sensor, resulting in a total of 60 features extracted. An explanatory representation of the obtained features is presented in Table 1. Autoencoder is a dimension reduction approach. In this way, the dataset represented by 60 features is provided to be represented in two dimensions with hidden units.

Table 1. Annotated representation of features

Feature number	Sensor source	Applied statistics	Feature name
1-10	Accelerometer X	Min Max Mean Standard deviation Mean energy Mean curve length Zero crossing Q1 Q3 Sum	AccX+Applied statistics
11-20	Accelerometer Y		AccY+Applied statistics
21-30	Accelerometer Z		AccZ+Applied statistics
31-40	Gyroscope X		GyrX+Applied statistics
41-50	Gyroscope Y		GyrY+Applied statistics
51-60	Gyroscope Z		GyrZ+Applied statistics

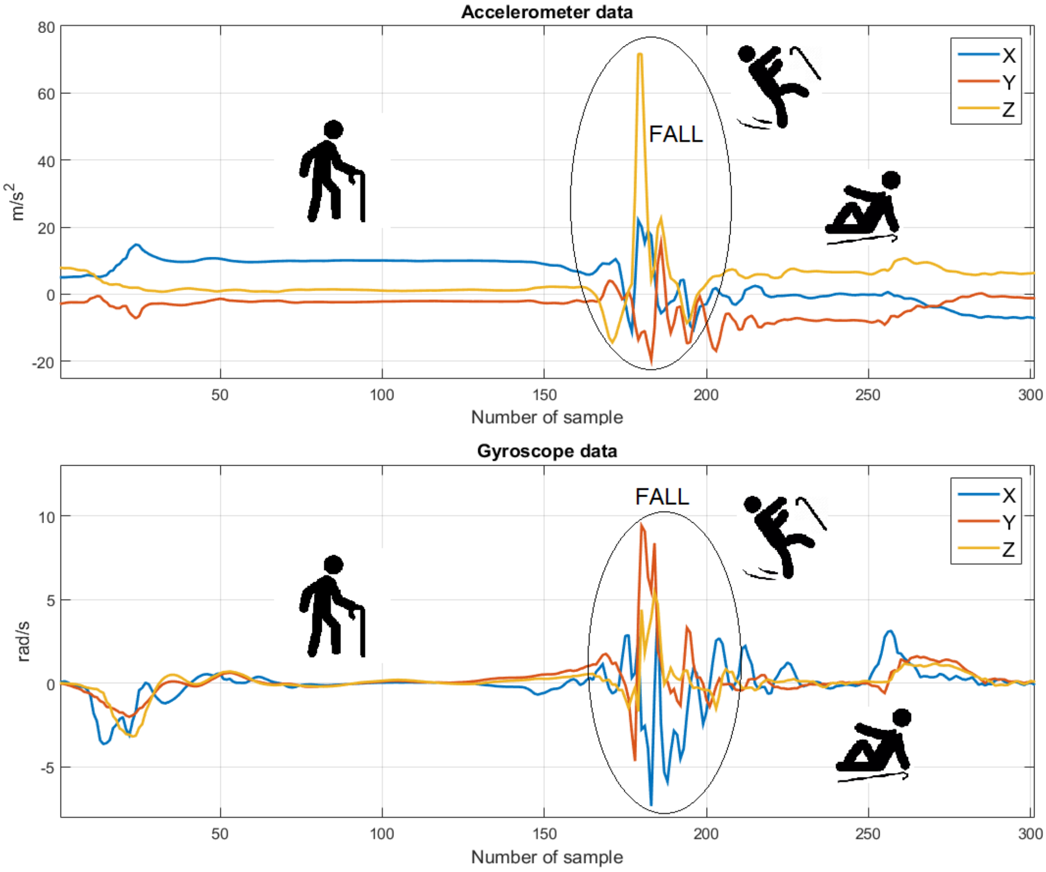

Figure 3. Sample accelerometer and gyroscope data of falling action

3.2. Experimental Results and Discussion

In this study, an unbalanced dataset containing two classes, "fall" and "not_fall," was used to detect falls from smartwatch sensor data. To measure the classification performance, the classification accuracy, precision, recall, and f-score values were calculated, which are presented in equations 1-4.

$$CA = \frac{TP+TN}{TP+FP+TN+FN} x100\% \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F - score = 2x\frac{Precision\ x\ Recall}{Precision+Recall} \quad (4)$$

A classification task was performed on smartwatch data to detect falls, with a very short window interval of 0.7 seconds. Given the limited processing power of smartwatches, runtime becomes an important factor to consider. To address this, an autoencoder-based dimensionality reduction method was applied to the dataset before performing classification using the C4.5, naive Bayes, and logistic regression methods. The experimental flow chart and performance evaluation are presented in Figure 4, while the confusion matrices for the classification results before and after dimensionality reduction are presented in Table 2 and Table 3, respectively.

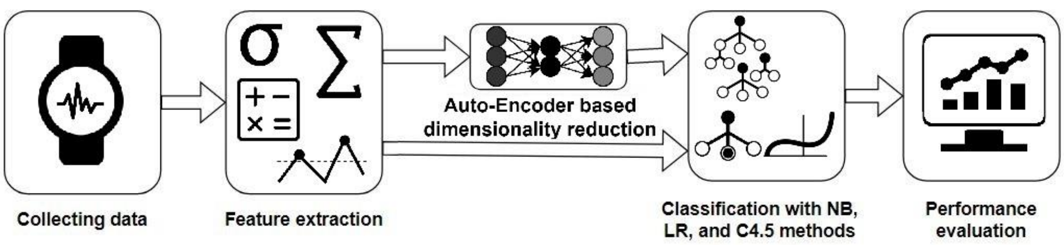

Figure 4. Flow chart of experiments

Table 2. The confusion matrices of the results were obtained without dimensionality reduction

NB	NOT_FALL	FALL
NOT_FALL	716	12
FALL	0	104

LR	NOT_FALL	FALL
NOT_FALL	726	2
FALL	3	101

C4.5	NOT_FALL	FALL
NOT_FALL	727	1
FALL	3	101

Table 3. The confusion matrices of the results were obtained with dimensionality reduction

NB	NOT_FALL	FALL
NOT_FALL	726	2
FALL	2	102

LR	NOT_FALL	FALL
NOT_FALL	727	1
FALL	2	102

C4.5	NOT_FALL	FALL
NOT_FALL	727	1
FALL	3	101

When examining the confusion matrices, it can be observed that the NB method classified the fall class without error before the dimensionality reduction process, but 12 misclassifications occurred in the not_fall class, leading to a reduction in classification accuracy. On the other hand, the LR method showed an increase in success rates for both fall and not_fall classes after dimensionality reduction. In the C4.5 method, no changes were observed in the classifications. Performance measurements and run times calculated based on confusion matrices are presented in Table 4, and a graphical representation of these measurements is presented in Figure 5.

The highest classification accuracy and f-score values before dimensionality reduction were obtained from the C4.5 method, with 99.52% and 0.9806, respectively. The run time for this method was calculated as 0.2346. After dimensionality reduction, the classification accuracy and f-score values of the NB and LR methods increased. The highest success was achieved with the LR method, with a classification accuracy of 99.64% and an f-score of 0.9855. The differences resulting from the experiments performed before and after dimension reduction are summarized in Table 5.

Table 5. The difference resulting from dimensionality reduction

	CA	Precision	Recall	F-score	Run time
NB	0.96	-0.0192	0.0842	0.0353	-0.1615
LR	0.24	0.0096	0.0097	0.0096	-0.6059
C4.5	0	0	0	0	-0.2109

The autoencoder-based dimensionality reduction process increased the classification accuracy and f-score values of the NB and LR methods. The accuracy increased by 0.96 points for NB and 0.24 points for LR. Additionally, the f-score values increased by 0.0353 and 0.0096, respectively. However, no change was observed in the performance measurements of the C4.5 method. There was a decrease in run times in all methods, with the maximum reduction calculated as 0.6059 s in LR, which was the most successful method.

It is not possible to directly compare the findings obtained in this study with previous studies. Because related studies use different datasets and different artificial intelligence approaches. There are several studies examining fall detection in the elderly. Anitha and Baghavathi Priya (2022) proposed a deep learning model for the detection of falls. The vision-based system performs classification with 99.9% accuracy. Galvao *et al.* (2021) proposed different topologies of a multimodal convolutional neural network trained to detect falls based on RGB images and information from accelerometers for fall detection.

Table 4. Performance measurements and run times for classifications

	Without dimensionality reduction					**With dimensionality reduction**				
	CA	**Precision**	**Recall**	**F-score**	**Run time**	**CA**	**Precision**	**Recall**	**F-score**	**Run time**
NB	98.56	1.0000	0.8966	0.9455	0.1840	99.52	0.9808	0.9808	0.9808	0.0225
LR	99.40	0.9712	0.9806	0.9759	0.7463	99.64	0.9808	0.9903	0.9855	0.1404
C4.5	99.52	0.9712	0.9902	0.9806	0.2346	99.52	0.9712	0.9902	0.9806	0.0237

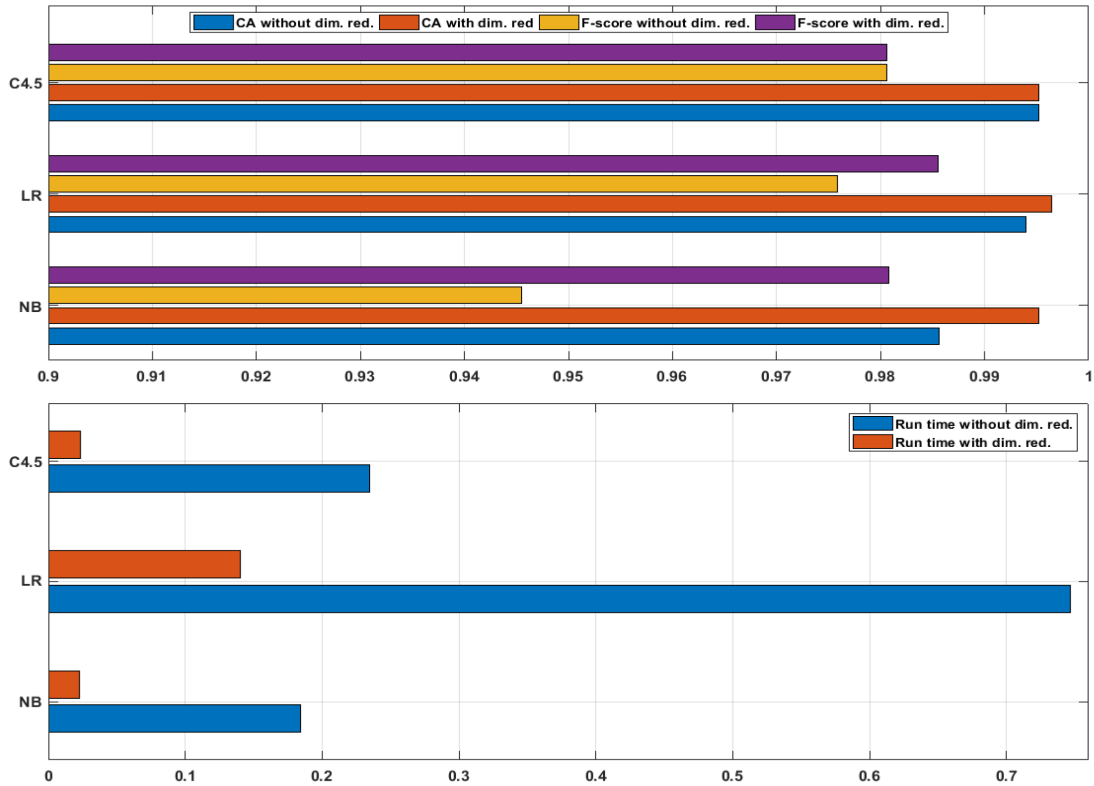

Figure 5. Graphical representation of performance measurements

The proposed model achieved 99.87% and 99.99% success on two different datasets. Wang *et al.* (2019) aimed to demonstrate the effectiveness of detecting falls using a wearable accelerometer. They achieved a classification success of over 99.9% with the CNN method. Kausar *et al.* (2022) performed binary classification of the data obtained from a wearable accelerometer device with machine learning approaches. Three of the four machine learning approaches tested achieved 99.9% classification accuracy. Salah *et al.* (2022) mentioned the limitations of hardware resources of devices used for fall detection and tried to solve this problem. In this study, in which accelerometer data and CNN method were used, the classification success was 95.55%. Jain and Semwal (2022) used deep learning methods and wearable device sensors to detect falls within 0.5 seconds with 99.24% sensitivity and 98.79% f1-score. Durgun (2023) performed the detection of falls in the elderly with an accelerometer sensor with an accuracy of 98.5%. Sözer (2022) suggested an anomaly detection approach to detect falls. He used accelerometer data and an average of 91.3% success was achieved as a result of the experiments. When the previous studies are evaluated in general, it is seen that falls are classified with a success rate of over 99%. In this study, this success was calculated as 99.64%. Although there are vision-based studies (Anitha and Baghavathi Priya, 2022; Galvão *et al.*, 2021), it is seen that wearable accelerometer sensors are used in most of the related studies. In this study, a smart watch was used as a more suitable approach. Moreover, in addition to the accelerometer sensor, the gyroscope sensor was also utilized. Additionally, the running time was calculated between 0.02 and 0.14 seconds with the proposed autoencoder-based approach. This allows the system to be easily used offline on mobile devices.

3.3. System Design

Based on the experimental findings, the method with the highest classification success and the lowest computational cost was determined. It was decided to use the autoencoder-based dimensionality reduction method in the architecture to be designed and then perform classification with the LR method.

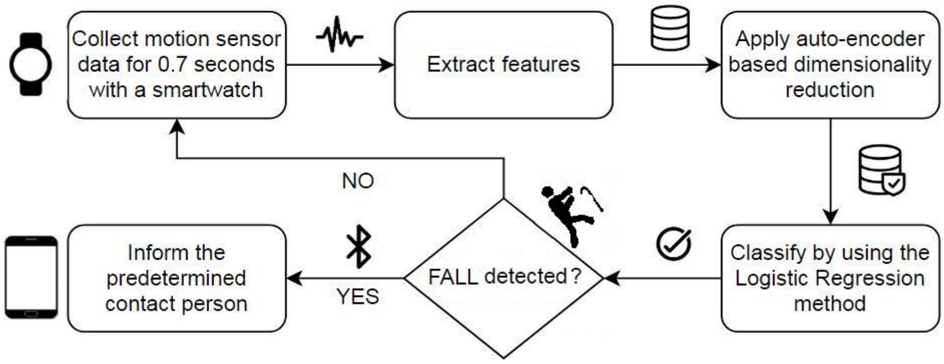

Figure 6. The architecture of the developed system

Accordingly, the system will generate a pattern every 0.7 seconds and extract 60 features from the obtained data. Then, the dimensionality of the dataset will be reduced to further reduce computational costs. Afterward, a high-accuracy classification will be performed using the LR method. When the system detects a fall, the situation will be notified to previously determined individuals or organizations via the smartphone to which the smartwatch is connected, and early intervention will be made. The architecture of the developed system is presented in Figure 6.

An example of the information message sent to the relevant person as a result of the operation of the designed system is shown in Figure 7. The recipient of the message can obtain directions by clicking on the location provided in the message via the map application. Furthermore, the heart rate information during the fall event offers the opportunity to interpret the health status of the person.

4. Conclusion

Falls are a major risk factor, particularly for the elderly, making it crucial to detect unavoidable falls and intervene as soon as possible. This study successfully utilized machine learning approaches to accurately detect smartwatch sensor data. To increase classification success while reducing computation time, an autoencoder-based dimensionality reduction method was applied to the dataset prepared for fall detection.

After preparing the dataset for fall detection, machine learning approaches including NB, LR, and C4.5 decision tree methods were utilized for classification, which is commonly used and successful methods in the literature. Autoencoder-based dimensionality reduction was applied to increase classification accuracy and decrease computation time. The LR method achieved a 0.24-point increase in success and an 81% decrease in computation time after dimensionality reduction. This reduction in workload will enable the smartwatch to perform the classification process more efficiently, leading to more accurate results. These results demonstrate that the system can easily be implemented on smartwatches. The system architecture is designed and presented based on these findings.

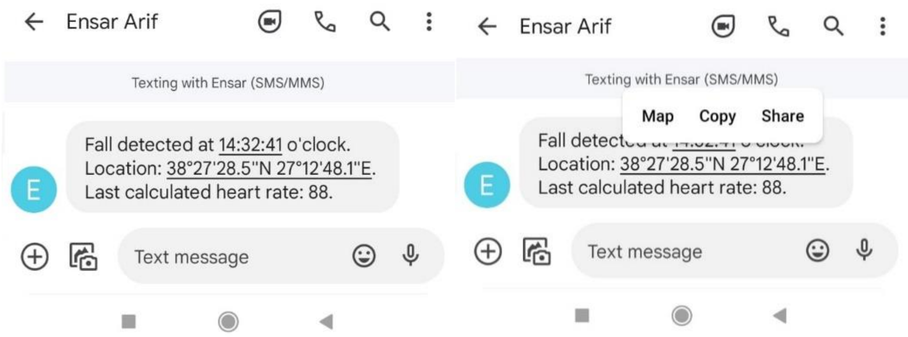

Figure 7. An example of a system-generated informational SMS.

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Web resources

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