**Engineering Sciences**
ISSN: 1308-7231
Article ID: 1A0478

Status : Research Article
Received: 11.12.2021
Accepted: 28.04.2022

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| **DOI** | http://dx.doi.org/10.12739/NWSA.2022.17.2.1A0478 | |
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# A HYBRID DEEP LEARNING BASED CLASSIFICATION FOR SOME BASIC MOVEMENTS IN PHYSICAL REHABILITATION

**ABSTRACT**

It is important to perform basic rehabilitation movements such as walking and sitting, which are planned individually, for the follow-up of the patient undergoing physical rehabilitation treatment and to examine the development of the patient over time. In this paper, movement classification based on hybrid deep learning algorithm is proposed to determine if the exercises given by the doctor are performed by the patient accurately. Six basic movements are classified as standing, sitting, laying, walking, walking upstairs, walking downstairs by means of the proposed Alexnet-SVM (Alexnet-Support Vector Machine) hybrid model. During the training and testing stages of the system, 1492 movement signals obtained from smartphone (Samsung Galaxy S II) on the waist are used. For the classification of movement signals by hybrid Alexnet-SVM, at first, the spectrogram images of the signals are obtained by means of Short-time Fourier transform. In order to use the obtained spectrographic images directly in Alexnet-SVM architecture, crop and resize preprocessing are applied. To show the superiority of the proposed Alexnet-SVM, the results are compared with the results of Alexnet, Resnet18 and Resnet18-SVM. The performance parameters of the proposed Hybrid Alexnet-SVM classifier are calculated using accuracy and F1-scores, resulting in 87.67% and 93.4%, respectively. The results obtained facilitate the follow-up of the patients who have lost their mobility, whether they are doing the movement correctly and it is possible to determine whether the correct treatment is applied or not.

**Keywords:** Deep learning, Movement Human Actions ssification, Alexnet, Resnet18, SVM

## 1. INTRODUCTION

Human Activity Recognititon (HAR) is a broad field of study related to describing a person's specific movement or movement based on sensor data. Movements are typical activities such as walking, talking, standing and sitting in indoor areas. Sensor data can be recorded remotely, such as video, radar or other wireless methods. Alternatively, data can be recorded directly, such as special equipment or smartphones with accelerometers and gyroscopes. Associating recorded sensor data with human activities is a difficult problem. Because the movement differs in terms of how it is made from person to person. Despite this difficulty, it is especially important for physical therapists to monitor the treatment of patients who have partially lost their mobility and to obtain general information about the patient's condition. Physical therapy is applied to correct posture and muscle imbalance, increase mobility and endurance. Physical therapy can be of great benefit in

**How to Cite:**
Çınar, A. and Şenler Yıldırım, Ş., (2022). A Hybrid Deep Learning Based Classification for Some Basic Movements in Physical Rehabilitation. Engineering Sciences, 17(2):9-20, DOI: 10.12739/NWSA.2022.17.2.1A0478.

patients with neurological disorders such as stroke, multiply sclerosis, Parkinson's disease, cerebral palsy and spinal cord injury. Physical therapy movements focus on re-training and control of muscles, improvement of daily functions, gaining strength and flexibility, development of fine and gross motor system skills, recovery of gait, training of recovery and movement functions. Rehabilitation initiated with physical therapy is a clinical and effective intervention for patients with negative deformities due to injury, illness or disability. In particular, determining the course of treatment to be applied to patients is of great importance for the doctor. Specialist systems are needed to check that the treatment given to the patient is correct and to determine whether the movements are performed correctly. Such systems facilitate the analysis of human activity recognition and human behavior.

## 2. RESEARCH SIGNIFICANCE

Human activity recognition is important in a variety of applications, especially in physical therapy patients. Therefore, there are many approaches related to movement recognition in the literature [1, 2, 3 and 4]. In the action recognition problem, machine learning approaches are used to extract features manually and classify movements according to these features [6 and 7]. The purpose of feature extraction is to determine the behaviours such as fingers, arms, legs and walking. Different size reduction methods such as Principal Component Analysis (PCA) and Fourier Transformation (FT), along with machine learning algorithms, are widely used in movement analysis [8 and 9]. In addition, statistical properties such as Average, median, maximum, minimum or signal size, standard deviation, classifiers such as Support Vector Machine, Naive Bayes, Random Forest or Dynamic Time Warp (DTW) or Hidden Markov Model (HMM) classification can be made as an input to the models [10, 11 and 12]. Mannini et.al. discussed how to classify human physical activity using accelerometers on the body. A 2-stage training process was carried out by applying pretreatment to the data collected through the accelerometer. In the first stage of the training process, feature extraction was made. As a result of the training, transition and emission parameters of the cHMM-based sequential classifier were determined. In the second stage, classification was completed by applying Baum-Welch and Viterbi algorithms. Around 99% accuracy has been achieved [13]. Mannini et al. proposed a classifier based on Hidden Markov Models (HMM), discussing how human physical activity can be classified using accelerometers on the body. Classification was carried out by analyzing a dataset of Accelerometer time series. Sensibility and specificity parameters were 96.4% and 93.7%, respectively [14].

Apart from the studies, the movement classification can be performed by making feature extraction with deep learning algorithms that are popular in recent years [15, 16, 17 and 18]. By using deep learning methods such as convolutional neural networks and repetitive neural networks, talented and highly successful results are obtained by automatically learning features from raw sensor data. Apart from conventional machine learning algorithms, convolutional neural networks and LSTM (Long Short-Term Memory) or both are best suited for learning properties from raw sensor data and predicting associated motion. These models were trained by a large set of labeled data sets containing multiple labels. Baccouche et al. presented a multiple 3D Deep Learning and 3D Evolution Neural Networks for human motion recognition [15]. Seok et al. proposed a deep reinforcement learning algorithm to recognize human arm motion models using the IoT sensor device.

Supervised learning based methods such as CNN (Convolutional Neural Network) and RNN (Recurrent Neural Networks) were investigated by using HCI (Human Computer Interaction) device. In addition, the deep reinforcement learning approach were also investigated. CNN performance with the DQN (Deep Q-Network) model was compared with long-term memory (LSTM) models with DQN. The results show that the CNN-based DQN model is more stable than the LSTM-based model and provides a high classification accuracy of 98.33% to predict arm movement models [16]. Lim et al. used arm motion classifiers to improve Brain-Computer Interface BCI performance. The BCI helps control external devices by decoding patterns of motion-related electrical signals in the brain cortex. In their studies, they obtained low accuracy value to classify arm movement. They used the deep neural network structure to overcome this problem, that is, to increase accuracy. As a result of this study, it was emphasized that a comparison between neurological features and visualized features could be made in the future and this study could be widely used in BCI [18]. Jaouedi et al. presented a new approach to the recognition of human action based on the hybrid deep learning model. The proposed approach has been evaluated in UCF Sports, UCF101 and KTH datasets. With Gated Recurrent Neural Networks, the accuracy of the KTH data set was 96.3% [19]. In their polysomnography (PSG) studies, Carvelli et al. proposed a fully automated deep learning-based method for scoring leg movements (LMs) asleep. It contains data from three cohorts, the Wisconsin Cohort (WSC), the Stanford Sleep Cohort (SSC), and the MrOS Sleep Study. The performance of the system has been compared with individual expert technicians and existing PLM detectors. 0.85 F1-Score was obtained [20]. Gu et al. used multiple models to characterize both global and local movement features. Global motion models are efficiently represented with depth-based 3-channel Motion History Images (MHI). Meanwhile, local spatial and temporal patterns were removed from the skeleton chart. The proposed framework was evaluated on two RGB-D datasets. Experimental results show the effectiveness of proposed approach. As a result of the study, over 90% accuracy was obtained [21].

In this paper, the Alexnet-SVM hybrid model, which is one of the deep learning algorithms, which is popular in terms of accuracy and precision in recent years, has been proposed for the six basic classification of human movement. With the proposed hybrid model, motion classification are performed with an accuracy rate of 87.67%.

The contribution of this study to the literature can be summarized as follows. The proposed classification SVM architecture, which has a robust architecture within the classification algorithms and allows multiple classification, are used instead of the standard softmax classifier in the last layer of Alexnet. It is a system that helps follow-up the development of patients who have difficulties in working mobility.

**Highlights:**

- Alexnet-SVM hybrid model from deep learning algorithms.
- Six basic movements are classified as standing, sitting, laying, walking, walking upstairs, walking downstairs by means of the Alexnet-SVM hybrid model.
- During the training and testing stages of the system, 1492 movement signals obtained from smartphone on the waist are used.

## 3. DATA

In movement recognition problems, the first step is to acqiure body motion signals. Data streams obtained by sensors placed in the waist are usually divided into sub-arrays called windows, and each window is associated with a wider activity called a sliding window approach. The definitions of movement data used in this article are as follows

[22]. The equipment used to collect the data is tied up in the waist region of the person performing the movement (Figure 1).

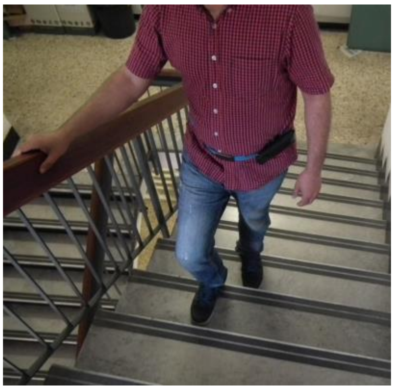


Figure 1. Obtaining of motion data

The sensor measurements are carried out the 30 persons between the ages of 22-78. Each person realized six activities, like that Walking, Walking_Upstairs, Walking_DownStairs, Sitting, Standing, Laying. These data area obtained by means of smartphone (Samsung Galaxy S II) on the waist. Using the embedded accelerometer and gyroscope on the mobile phone, 3-axial linear acceleration and 3-axial angular velocity were captured at a constant speed of 50Hz. Experiments are recorded on video to manually tag data.

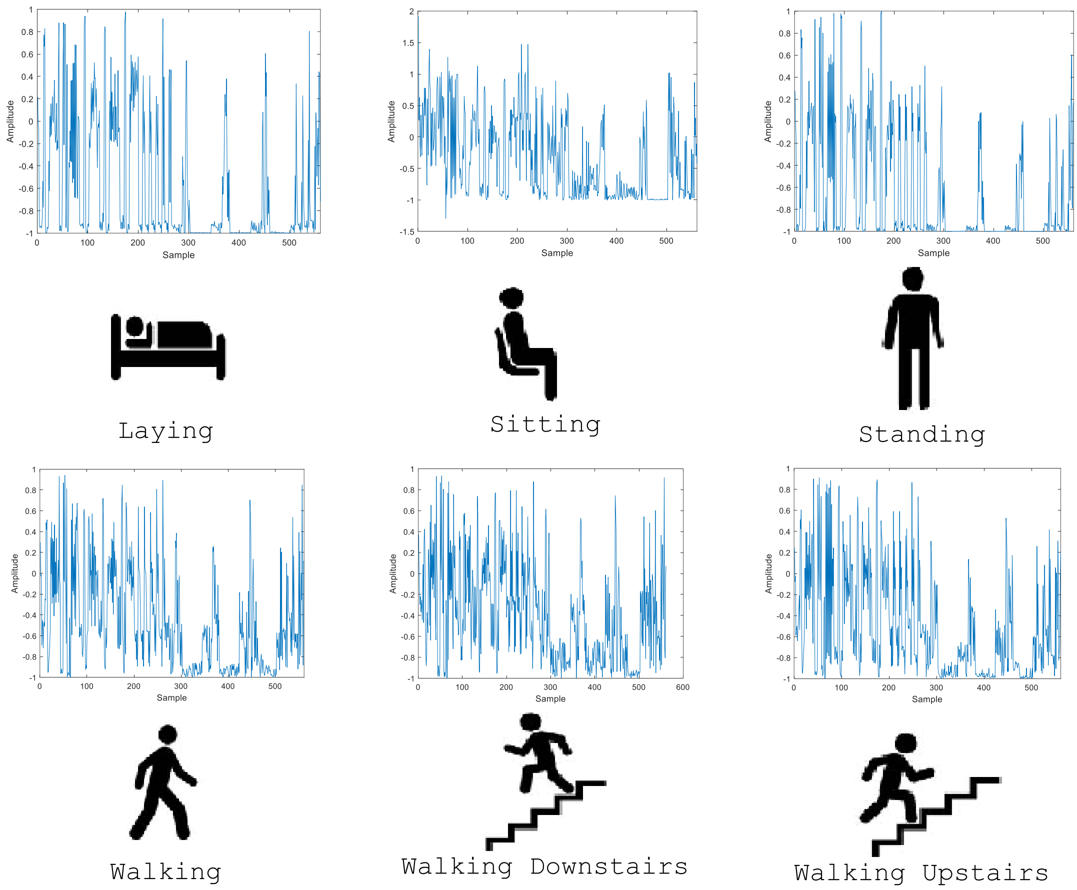



Figure 2. Main six movements

Sensor signals were pretreated by applying noise filters and then sampled from fixed-width sliding windows for 2.56 sec and 50% overlap (128 read/window). The sensor acceleration signal with gravity and body motion components are divided into body acceleration and gravity using a filter like that Butterworth low-pass filter. It is assumed that the force of gravity only has low frequency components, so a filter with a cutting frequency of 0.3 Hz was preferred. A feature vector was obtained by calculating variables from time and frequency domain from each window. Figure 2 shows the amplitude curve and movement status.

## 4. METHOD

Each of the training and test data used for motion classification is a one-dimensional matrix of sensors and a total of 561 features. The matrix contains the basic statistical properties of a movement such as energy, standard deviation, mean, entropy and correlation to x-y-z axes. In order to process these signals received from the sensors in deep learning algorithms, pre-processing is applied to the matrix that defines each movement. As a result of the preprocessing sensor signals have been converted to images. These images are classified with hybrid Alexnet-SVM architecture and classification performance is determined. Figure 3 shows the schematic diagram used to classify six movements.

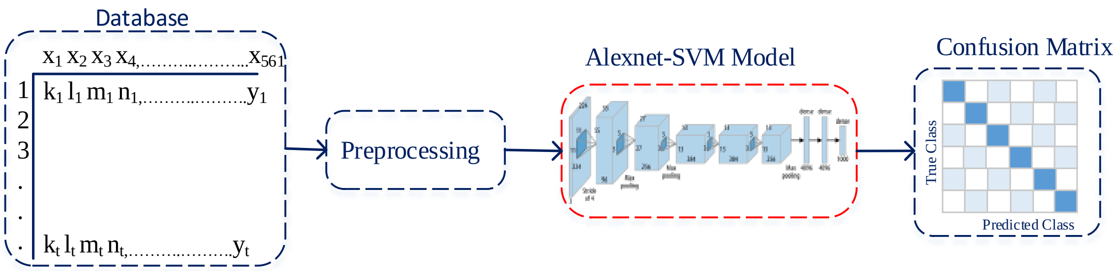



Figure 3. The proposed Hybrid Alexnet-SVM classification

### 4.1. Preprocessing

The preprocessing steps applied to each movement data are spectrogram crop and resize. The purpose of these stages is to give the motion data as a two-dimensional image input to the proposed deep learning architecture. Since initial motion data is in the form of time series, a spectrogram image is obtained by applying STFT(Short Term Fourier Transform) to each motion data. For the noise signals that will occur on this image, images are transformed into 227x227x3 size by applying crop operation. The following sections show how these operations are performed.

#### 4.1.1. Spectrogram

The spectrogram is a visual way to represent the signal strength or "height" of a signal over time at various frequencies available in a particular waveform. It not only sees if there is more or less energy at 2Hz and 10Hz, but it also shows how energy levels change over time. STFT, sinusoidal frequency and phase content as local parts of a signal change over time. In application, the procedure for calculating STFTs is to divide a longer time signal into shorter segments of equal length and then calculate the Fourier transform separately in each short segment. This depicts the Fourier Spectrum in each short segment. It then plots changing spectra, often as a function of time, known as a spectrogram or waterfall chart.

In the case of discrete time, the data to be converted can be broken into pieces or frames (these often overlap each other to reduce boundary artifacts). Each batch is transformed into Fourier and added to a matrix that records the magnitude and phase for each point in the complex result, time and frequency. This can be expressed as follows:

$$STFT\{x(t)\}(\tau,\omega) \equiv X(\tau,\omega) = \int_{-\infty}^{\infty} x(t)w(t-\tau)\, e^{-i\omega t} dt \quad (1)$$

Where signal is $x[n]$ and window is $w[n]$. In this case, $m$ is discrete and $w$ is continuous, but in most typical applications STFT is performed on a computer using the Fast Fourier Transform, so both variables are discrete and quantitated. Figure 4 shows one of the spectrogram images of each of the 6 classes.

The squared magnitude of the STFT gives a spectrogram representation of the Power Spectral Density of the function:

$$\text{spectrogram}\{x(t)\}(\tau,\omega) \equiv |X(\tau,\omega)|^2 \quad (2)$$

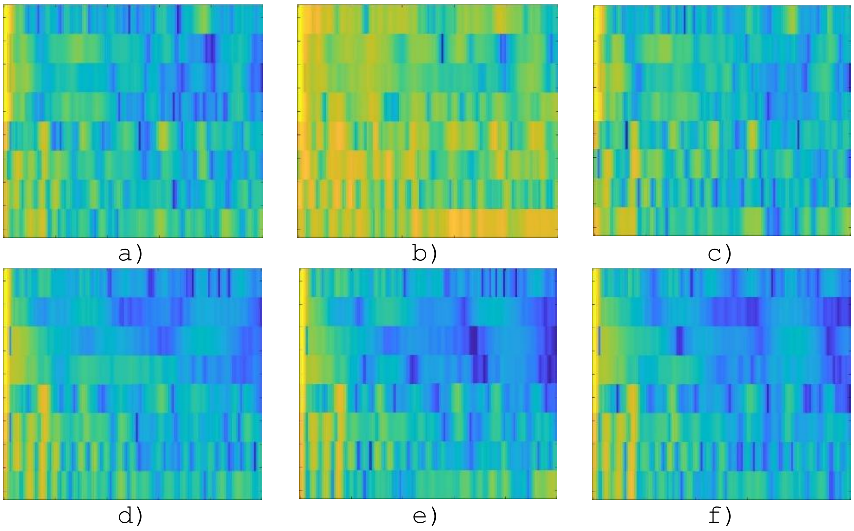



Figure 4. a) Laying, b) Sitting, c) Standing, d) Walking e) Walking Downstairs f) Walking Upstairs spectrogram sample images

#### 4.1.2. Resize Images

In this study, the spectrogram images is obtained by applying Short Time Fourier Transform (STFT) to the raw movement data of each class. The dimensions of original images are 875×656. Firstly, the crop process is applied to the images and then to the resize. The resulting images are 227x227x3 size.

### 4.2. Alexnet Convolution Neural Network

Firstly, Alex Krizhevsky et al. proposed a basic, simple and effective CNN architecture consisting of layers like convolution, Relu, pooling, fully connected, applicable to object recognition and classification problems[23]. AlexNet consists of five convolution layers. One or more of the Relu, pooling, normalization layers added at the end of each layer are used. After the fifth layer, the architecture is terminated by applying flatten, fully connected and softmax layers. For the AlexNet architecture, feature extraction is performed by optimizing the entire cost function with the Stochastic Gradient Descent (SGD) algorithm during the back propagation optimization process.

One of the main troubles of Alexnet architecture is the non-transparency in the intermediate layers during the overall classification procedure, which makes the training process difficult to observe. Another problem refers to the robustness and discriminative ability of the learned features, especially in the last layers of the network, which can significantly influence the performance. Considering these problems, basic classification algorithms can be applied instead of the classification layer of Alexnet architecture to increase the performance. In this paper, the Alexnet-SVM architecture shown in Figure 5 is used to classify six basic movements of standing, sitting, laying, walking, walking upstairs, walking downstairs.

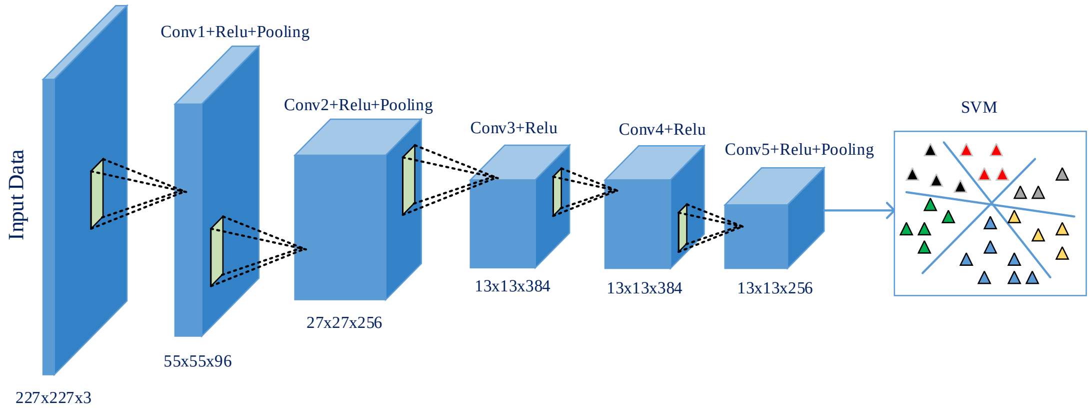



Figure 5. The proposed Hybrid Alexnet-SVM architecture

The layers of proposed Hybrid Alexnet-SVM architecture are explained as follows.

Convolutional Layer-This layer which is responsible for perceiving the features of the image is the main structure of CNN. This layer applies some filters to the image to get rid of low and high level features in the image. The discrete time convolution process is calculated in equation 3.

$$s(t) = (x * w)(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a) \quad (3)$$

$w$: $kernel(filter), x$: $input, t$: $times, s$: $Result$

Equation 4 is used when the input data is two-dimensional.

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i,j)K(i-m, j-n) \quad (4)$$

The terms i and j indicate the positions of the new matrix obtained after the convolution process. The used method in this process is positioned so that the center of the filter is at the starting point. If cross entropy is to be performed, convolution is calculated as in equation 5.

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n (i+m, j+n)K(m,n) \quad (5)$$

Non-Linearity Layer-Non-Linearity (nonlinear) layer is generally used after all Convolutional layers. Because all layers can be a linear function, the Neural Network acts as a single perception, so the result can be calculated as a linear combination of outputs. This layer is called as activation layer. Since the Rectifier (ReLu) function gives the best results on the speed of Neural Network training, the max-Relu function is used like that equation 6 and 7.

$$\text{Relu: } f(x) = \begin{cases} 0, x < 0 \\ x, x \geq 0 \end{cases}, \quad f(x)' = \begin{cases} 0, x < 0 \\ 1, x \geq 0 \end{cases} \quad (6)$$

$$f(x) = \max(0, x) \quad (7)$$

Pooling (Downsampling) Layer-This layer is a layer that is frequently added between consecutive convolutional layers. The task of this layer is to reduce the sliding size of the image and the parameters and calculations in the network. In this way, incompatibility in the network is checked. Algorithms such as Average pooling, and L2-norm pooling and max Pooling are used.

Flattening Layer-The task of this layer is simply to prepare the data at the entrance of the last and most important layer, Fully Connected Layer. Generally, neural networks receive input data from a one-dimensional array. The data in this neural network is the one-dimensional array of matrixes from the Convolutional and Pooling layer.

Fully-Connected Layer-This layer is the last and most important layer of ConvNet. It takes the data from the flattening process and performs the learning process via the neural network. Equations 8 and 9 are used to put the input data into one-dimensional matrix form.

$$u_i^l = \sum_j w_{ji}^{l-1} y_j^{l-1} \quad (8)$$

$$y_i^l = f\left(u_i^l\right) + b^{(l)} \quad (9)$$

$l$ : Layer number,

$i,j$ : Neuron number,

$y_i^l$ : the value in the output layer created,

$w_{ji}^{l-1}$ : The weight value in the hidden layer,

$y_j^{l-1}$ : The value of input neurons,

$u_i^l$ : The value of the output layer before the activation function,

$b^{(l)}$ : deviation value

The purpose of SVM is to find the hyperplanes that classify feature vectors extracted from images [24]. In order to evaluate the performance of SVM algorithm correctly, k-Cross validation is applied to the data set. After that, the data set is divided into a training and test set. The value of k chosen for this process significantly affects the success of the model. Therefore, k-fold cros validation value is taken as 10.

## 5. FINDINGS AND DISCUSSIONS

A confusion matrix was used to describe the performance of the Alexnet-SVM classification model. The basic parameters used to determine the classification performance are given in equation 10.

$$\text{Precision(P)} = \frac{\text{TP}}{\text{TP+FP}}$$

$$\text{Recall(R)} = \frac{\text{TP}}{\text{TP+FN}}$$

$$\text{Accuracy(A)} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}$$

$$\text{F1\_Score}(F_1) = \frac{\text{2TP}}{\text{2TP+FP+FN}}$$

$$\text{kappa(k)} = \frac{\text{accuracy}-\text{rAccuracy}}{1-\text{rAccuracy}} \quad (10)$$

Accuracy is the most important parameter used to measure the success of a model, but it is not sufficient alone. High accuracy in classification of unbiased data, which is not evenly distributed, does not indicate a high classification performance. Therefore, it is necessary to evaluate the results of other metrics as well as accuracy. Precision shows how many of the values estimated as positive from the movements are actually positive. Precision False Positive is very important when the forecast is high. If any correct or incorrect movement is calculated to be incorrect, correct motion detection will not be possible in this case. Therefore, high precision value is an important criterion in classification model selection.

Recall shows how many of the correct moves (Positive) are estimated as Positive. The sensitivity value is False Negative, which is the metric that should be used in cases where the estimation cost is high.

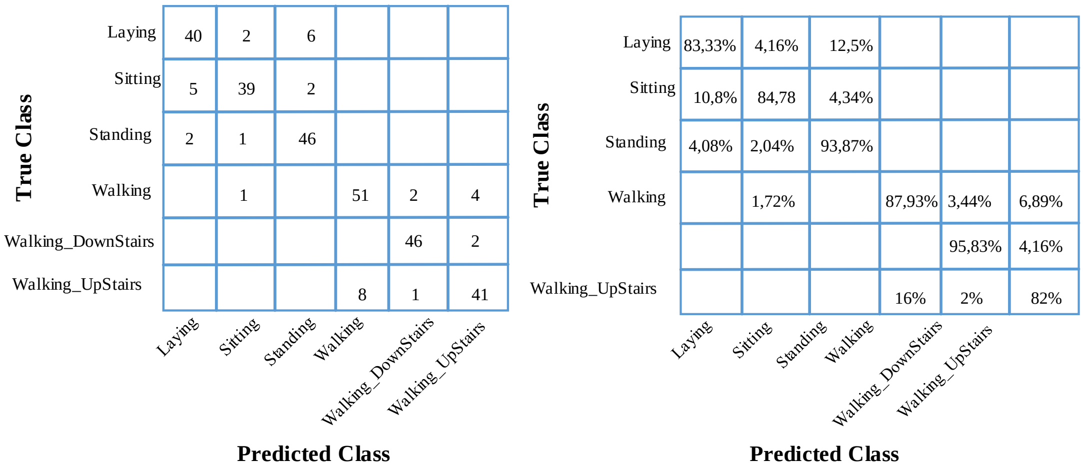
F1-Score: The F1-Score parameter associated with Recall and Precision is calculated using the harmanonic mean. The reason for harmonic averages instead of a simple averages is that possible extreme conditions should be taken into account in the classification results. If a simple average is used, the F1 Score is 0.5 in a classification model with a Precision value of 1 and a Recall value of 0. This result is misleading. The main reason for using F1 Score instead of Accuracy is that the results will be interpreted more accurately in the classification of unevenly distributed data sets. In addition, F1-Score is used in which a measurement metric that includes not only False Negative or False Positive but also all error costs is needed.

The Kappa coefficient measures the consistency between classification and accuracy values. A Kappa value of 1 represents the perfect classification, while 0 represents the failure of the classification. rAccuracy is calculated as in the equation 11.

$$\text{rAccuracy} = \frac{(\text{TN+FP})(\text{TN+FN})+(\text{FN+TP})(\text{FP+TP})}{\text{Total}^2} \quad (11)$$

The number of samples used for Lying, Standing, Sitting, Walking, Walking Upstairs and Walking Down stairs classes are 239, 229, 243, 289, 238, 254 respectively. 80% of the total 1492 movement data was randomly selected for training and 20% for testing. Figure 6 shows the confusion matrix both numerical and percentage obtained for 6 classes for AlexNET. Table 1 depicts values of performance parameters. When each class is evaluated separately, the accuracy of all classes is above 94%. Only the use of accuracy can give misleading results about classification performance (Table 1). In evaluating the movements by the classifier, it is important to evaluate the movemevt as FN and FP. Precision for each class is between 80% and 96%, recall between 83% -94%.

According to these results, it can be seen that the classifier makes many classifications in FP and FN class. Considering the Precision and Recall parameters together, the F1-Score is between 83% and 95%. According to Table 1, the F1-score has a lower value than the accuracy value and the correct classification performance is seen in the 87%-88% band. Overall accuracy was calculated as 87.67%, F1-Score 93.4%. Kappa coefficient, which is parallel to overal accuracy, is 85.2%.




a) b)

Figure 6. a)Confusion Matrix for six movement b) Confusion Matrix as Percentage

The confusion matrix shows an interesting result for 6 movements. In the classification of movements in the Walking, Walking Upstairs and Walking Downstairs classes, all movements are assigned to one of these three classes. The similar situation is true for Laying, Standing, Sitting classes too.

Table 1. Alexnet-SVM classification performance parameter results

| Class | n(Truth) | n(Classified) | A(%) | P | R | $F_1$ |
|---|---|---|---|---|---|---|
| Laying | 48 | 48 | 94.67 | 0.83 | 0.83 | 0.83 |
| Sitting | 43 | 46 | 96.33 | 0.85 | 0.91 | 0.88 |
| Standing | 54 | 49 | 96.33 | 0.94 | 0.85 | 0.89 |
| Walking | 59 | 58 | 95 | 0.88 | 0.86 | 0.87 |
| Walking_Downstairs | 49 | 48 | 98.33 | 0.96 | 0.94 | 0.95 |
| Walking_Upstairs | 47 | 51 | 94.67 | 0.80 | 0.87 | 0.84 |

To demonstrate the superiority of the proposed method, the classification was carried out with Alexnet, Resnet18 and Resnet18-SVM. Table 2 presents the comparison in terms of accuracy and F1-Score. As a result, Alexnet-SVM has the highest classification success.

Table 2. Comparision results

| Class | Alexnet | | Resnet18 | | Resnet18-SVM | | Alexnet-SVM | |
|---|---|---|---|---|---|---|---|---|
| | A(%) | $F_1$ | A(%) | $F_1$ | A(%) | $F_1$ | A(%) | $F_1$ |
| Laying | 91.07 | 0.76 | 89.07 | 0.70 | 95 | 0.95 | 96.67 | 0.83 |
| Sitting | 87.19 | 0.59 | 88.25 | 0.51 | 95.58 | 0.63 | 96.33 | 0.88 |
| Standing | 88.95 | 0.66 | 86.6 | 0.61 | 92.98 | 0.63 | 96.33 | 0.89 |
| Walking | 81.9 | 0.33 | 82.26 | 0.54 | 90.97 | 0.64 | 95 | 0.87 |
| Walking_Downstairs | 85.43 | 0.67 | 86.37 | 0.63 | 93.87 | 0.71 | 98.33 | 0.95 |
| Walking_Upstairs | 91.89 | 0.76 | 92.95 | 0.76 | 97.15 | 0.78 | 94.67 | 0.84 |

## 6. CONCLUSIONS

In this paper, Alexnet-SVM hybrid model was proposed for classification of six basic human movements. According to the results, the classification performance, F1-Score was calculated as 93.4%. This value has indicated the classification success of six movements. The success of the proposed model may be said in high, even if walking upstairs and walking downstairs movements with similar dynamics such as walking negatively affect the classification performance. A similar situation exists in the movement of sitting, standing and reaching. A major contribution of the paper is that, unlike the known deep learning architectures, using the hybrid Alexnet-SVM classification architecture provides higher f1-score and accuracy results. Depending on the classification category, it can be determined whether the movements are done correctly with the proposed method. For example, it is possible to determine whether a person in need of physical rehabilitation is correctly classified as a movement. As a result, the physical problem of the person doing the movement can be mentioned. It is possible to transform the proposed system into a structure that can be used for patient treatment, especially physiotherapists. As a future work, the method can be applied to invasive robotic control applications.

**CONFLICT OF INTEREST**

The authors declared no conflict of interest.

**FINANCIAL DISCLOSURE**

The authors declare that this study has received no financial support.

**DECLARATION OF ETHICAL STANDARDS**

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

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