DEEP TRANSFER LEARNING ALGORITHMS FOR PERSON RECOGNITION USING WEARABLE SENSOR DATA

Şafak KILIÇ[1], Yılmaz KAYA[2], İman ASKERZADE[3]

[1]Siirt University, Department of Computer Engineering, Siirt TURKEY
[2]Siirt University, Department of Computer Engineering, Siirt TURKEY
[3]Ankara University, Department of Computer Engineering, Ankara TURKEY

Abstract - *Biometric systems are also one of the fields of information technology that is constantly being used in all areas of human security. Topics such as person recognition (PR), age estimation and gender recognition are among the topics of human-computer interaction that have been widely discussed in both academic and other fields in recent years PR is the method of evaluating the individual on the basis of the biometric attributes obtained. In this analysis, PR activity was performed by transferring deep learning methods using signals obtained from accelerometer, magnetometer and gyroscope sensors attached to 5 different areas of the human population. In the analysis, people were decided by different physical behavior and successful actions in PR were defined In addition, the active body areas in PR have been established. High success rates of deep learning architectures have typically been observed. This study has shown that wearable accelerometer, gyroscope, magnetometer signals can be used as a modern biometric device to deter identity fraud attacks. With the deep transfer learning approaches used, human recognition procedures have been carried out and high successes have been achieved. In summary, the proposed approach could be very useful for the efficient use of wearable sensor signals in biometric applications.*

Key Words: Transfer Learning, Sensor Signal, Person Recognition, Deep Learning, wearable technologies

1.INTRODUCTION

Person recognition system has been one of the popular areas that researchers have focused on using various methods in recent decades. There are many unique features in the human body. Therefore, the system is capable of detecting these characteristics and distinguishing them from other people. Systems that define people's physical or behavioral characteristics are called biometric systems. [1]. Biometrics science examines individual physical or behavioral characteristics. Physiological features are those that generally remain constant and do not change easily over time. Characteristics based on behavioral properties, on the other hand, can vary over time and rely on the contextBiometric identification systems based on physiological features such as face, fingerprint, hand geometry, iris and retina or behavioral features such as gait, signature and speech have been developed in recent years. However, these strategies have a substantial drawback in that they can be imitated [2; 3; 4]. Examples of such frauds may be imitation of sound, the use of lenses copied from the iris, and artificial disguise.

Therefore, in recent years, other descriptive systems based on the individual's behavior or characteristics called biometric based on signals measured from different parts of the person have been implemented [5; 6]. Various medical signs have also been used as biometric data in the literature. EEG [7; 8; 6; 9], ECG [10; 11; 12; 13; 14; 15], accelerometer [16; 17] have been used in the development of biometric systems. Studies have been carried out to show that medical signals are unique to individuals [8; 18; 10].

In the study of Alyasseri et al. [19], person recognition was performed using multi-channel EEG signals. In addition, effective EEG channels were determined in the study. In the study performed by Sun et al. Using EEG signals, the person recognition process was performed [9]. Their results indicated that a 99.56% success rate by applying the traditional 1D-LSTM deep learning method to 16-channel EEG signals. Rodrigues et al. reported a success rate of 87% in their study of person recognition using EEG signals [6].

Altan et al. have developed a biometric framework using ECG signals [20]. General physical state, stress level, activity level, and more specificity of people could significantly alter the waves in the ECG. Waveforms, as well as temporal properties, have always shown that they have different properties for different people [20]. In another report, the authors identified an individual using cardiac dynamics in ECG signals with RBF as an attribute [11]. They have shown that the temporal relations and shapes of the ECG signals are different for each person and can be used as biometric information. In their study, Goshvarpour developed a biometric system using the MP (matching pursuit) coefficients of ECG signals with different machine learning methods such as PNN, Knn, LDA. The performance of the system was reported as 99.68% [12]. Additionally, the person identification process was carried out by evaluating the pressure signals made on the ground of people walking on a ground [21]. In the study reported, a success rate of 92% was observed.

Accelerometer signals are also used in person recognition. In the study of San-Segundo et al. [16], they developed a biometric system based on the signals they receive from accelerometer sensors of smartphones. They performed the person recognition process by applying Gaussian model to the signals they obtained by executing the people. In another study by the same authors, the person identification process was performed on the same data set by proposing i-vector analysis and a PLDA-based approach [17].

2. MODERN LEARNING TECHNIQUES

Traditional machine learning techniques are limited by their ability to process natural data in raw forms. For many years, pattern recognition and machine learning systems required careful engineering and expertise to design feature extractors. Deep learning enabled systems that do not require feature extraction.

Deep learning networks have been used for computer vision and image classification. Recurrent neural networks are widely used in signal classification methods. The main problem with recurrent neural networks is adjusting parameters. CNNs are very effective methods of computer vision and there is no need for parameter selection in CNNS. Therefore, we used pre-trained CNNs (VGG16, VGG19, MobileNetV1, MobileNetV2, DenseNet121, DenseNet169, DenseNet201, InceptionV3 and Xception) as feature extractors, and the effectiveness of this feature is shown using two extractor states.

In CNN-based signal classification methods, spectrograms of the signals are used as inputs to CNNs. In this study, vector to matrix transformation was used and signals were transformed into images using this transformation. To illustrate the success of the proposed community deep feature extractor, two cases have been identified, namely person identification and classification of daily sport activities. These are two signal classification problems. The proposed deep learning-based feature extractor community achieved a recognition rate of 98.79% for person recognition. It also achieved 100% recognition rate for 19 days of sports activity detection. These results prove the success of the proposed method.

In this study, the performance of different deep learning architectures on person detection and motion detection was examined. The deep learning architectures used in our study were: VGG16, VGG19, MobileNetV1, MobileNetV2, DenseNet121, DenseNet169, DenseNet201, InceptionV3 and Xception.

In this section, the details of Deep Learning techniques will be examined under VGG16, VGG19, MobileNetV1, MobileNetV2, DenseNet121, DenseNet169, DenseNet201, InceptionV3 and Xception deep learning algorithms and Transfer Learning subheadings.

The architectures in this article are used for feature extraction. Specifications and models are also derived from the FC-8 layer. The FC-8 layer extracts 1000 features [22]. In three models, the filter is 3 × 3, the number of steps is two, and the pooling type is maximum. The education process in ANN architectures was carried out with transfer learning. Additionally, activation codes “ImageDatastore” and “augmentedImageDatastore” were used in the process of converting data set images to input sizes of ANN models.

2.1. Deep Learning

Deep learning is an advanced approach of artificial neural networks. It has progressed from single layer artificial neural networks to multilayer artificial neural networks and then to the formation of deep learning algorithms. Mathematical model of human brain cells that form the basis of artificial neural networks; computer vision, signal processing, audio processing, classification, diagnosis, etc. has led to its use in many areas In a process dominated by today's information technology, all kinds of operations are carried out in computer environment; It is important in terms of time, cost and labor. At every stage of this process, artificial neural networks became available and gave correct results and were accepted. Many large information technology companies deal with artificial neural networks and use integrated products with the artificial neural network structures they have developed [23; 24; 25]. Deep learning algorithms were put forward with the article published by Geoffrey Hinton and Ruslan Salakhutdinas (Hinton et al 2016) and many deep learning algorithms emerged in the following years [25].

It has a multi-layered artificial neural network structure created in deep learning algorithms. In this multi-layered structure, feature extractions of the image are created within the neural network layers. The layered structure reveals the weight values in the education process by removing the attributes in the hidden layer. With the convolution process, the edge and features of the image are determined and other layers in the network take these properties and transmit them to a substrate. The first layer is known as the input layer and the last layer is known as the classification layer. There is convolution, max pooling, dropout, normalization, Relu, Softmax layer, Full connected layer layers in the processes in the middle layer between these two layers [26; 27].

Deep learning is an advanced approach of artificial neural networks. It has progressed from single layer artificial neural networks to multilayer artificial neural networks and then to the formation of deep learning algorithms.

2.1. VGG16

VGG-16 network model is a novel technique and this is the first time it was used in the literature. The VGG-16 is based on the idea that ANNs that have become popular with AlexNet can achieve higher performance with more layers. The network, consisting of 13 convolutions and 3 fully connected layers (FCL), contains 138 million parameters [28]. VGG-16 uses ReLu as the activation function in the same way while using smaller sized filters (2x2 and 3x3) compared to AlexNet. This architecture has an increasing network structure. The image input resolution is 224 × 224 pixels. The filter size in the convolutional layer is 3 × 3 pixels. In this architecture, the last layers consist of fully linked layers used for feature extraction.

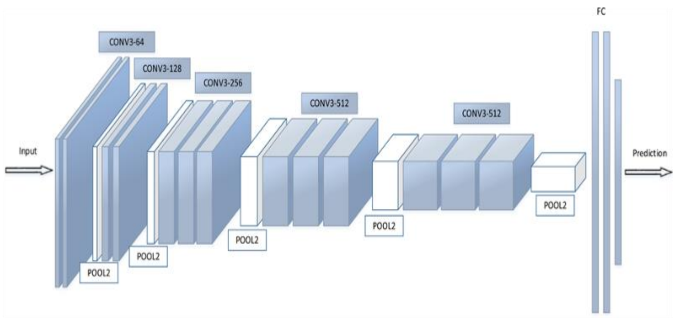


Figure 1 Architecture of VGG-16 [28]

The main layers of the VGG-19 architecture consist of 16 convolutional layers, five pooling layers and three fully connected layers. This architecture has a total of 24 main layers. Since the VGG-19 has a deep network, the filters used in the convolutional layer are used to reduce the number of parameters. The size of the filter chosen in this architecture is 3 × 3 pixels. The VGG-19 architecture includes approximately 138 million parameters [29].

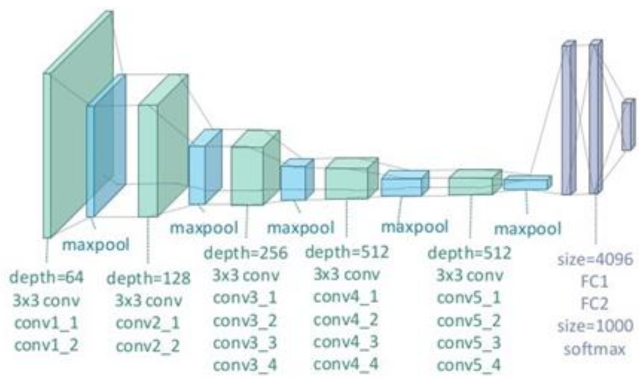


Figure 2 Architecture of VGG19 [29]

2.2. Inceptionv1, Inceptionv3 Ve Xception

Inceptionv1, also known as GoogLeNET, was developed by Google engineers, inspired by the "Network-In-Network" study [30]. The main feature that distinguishes the Incepitonv1 network from previous networks is that it uses Inception modules, which are designed differently than stacking convolution layers on top of each other to provide network depth. Each Inception module shown in Figure 3 contains a series of convolution layers connected to each other in parallel. In these convolution layers, 1 x 1, 3 x 3 and 5 x 5 size filters are used to extract different features from the image. Each set of layers is combined at the end of the module to form the output of the module. 1 x 1 filters are used for size reduction, thus reducing the processing load. In addition, the activation functions used in 1 x 1 filters disrupt the linearity, which helps the generalization of the network. Inceptionv1 network consists of 22 layers and includes 5 million parameters. In Inceptionv3 architecture, which was developed as the successor of Inceptionv1 architecture, representation bottleneck was tried to be eliminated, large filters were parsed into smaller filters, and the width and depth of the network were tried to be balanced. Elimination of representation bottleneck is achieved by pooling after convolution layers. Although it is costlier in terms of processing power, the representation ability of the network is better transferred to a substrate. Filters of dimensions' n x n are factored into 1 x n and n x 1. The convolution process performed with these asymmetric filters reduces the amount of processing by 33% compared to the version with an n x n filter. Another method recommended to reduce the need for processing power is to perform the operation performed by large size filters with more small size filters that can perform the same operation.

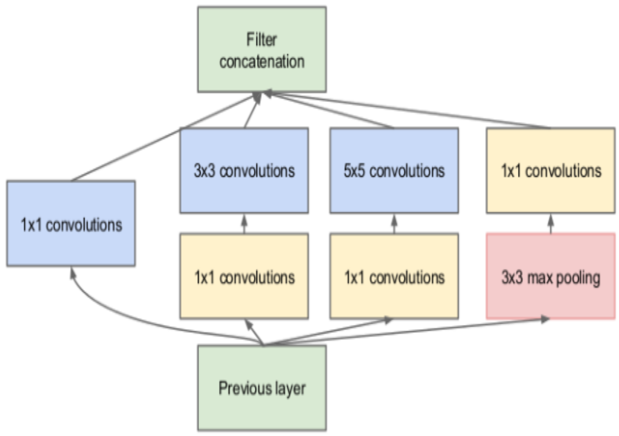
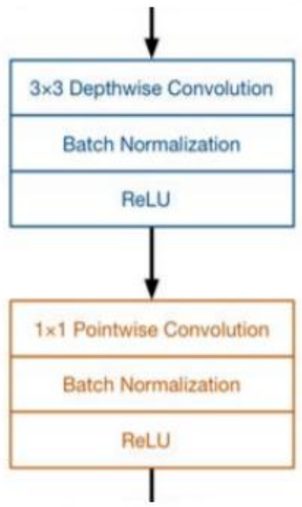


Figure 3 Architecture of INCEPTION V1 [30]

2.3. MobileNetV1 ve MobileNetV2

MobileNet architecture offered for mobile and embedded vision applications was developed by the Google team. In this lightweight architecture created with deeply decomposable convolution layers, two global hyperparemeters can choose between delay and performance. Thanks to these parameters, the developer can obtain the desired network according to his own problem criteria. The biggest difference of MobileNetV2 network from MobileNetV1 network is the reverse residual structure used [32].



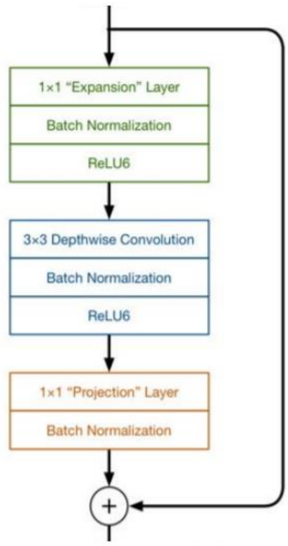


Figure 4 Architecture of MobileNeV1 [32]

Figure 5 Architecture of MobileNetV2 [32]

2.4. Transfer Learning

In practice, very few people try to build an artificial neural network from scratch, train it, and calculate its weights [31]. A network previously trained for one task can be used for other similar tasks. For this purpose, the fully connected layers at the end of the artificial network must be removed. After removing fully connected layers, a classifier based on the new problem being worked on must be added. The rest of the network is used as a feature extractor for the new dataset.

Learning transfer methods are used as a solution to this problem in the education of deep learning architectures. The basic idea of the learning transfer in deep architecture is to take an artificial neural network model, which was previously trained on a data set, and to train the last layers where the classification is made in line with new problems. Thus, instead of starting training from scratch for each problem, training starts using the parameter data of the previously trained network. The motivation behind this method is that the first layers usually train low features such as color lines and simple shapes that are common to every image recognition problem. For this reason, training transfer is a logical method when it does not have enough processing power for a large enough data set. However, differences in the fine tuning of the training transfer significantly affect the deep architectural success. For this reason, the training process should be carried out in a controlled manner, and it should answer many questions such as in which layers the training transfer will be made and what the initial values should be. In this study, educational transfer architectures in deep architectures were examined and evaluated with the network data set we created by training with VGG16, VGG19, MobileNet V1, MobileNet V2, Dense121, Dense169, Dense201, xception architectures in image processing liters.

3. PERSON RECOGNITION

In this study, a biometric system has been developed with transfer deep learning methods using accelerometer, gyroscope and magnetometer signals obtained through Xsens MTx sensors. Transfer deep learning methods have become one of the basic building blocks of machine learning with the increase in the processing power of computers and especially the development of GPU supported technologies. For large data sets, deep learning methods have achieved high success rates. Deep learning achieves great success in many computer vision and person recognition problems such as handwriting recognition, object classification, object finding, scene recognition, face recognition. However, millions of parameters have to be adjusted in deep learning methods and also require costly hardware such as graphics processing unit, tensor processing unit. One of the most important problems of deep webs is weight assignment. Deep learning methods require large data sets to assign the correct weight, and the execution time of this process is long. Pre-trained networks are used to overcome this problem, and these networks are often trained in the ImageNet dataset. In pre-trained networks, calculated final weights are used. Therefore, high classification rates can be achieved in a short execution time using the pre-trained network.

The signals obtained from the sensors were first transformed into images and then the person recognition process was performed using deep transfer methods. In this study, it is shown that deep learning convolutional neural network models, which were previously used for object recognition, can also be used for the person identification problem. After the neural network model of the architectures was taken together with the current layer weights, it was subjected to transfer learning process with different data sets. It is shown that the deep learning approach can also be used for problems with small data sets. Thus, the structure of deep learning architectures developed with the aim of object recognition has been made suitable for the person recognition problem. The main contributions of this study are the development of a biometric system from signals measured from wearable sensors (accelerometer, gyroscope and magnetometer). A new approach has been proposed for the biometric system. Transfer deep learning methods were used for person recognition.

4. EXPERIMENT

The rest of this study is organized as follows: Section 4.1 describes the data set used in the study. The method of converting the signal to image is introduced in section 4.2. The experiments and results are discussed in Chapter 5. Important results are discussed in Chapter 6.

4.1 Data Set

In this study, Daily and Sports Activities Data Set data set obtained from UCI database was used [33; 34; 35]. The data of 19 different movements (activations) previously determined and were created for this study by means of Xsens MTx sensors attached to the designated areas of people. Sensors were mounted in 5 different areas of the subjects and data were collected. The points where the sensors are located on the body were determined as chest level, right wrist, left wrist, right (above knee) and left legs (above knee) (Figure 1). There are 9 sensors in each Xsens MTx unit (x, y, z accelerometers, x, y, z gyroscopes, x, y, z magnetometers).

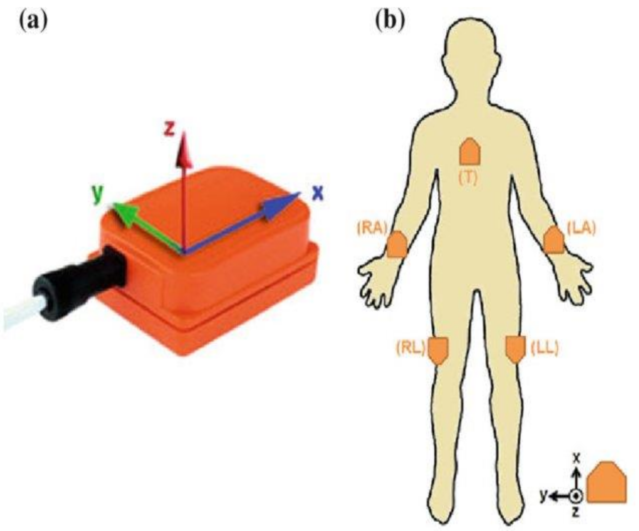


Figure 6 Attaching the sensors to 5 different areas of the subjects. (A) Xsens MTx, (B) sensor mounted zones (Dobrucalı and Barshan,2013).

In this study, data was obtained from 19 different movements from the data set initiated by previously selected 4 men and 4 women. Subjects exhibited the specified movements for 5 minutes. The movements performed by the subjects are given in Table 1.

Table- 1 The movements performed by the subjects

Activity Code	Activity Name
A1	sitting activity
A2	standing activity
A3	recumbency activity
A4	lying on the right side
A5	moving up to upstairs
A6	moving down to downstairs
A7	standing activity in elevator
A8	standing activity in elevator while it moves
A9	walking in the parking lot
A10	walking activity on treadmill parallel to the ground at a rate of 4 km/hour
A11	walking activity on treadmill with 15 degree angle to the ground at a rate of 4 km/hour
A12	running activity at a rate of 8 km/hour
A13	step exercising activity
A14	elliptical cycle activity
A15	riding bicycle activity in horizontal position
A16	riding bicycle activity in vertical position
A17	rowing activity
A18	bouncing activity
A19	playing basketball

4.2. Experiment

The recommended approach for person identification with deep transfer learning methods is shown in the figure below. The operations performed at each stage are given briefly.

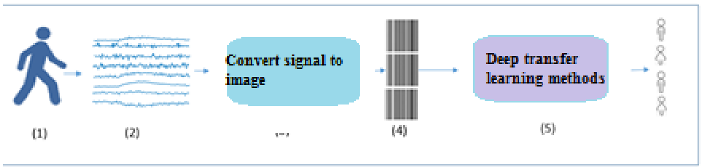


Figure 7 Person Recognotion by deep transfer learning technique schema (PR-)

Block 1: At this stage, Wearable sensors were attached to the subjects Xsens MTx sensor units were installed in 5 different areas of the subjects.

Block 2: Signals from a total of 45 channels were recorded with accelerometer, gyroscope and magnetometer sensors from 5 different regions of the subjects.

Block 3: Signs for each movement in Table 1 have been measured as 5 minutes. Later, these signs were divided into 5-second segments. Since the sampling frequency is 25, signs of 5x25 = 125 length were obtained. First of all, the values of the signs have been converted into values between 0-255 with the following equation. Since the number of channels is 45, images in the form of 125x45 were obtained.

$$New\ X_i = round\left(\left[\frac{X_i - Min(X)}{Max(X) - Min(X)}\right] x255\right) \tag{1}$$

As an example, the images of the signs of standing movement for each subject are given in Figure 8.

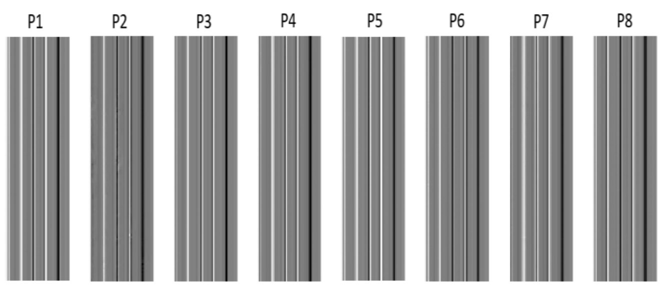


Figure 8 Images of sitting motion signs for each person.

Block 4: Indicates the images created. These images are given to deep transfer learning methods.

Block 5: Images are classified using deep transfer learning techniques. At this stage, VGG16, VGG19, MobileNetV1, MobileNetV2, DenseNet121, DenseNet169, DenseNet201, InceptionV3 and Xception deep transfer learning techniques were used.

5. RESULTS

Dataset The data set used in this study consists of the signals obtained for 19 different movements from 8 individuals, 4 males and 4 females. Each movement is divided into 60 segments. Therefore, the data set consists of 19x8x60 = 9120 signal matrices. After these signal matrices were transformed into images, deep transfer learning techniques were used. As a result, 9120 images were obtained to test the success of our system. 9 different deep learning based architectures are used. Success rates were calculated as formula 2.

$$F(x) = 100 * \frac{\#\, True\ classified}{\#\, True\ classified + \#\, False\ classified}\ (\%) \qquad (2)$$

The success rates achieved with the architectures used for person recognition are given in Table 2.

Table- 2 The success rates achieved with the architectures used for person recognition

Model	Success rate%
VGG16	12,06
VGG19	10,52
MobileNetV1	96,82
MobileNetV2	98,46
DenseNet121	98,46
DenseNet169	98,79
DenseNet201	98,68
InceptionV3	97,36
Xception	97,58

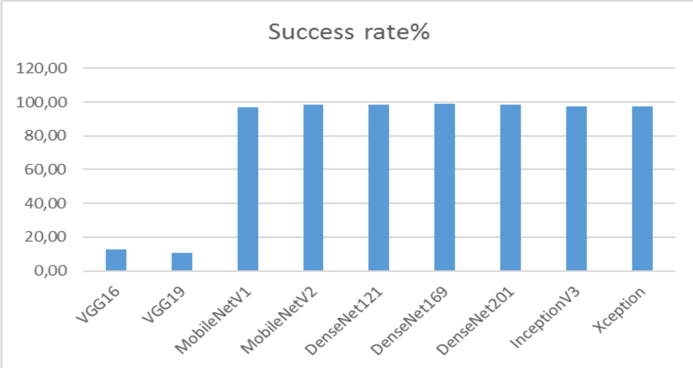


Figure 9 The success rates achieved with the architectures used for person recognition are given

The success rates obtained by using all the signals belonging to 19 different movements exhibited by people with the deep learning methods specified in Table 2 are given in Figure 9. Looking at the results, the highest success with a 98.79% success rate belongs to DenseNet169 network. It has been determined that VGG networks fail on the person recognition problem. Success rates are generally seen that deep learning transfer methods offer an effective work in person recognition.

Table- 3 Performance values obtained for each movement

Activity	VGG16	VGG19	MobileNet V1	MobileNet V2	Dense 121	Dense 169	Dense 201	Inception V3	Xception
A1	12,5	10,4	100	64,5	100	100	100	93,7	93,2
A2	10,4	10,4	100	12,5	100	97,9	97,9	100	100
A3	8,3	97,9	97,9	25	100	97,9	100	100	100
A4	100	45,83	93,75	47,916	100	100	97,9	97,9	97,9
A5	14,5	95,8	93,7	18,7	91,6	97,9	93,7	95,8	95,8
A6	10,4	91,6	95,8	22,9	97,9	95,8	97,9	93,7	97,9
A7	18,7	8,3	97,9	6,2	97,9	97,9	100	100	100
A8	8,3	10,4	62,5	16,6	77	91,6	85,4	75	83,3
A9	10,4	8,3	95,8	4,1	89,5	100	100	87,5	100
A10	8,3	10,4	100	10,4	100	100	93,7	100	97,9
A11	16,6	2	100	16,6	97,9	100	97,9	97,9	95,8
A12	100	100	100	16,6	100	100	95,83	95,8	100
A13	100	97,9	95,8	95,8	93,7	100	93,7	100	100
A14	18,7	97,9	97,9	22,9	100	100	100	97,9	97,9
A15	100	100	91,6	18,7	97,9	95,8	97,9	95,8	93,7
A16	12,5	12,5	95,8	16,6	93,7	97,9	91,6	83,3	100
A17	10,4	89,5	87,5	27	79,1	79,1	79,1	75	93,7
A18	68,7	95,8	79,1	27	87,5	75	81,2	58,3	87,5
A19	6,2	6,2	75	56,2	52	64,5	66,6	95,8	66,6

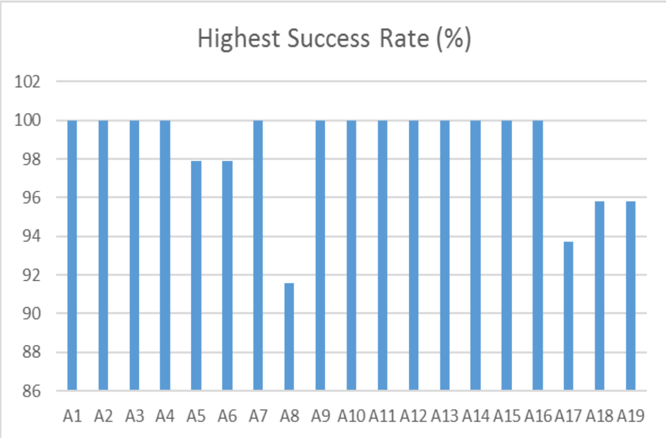


Figure 1 The effect of every action on person recognition

Another part of our study is to determine the effect of every action on person recognition. There are 480 images of each movement. Person recognition performance values obtained for each movement are given in Table 3. In Figure 10, the best results of each movement on person recognition are presented. Looking at Figure 10, it is understood that most of the movements achieve 100% success and the remaining movements have a high success rate. When Table 3 is examined, it is observed that the most successful deep learning transfer method is DenseNet169. With this method, sitting movement, lying on the right side, walking movement in the parking lot, walking movement on the treadmill parallel to the ground at 4km / h, treadmill walking movement at an angle of 15 degrees to the ground at 4km / h, running movement at 8km / hour, step Exercising movement and elliptical cycling movement were determined with 100% success rate. Although the detection of basketball playing movement is less successful in transfer deep learning methods in general, the Inception V3 model has been successful in detecting this movement.

Table- 4 The highest success rates obtained according to different deep learning architectures

Region	VGG 16	VGG 19	Mobile Net V1	Mobile Net V2	Dense 121	Dense 169	Dense 201	Inception V3	Xception
Chest	92,2	11,1	94,5	93,8	94,4	94,5	94,4	94,62	95,8
Right Arm	11	93,8	92,1	92,1	93,09	93,2	92,43	92,1	100
Left Arm	11,9	11	91,1	89,9	92,2	92,2	91,8	90,4	93,7
Right Leg	11,8	13,4	93,6	92,3	96,2	95,2	93,6	93,8	97,9
Left Leg	15,8	12	91,9	92	95,6	94,9	94,6	93,4	94,4

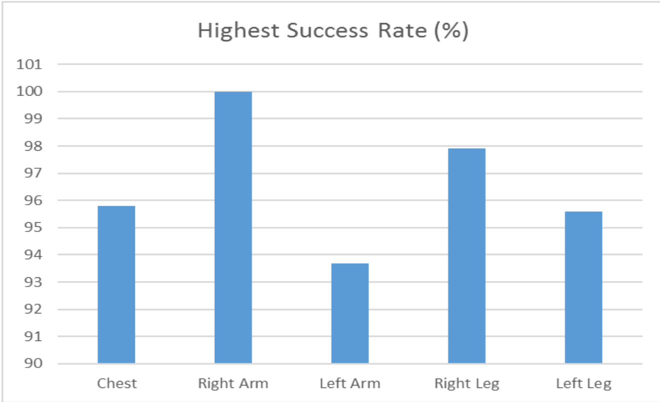


Figure 2 The highest success rates obtained according to different deep learning architectures

Deep transfer learning techniques were applied after the signals obtained from each region were transformed into images to indicate the effects of the regions on person recognition. When images by region are used, the image sizes are used at a lower size of 125x9. The success rates achieved are given in Table 4. The highest success rates obtained according to different deep learning architectures are given in Figure 11. It has been observed that the data obtained from the sensor on the right leg constitute the data with the highest impact on person recognition.

6. CONCLUSIONS

Several biometric systems have been developed in recent years. Biometric systems such as face, speech, fingerprint, palm print, ear shape, gait have established a wide variety of applications in security systems. Most of these systems, however, create significant drawbacks as they can be imitated. New biometric systems based on medical signals have been set up to solve these problems. In this research, a biometric method was established to identify the individual using the signals of the wearable sensor. The main aim of this study is to show that the accelerometer, gyroscope and magnetometer signals obtained from wearable sensors are efficient in the identification of the individual.

Biometric systems can also be safer than other systems, such as fingerprints, face, palm and iris, depending on the physical activity of the person. The explanation for this is that it is easier to copy in systems such as fingerprint, face and palm. It is more difficult to imitate walking and similar physical activities. In other studies, we have done, we have proven that people recognition processes give more successful results with sensor signals [36;37;38;39].

REFERENCES

[1] B. Ngugi, A. Kamis, and M. Tremaine, "Intention to use biometric systems," e-Service Journal: A Journal of Electronic Services in the Public and Private Sectors, vol. 7, no. 3, pp. 20-46, 2011.

[2] T. Matsumoto, H. Matsumoto, K. Yamada, and S. Hoshino, "Impact of artificial" gummy" fingers on fingerprint systems," in Optical Security and Counterfeit Deterrence Techniques IV, 2002, vol. 4677: International Society for Optics and Photonics, pp. 275-289.

[3] J. Yu, C. Fang, J. Xu, E.-C. Chang, and Z. Li, "ID repetition in Kad," in 2009 IEEE Ninth International Conference on Peer-to-Peer Computing, 2009: IEEE, pp. 111-120.

[4] G. Gainotti, "Laterality effects in normal subjects' recognition of familiar faces, voices and names. Perceptual and representational components," Neuropsychologia, vol. 51, no. 7, pp. 1151-1160, 2013.

[5] J. Galbally, S. Marcel, and J. Fierrez, "Biometric antispoofing methods: A survey in face recognition," IEEE Access, vol. 2, pp. 1530-1552, 2014.

[6] D. Rodrigues, G. F. Silva, J. P. Papa, A. N. Marana, and X.-S. Yang, "EEG-based person identification through binary flower pollination algorithm," Expert Systems with Applications, vol. 62, pp. 81-90, 2016.

[7] S. Marcel and J. d. R. Millán, "Person authentication using brainwaves (EEG) and maximum a posteriori model adaptation," IEEE transactions on pattern analysis and machine intelligence, vol. 29, no. 4, pp. 743-752, 2007.

[8] Y. Dai, X. Wang, X. Li, and Y. Tan, "Sparse EEG compressive sensing for web-enabled person identification," Measurement, vol. 74, pp. 11-20, 2015.

[9] Y. Sun, F. P.-W. Lo, and B. Lo, "EEG-based user identification system using 1D-convolutional long short-term memory neural networks," Expert Systems with Applications, vol. 125, pp. 259-267, 2019.

[10] S. A. Israel, J. M. Irvine, A. Cheng, M. D. Wiederhold, and B. K. Wiederhold, "ECG to identify individuals," Pattern recognition, vol. 38, no. 1, pp. 133-142, 2005.

[11] M. Deng, C. Wang, M. Tang, and T. Zheng, "Extracting cardiac dynamics within ECG signal for human identification and cardiovascular diseases classification," Neural Networks, vol. 100, pp. 70-83, 2018.

[12] A. Goshvarpour and A. Goshvarpour, "Human identification using a new matching Pursuit-based feature set of ECG," Computer methods and programs in biomedicine, vol. 172, pp. 87-94, 2019.

[13] K. Su et al., "Human identification using finger vein and ECG signals," Neurocomputing, vol. 332, pp. 111-118, 2019.

[14] F. Sufi and I. Khalil, "Faster person identification using compressed ECG in time critical wireless telecardiology applications," Journal of Network and Computer Applications, vol. 34, no. 1, pp. 282-293, 2011.

[15] W. Chang, H. Wang, G. Yan, and C. Liu, "An EEG based familiar and unfamiliar person identification and classification system using feature extraction and directed functional brain network," Expert Systems with Applications, p. 113448, 2020.

[16] R. San-Segundo, R. Cordoba, J. Ferreiros, and L. F. D'Haro-Enriquez, "Frequency features and GMM-UBM approach for gait-based person identification using smartphone inertial signals," Pattern Recognition Letters, vol. 73, pp. 60-67, 2016.

[17] R. San-Segundo, J. D. Echeverry-Correa, C. Salamea-Palacios, S. L. Lutfi, and J. M. Pardo, "I-vector analysis for gait-based person identification using smartphone inertial signals," Pervasive and Mobile Computing, vol. 38, pp. 140-153, 2017.

[18] N. V. Boulgouris, K. N. Plataniotis, and E. Micheli-Tzanakou, Biometrics: theory, methods, and applications. John Wiley & Sons, 2009.

[19] Z. A. A. Alyasseri, A. T. Khader, M. A. Al-Betar, and O. A. Alomari, "Person Identification using EEG Channel Selection with Hybrid Flower Pollination Algorithm," Pattern Recognition, p. 107393, 2020.

[20] G. Altan, Y. Kutlu, and M. Yeniad, "ECG based human identification using Second Order Difference Plots," Computer methods and programs in biomedicine, vol. 170, pp. 81-93, 2019.

[21] J. Suutala and J. Röning, "Methods for person identification on a pressure-sensitive floor: Experiments with multiple classifiers and reject option," Information Fusion, vol. 9, no. 1, pp. 21-40, 2008.

[22] G. Zhong, S. Yan, K. Huang, Y. Cai, and J. Dong, "Reducing and stretching deep convolutional activation features for accurate image classification," Cognitive Computation, vol. 10, no. 1, pp. 179-186, 2018.

[23] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," Communications of the ACM, vol. 60, no. 6, pp. 84-90, 2017.

[24] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," nature, vol. 521, no. 7553, pp. 436-444, 2015.

[25] I. Goodfellow, Y. Bengio, A. Courville, and Y. Bengio, Deep learning (no. 2). MIT press Cambridge, 2016.

[26] J. Schmidhuber, "Deep learning in neural networks: An overview," Neural networks, vol. 61, pp. 85-117, 2015.

[27] Y. Guo, Y. Liu, A. Oerlemans, S. Lao, S. Wu, and M. S. Lew, "Deep learning for visual understanding: A review," Neurocomputing, vol. 187, pp. 27-48, 2016.

[28] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," arXiv preprint arXiv:1409.1556, 2014.

[29] M. Mateen, J. Wen, S. Song, and Z. Huang, "Fundus image classification using VGG-19 architecture with PCA and SVD," Symmetry, vol. 11, no. 1, p. 1, 2019.

[30] M. Lin, Q. Chen, and S. Yan, "Network in network," arXiv preprint arXiv:1312.4400, 2013.

[31] Ü. Metehan, E. BOSTANCİ, M. S. GUZEL, and A. AYDIN, "MODERN LEARNING TECNIQUES AND PLANT IMAGE CLASSIFICATION," Communications Faculty of Sciences University of Ankara Series A2-A3 Physical Sciences and Engineering, vol. 62, no. 2, pp. 153-163.

[32] Z. Qin, Z. Zhang, X. Chen, C. Wang, and Y. Peng, "Fd-mobilenet: Improved mobilenet with a fast downsampling strategy," in 2018 25th IEEE International Conference on Image Processing (ICIP), 2018: IEEE, pp. 1363-1367.

[33] K. Altun, B. Barshan, and O. Tunçel, "Comparative study on classifying human activities with miniature inertial and magnetic sensors," Pattern Recognition, vol. 43, no. 10, pp. 3605-3620, 2010.

[34] B. Barshan and M. C. Yüksek, "Recognizing daily and sports activities in two open source machine learning environments using body-worn sensor units," The Computer Journal, vol. 57, no. 11, pp. 1649-1667, 2014.

[35] K. Altun and B. Barshan, "Human activity recognition using inertial/magnetic sensor units," in International workshop on human behavior understanding, 2010: Springer, pp. 38-51.

[36] Ş. Kılıç., Y. Kaya and İ.,Askerbeyli, "A New Approach for Human Recognition Through Wearable Sensor Signals", Arab J Sci Eng 46, 4175–4189 (2021).

[37] Ş. Kiliç, İ. Askerzade and Y. Kaya, "Using ResNet Transfer Deep Learning Methods in Person Identification According to Physical Actions," in IEEE Access, vol. 8, pp. 220364-220373, 2020, doi: 10.1109/ACCESS.2020.3040649.

[38] F. Kuncan, .,Y. KAYA AND M. Kuncan., (2019). A Novel Approach for Activity Recognition with Down-Sampling 1D Local Binary Pattern, Advances in Electrical and Computer Engineering, 19(1), 35-44.

[39] F. Kuncan, .,Y. KAYA AND M. Kuncan., (2019). New approaches based on local binary patterns for gender identification from sensor signals, Journal of Faculty of Engineering and Architecture of Gazi University, 34 (4), 2173-2186.

BIOGRAPHIES

SAFAK KILIC was born in Malatya, TR, TURKEY in 1988. He received the B.S. degree in computer education and instructional technology FROM Firat University, Elazig, Turkey in 2011, and the M.S. degree in computer science from University of Brighton, Brighton .UK in 2015. He is currently pursuing the Ph.D. degree in computer engineering at Ankara University, Ankara, TR, Turkey.

YILMAZ KAYA received the B.S. degree in computer engineering from Selcuk University, Konya, Turkey, in 2000 and the M.S. degree in biometrics and genetics from Yuzuncuyil University, Van, Turkey, in 2006, and a Ph.D. degree in biometrics and genetics from Yuzuncuyil University, Van, Turkey, in 2010.He is an Assistant Professor in the Department of Computer Engineering, Siirt University.

İMAN ASKERBEYLİ received the B.S. and Msc degree in from Moscow State University, Moscow, Russian Federation, in 1985 and a Ph.D. degree from Moscow State University, Azerbaijan Academy of Sciences, Baku, Azerbaijan, in 1995.He is a Professor in the Department of Computer Engineering, Ankara University.