# ECG Arrhythmia Classification based on Convolutional Autoencoders and Transfer Learning

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**ABSTRACT:**
An Electrocardiogram (ECG) is a test that is done with the objective of monitoring the heart's rhythm and electrical activity. It is conducted by attaching a specific type of sensor to the subject's skin to detect the signals generated by the heartbeats. These signals can reveal significant information about the wellness of the subjects' heart state, and cardiologists use them to detect abnormalities. Due to the prevalence of heart diseases amongst individuals around the globe, there is an urgent need to design computer-aided approaches to automatically analyze ECG signals. Recently, computer vision-based techniques have demonstrated remarkable performance in medical image analysis in a variety of applications and use cases. This paper proposes an approach based on Convolutional Autoencoders (CAEs) and Transfer Learning (TL). Our approach is an ensemble way of learning, the most useful features from both the signal itself, which is the input of the CAE, and the spectrogram version of the same signal, which is fed to a convolutional feature extractor named MobileNetV1. Based on the experiments conducted on a dataset collected from 3 well-known hospitals in Baghdad, Iraq, the proposed method claims good performance in classifying four types of problems in the ECG signals. Achieving an accuracy of 97.3% proves that our approach can be remarkably fruitful in situations where access to expert human resources is scarce.

**KEYWORDS:** Electrocardiogram (ECG), Deep Learning, Transfer Learning, Convolutional AutoEncoders, EfficientNet, Heart Arrhythmia Classification.

## 1. INTRODUCTION

ECG is a two-dimensional plane that continually displays the electrical activity of the human heart (Electrocardiogram) [1]. Analyzing this impulse provides a range of physiological data to examine cardiac activity [2]. Heart-related illnesses are serious issues for people around the globe. Obesity, diabetes, smoking, drinking alcoholic beverages, and other modern lifestyle choices are the primary causes of heart-related illnesses [3]. A variety of causes might impact a



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human heart's functioning. The characteristics retrieved from an electrocardiogram (ECG) signal were traditionally used to identify patterns and categorize the kind of arrhythmia seen in the signal [4]. Blood is pumped throughout the body as a result of the heart's rhythmic contractions and regular myocardial excitation. Each area of the body may experience changes as a result of the small current that the heart generates during myocardial contraction and conducts to the surface [5]. Most frequently used for ECG diagnosis are 12 leads with ten electrodes each, one of which is used as a reference for the others (usually is the right leg) [6]. Three waves, two intervals, and two segments make up a single cardiac cycle's ECG. P wave (atrial depolarization), QRS complex wave (ventral depolarization), and T wave are three major waves that represent the heart's three electrical phenomena throughout one cardiac cycle (repolarization) [7]. The time it takes for the heart to complete the associated electrical shift is indicated by the length of two intervals (PR interval and QT interval).

These features, which ultimately needed a great deal of engineering, optimization, or domain knowledge to offer high accuracy, included statistical, signal procession, and medical features [8]. Support Vector Machine (SVM) [9], Random Forest (RF) [10], K-Nearest Neighbor (KNN) [11], Feed Forward Neural Network [12], and a plethora of other classification techniques that show capacity in this job are typically used for classification once the features have been retrieved [13]. Fig. 1 illustrates the processes needed to solve an issue using a machine learning technique.

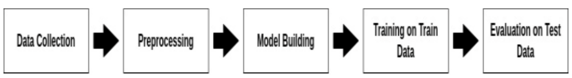


**Fig. 1.** An overview of a machine learning-based approach for ECG classification.

Since deep learning-based approaches have demonstrated remarkable performance in a variety of fields, researchers and engineers have been inspired to apply deep learning approaches to the field of biomedical image and signal processing [14],[15],[16]-[17]. As a result of the state-of-the-art results, these methods have recently attained in common pattern recognition tasks, they have been frequently applied in the domain of medical image analysis [18]-[19]-[20]-[21]. In this context, Recurrent Neural Networks (RNN), more especially Long Short Term Memory Networks (LSTM) [22] and Convolutional Neural networks (CNN) [23] and have demonstrated promising results in the ECG domain utilizing deep learning approaches [24]. The ability of a neural network to automatically learn complicated representative features directly from the data itself eliminates the need for human feature extraction and is one of the key benefits of employing Deep Neural Networks (DNNs) [25].

In the literature, a variety of approaches based on machine learning and deep learning have been put forward for analyzing ECG data [26]. In [27], the authors developed a deep CNN-based classifier for classifying grayscale images of ECG data. Their approach was built up predicting five classes in a dataset named MIT-BIH. The accuracy that they achieved was 99.05. Acharya et al., in [28], used a KNN classifier based on seven features extracted using Discrete Cosine Transform (DCT). They achieved an accuracy of 98.5 % on Physionet open-access databases containing two classes for the collected data. In [29], the authors used a KNN on 26 features obtained from ECG and VCG data and achieved an accuracy of 87.4 % on the MIT-BIH dataset. Furthermore, Sannino et al. [30] employed CNN-based feature extraction algorithms to analyze the ECG data's visual representation. Their approach was evaluated on a dataset obtained from 500 unique patients and achieved 86% accuracy.

In this paper, we have addressed the issues in the previous works and proposed a novel approach based on deep neural networks for classifying the ECG signals. Our approach extracts features obtained from both the signal itself and also the preprocessed format of it when converted to a spectrogram. This way, we are able to focus on better features for the downstream task of classification. Overall, our contributions to this paper are listed in the following:

1- Proposing a novel method for classifying ECG signals into four different classes, three of which exhibit abnormality in a heartbeat, and one of them shows the normal state of the heart.

2- Our approach is based on Convolutional Autoencoders and MobileNetV1, and it can extract features from the signal itself and its spectrogram version.

3- The proposed approach is evaluated on a dataset collected from real hospitals, which claims the results' reliability.

## 2. MATERIALS AND METHODS

### 2.1. Overview

This section contains an explanation of our proposed methodology. Fig. 2 illustrates an overview of the ensemble approach adopted for the classification of the target results.

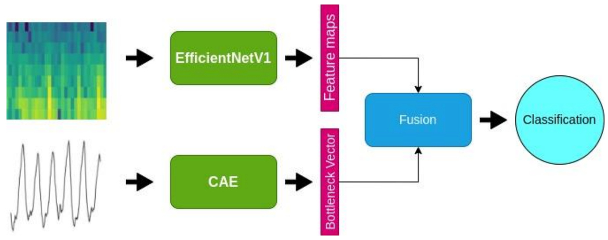


**Fig. 2.** The overview of the proposed method.

In Fig. 2, it is demonstrated that the spectrogram version of the signal enters EfficienetNetV1 as its input. Meanwhile, the signal itself is the input of the CAE module. The CAE learns to reconstruct the signal in a way that the difference between the output and the input becomes less. This way, we can build a representation of the signal in the latent space. As for the EfficientNetV1, it learns to extract useful features from the spectrogram, and by fusing these features with the latent representation generated by the CAE module, we can classify the inputs to the target classes.

### 2.2. Dataset

The dataset used in this study contains 30000 samples of ECG signals collected from two healthcare facilities in Iraq, namely Al-Andalus and Al Khayal. Fig. 3 illustrates a sample from the collected dataset.

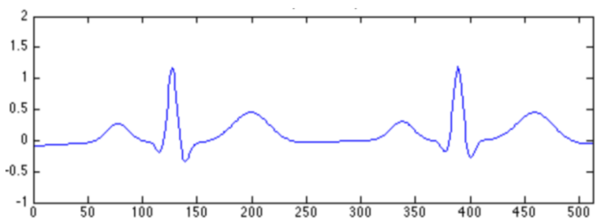


**Fig. 3**. An ECG signal sample after being plotted.

The dataset contains 10000 samples of normal signals and 10000 samples showing the arrhythmic state of the subject. For the purpose of this research, we split the dataset in a ratio of 80/20 for train and test. Table 1 shows the distribution of the data and the number of samples in each train and test set.

**Tab. 1.** The distribution of the data.

| Class | Total | Train | Test |
|---|---|---|---|
| Normal | 15000 | 12000 | 3000 |
| Arrhythmic | 15000 | 12000 | 3000 |

### 2.3. Preprocessing

When preparing data for machine learning, normalization is a scaling technique that modifies the values of numerical columns to use a standard scale [31]. Not all datasets in a model require it, and it is only necessary when the ranges of the features in machine learning models differ. Normalization is employed if the characteristics in the dataset have diverse ranges, even though it is not required for all datasets accessible in machine learning. It aids in improving a machine learning model's performance and dependability [32]. In this stage, we have two main steps for preprocessing the data. In the first step, we get the spectrogram of the signals and normalize produced images of spectrograms to have a specific standard deviation and mean for their pixel values. These images will be the input of the feature extraction module. The next step is to normalize the signals themselves with the aim of being fed to the CAE module.

### 2.4. EfficientNet

EfficientNet [33] is a convolutional neural network design and scaling technique that uses a compound coefficient to consistently scale all depth, breadth, and resolution parameters. The EfficientNet scaling approach evenly scales network breadth, depth, and resolution using a set of preset scaling coefficients, in contrast to standard practice, which scales these variables arbitrarily [34]. For instance, to employ times more computing power, we may simply raise the network depth, width, and picture size, where there are constant coefficients discovered via a tiny grid search on the small initial model. Network width, depth, and resolution are all uniformly scaled by EfficientNet using a compound coefficient. Compound scaling consistently scales each dimension with a predetermined fixed set of scaling coefficients as opposed to randomly increasing width, depth, or resolution. The developers of EfficientNet created seven models in different dimensions using the scaling approach and AutoML, outperforming most convolutional neural networks' state-of-the-art accuracy while operating far more effectively. The idea behind neural networks is that larger input images require more layers to enhance the receptive field and more channels to capture more minute patterns on the larger images [35]. In comparison to other random scaling techniques, the compound scaling approach also assisted in enhancing the model efficiency and accuracy of earlier CNN models, including MobileNet and ResNet, by around 1.4% and 0.7% ImageNet accuracy, respectively.

### 2.5. Convolutional Autoencoders

Convolutional Autoencoder (CAE) refers to a specific type of neural network used to learn data encodings in an unsupervised fashion [36]. An autoencoder aims to train the network to capture the most crucial elements of the input picture to learn lower-dimensional representation (encoding) for higher-dimensional data, often for dimensionality reduction [37]. Three components make up autoencoders: it has a module that shrinks the input data from the train-validate-test set into an encoded form that there are often many orders of magnitude less than the input data [38]. Additionally, it features a module that houses the condensed knowledge representations, making it the most crucial component of the network. A module that aids the network in "decompressing" knowledge representations and recovering the data from its encoded state is also included. Next, the output is contrasted with a source of truth. The overall appearance of the architecture is depicted in Fig. 4.

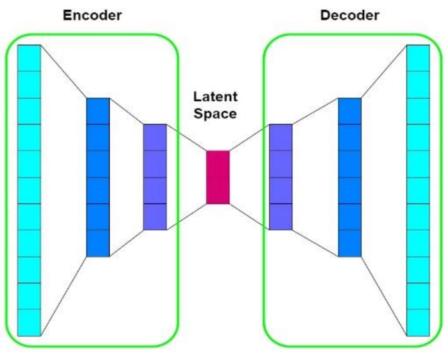


**Fig. 4**. The general architecture of a CAE-based network.

Compressing the data into a code is the encoder's responsibility. By linking a succession of pooling layers, each of which reduces the number of dimensions in the data, we may apply this phenomenon in neural networks. By retaining just the portions of the data that are meaningful enough to encode, we may denoise the data in this way [39]. The network's decoder component serves as the code's interpreter. Convolutional neural networks allow for the reconstruction of images using a specific algorithm. This element can be viewed as a decompression, interpretation, or value extraction tool.

## 3. EXPERIMENTAL RESULTS

### 3.1. Experimental Setup

Python 3.8 has been chosen as the programming language in this study to implement the proposed method. Additionally, Pytorch 1.1 serves as the deep learning framework that is utilized for model training and implementation. The computer utilized for this work featured a GeForce GTX 2070 graphics processor and an Intel® CoreTM i7-10500 processor running at 2.90 GHz (GPU).

### 3.2. Classification Metrics

This subsection details all the metrics which are used for evaluating our approach. These metrics are famous in every classification challenge and provide us with a trustworthy insight into the performance of the classifier.

1- Confusion Matrix (CM): A classification model's performance on a set of test data for which the real values are known is frequently described using a confusion matrix. It comprises four different elements, namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). TP is the number of positive samples that are predicted correctly. TN is the number of negative samples that are correctly classified as negative. FP is the number of actual negative samples that are incorrectly classified as positive. Finally, FN is the number of positive samples that are wrongly predicted as negative. Fig. 5 illustrates an example of CM.

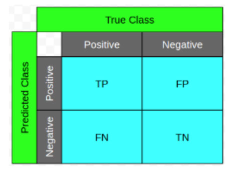


**Fig. 5.** The achieved CM for the Proposed Classifier.

2- Accuracy: $x = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}$

3- Precision: $x = \frac{\text{TP}}{\text{TP+ FP}}$

4- Recall: $x = \frac{\text{TP}}{\text{TP+ FN}}$

5- F1-Score: $x = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision+Recall}}$

6- AUC-ROC: Receiver Operating Characteristic (ROC) is a probability curve, and Area Under Curve (AUC) exhibits the level of separability of the classifier's decision boundaries.

### 3.3. Classification Performance

This subsection contains the classification results that are achieved by the proposed methodology. As stated previously, we have evaluated the method based on the metrics introduced in section 3.2. Fig. 6 demonstrates the CM obtained by the approach.

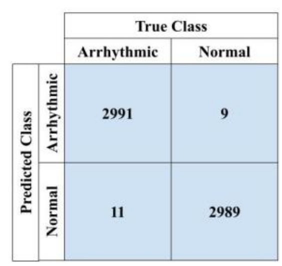


**Fig. 6.** The achieved CM for the Proposed Classifier.

Based on Fig. 6, it can be inferred that the values for TP, TN, FP, and FN are 2991, 2989, 9, and 11, respectively. Further, Table 2 details the achieved results based on the previously introduced metrics.

**Tab. 2.** Obtained classification results by the proposed method.

| Accuracy | Precision | Recall | F1-Score | AUC-RoC |
|---|---|---|---|---|
| 99.67 | 99.70 | 99.70 | 99.70 | 99.84 |

Furthermore, we provided Fig. 7, which demonstrates a comparison between our proposed methodology and other related research works.

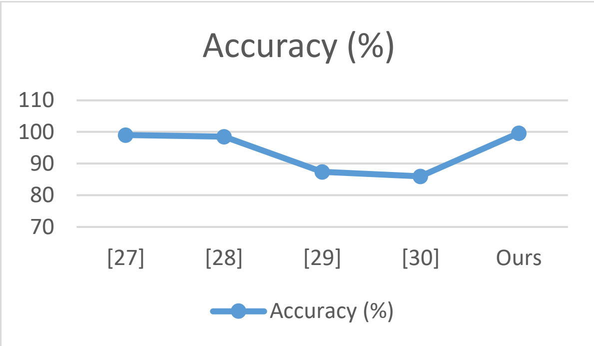


**Fig. 7.** The comparison between other works and our proposed method.

According to Fig, 7, it can be observed that our proposed methodology generates an excellent performance. It also has the best stability in terms of precision and recall metrics since these results are the same. In fact, this shows that the classifier has the same power with respect to recognizing TP, TN, FP, and FN samples within the collected dataset. Moreover, our proposed methodology has been trained and evaluated on a huge dataset of real subjects. Thus, its reliability can be claimed based on the results.

## 4. CONCLUSION

In this paper, we have proposed a novel ensemble learning algorithm based on CAE and Efficient for classifying ECG signals; the proposed method is able to analyze the samples collected from hospitals and real subjects and make the decision on the state of the signals in terms of their normal or abnormal (arrhythmic) state. The results achieved by our proposed method demonstrate robust performance in that it achieves an accuracy of 99.67%, which is significantly high and shows its reliability. Our proposed method can be utilized in the clinical procedures existing for accurately analyzing the ECG signals, and it provides clinicians with the opportunity to automate such diagnostic pipelines.

## REFERENCES

[1] Ebrahimi Z, Loni M, Daneshtalab M, Gharehbaghi A, **"A review on deep learning methods for ECG arrhythmia classification,"** *Expert Systems with Applications:* X. 2020 Sep 1;7:100033.

[2] Sahoo S, Dash M, Behera S, Sabut S, **"Machine learning approach to detect cardiac arrhythmias in ECG signals: a survey,"** *IRBM. 2020 Aug* 1; Vol. 41(4), pp. 185-94.

[3] Huang J, Chen B, Yao B, He W, **"ECG arrhythmia classification using STFT-based spectrogram and convolutional neural network,"** *IEEE access*. 2019 Jul 11;7:92871-80.

[4] Sai YP, **"A review on arrhythmia classification using ECG signals,"** *In2020 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS)*, pp. 1-6, IEEE, 2020.

[5] Mathunjwa BM, Lin YT, Lin CH, Abbod MF, Shieh JS **"ECG arrhythmia classification by using a recurrence plot and convolutional neural network**," *Biomedical Signal Processing and Control*. Vol. 64, 102262, 2021.

[6] Houssein EH, Ibrahim IE, Neggaz N, Hassaballah M, Wazery YM, **"An efficient ECG arrhythmia classification method based on Manta ray foraging optimization,"** *Expert Systems with Applications*. Vol. 181:115131, 2021.

[7] Sangaiah AK, Arumugam M, Bian GB, **"An intelligent learning approach for improving ECG signal classification and arrhythmia analysis,"** *Artificial intelligence in medicine*. Vol. 103:101788, 2020.

[8] Wu M, Lu Y, Yang W, Wong SY, **"A study on arrhythmia via ECG signal classification using the convolutional neural network,"** *Frontiers in computational neuroscience*. Vol. 14:564015, 2021.

[9] Pisner DA, Schnyer DM, **"Support vector machine,"** *In Machine learning*, pp. 101-121, Academic Press, 2020.

[10] Probst P, Wright MN, Boulesteix AL, **"Hyperparameters and tuning strategies for the random forest,"** *Wiley Interdisciplinary Reviews: data mining and knowledge discovery*. 2019 May;9(3):e1301.

[11] Dong Y, Ma X, Fu T, **"Electrical load forecasting: A deep learning approach based on K-nearest neighbors,"** Applied Soft Computing. 2021 Feb 1;99:106900.

[12] Samek W, Montavon G, Lapuschkin S, Anders CJ, Müller KR, **"Explaining deep neural networks and beyond: A review of methods and applications,"** *Proceedings of the IEEE*. Vol. 109(3), pp. 247-78, 2021.

[13] Alfaras M, Soriano MC, Ortín S, **"A fast machine learning model for ECG-based heartbeat classification and arrhythmia detection,"** *Frontiers in Physics*. Vol. 7:103, 2019.

[14] Sharghi E, Nourani V, Najafi H, Molajou A, **"Emotional ANN (EANN) and wavelet-ANN (WANN) approaches for Markovian and seasonal based modeling of rainfall-runoff process,"** *Water resources management*. Vol. 32(10), pp. 3441-56, 2018.

[15] Nourani V, Davanlou Tajbakhsh A, Molajou A, Gokcekus H, **"Hybrid wavelet-M5 model tree for rainfall-runoff modeling,"** *Journal of Hydrologic Engineering*. Vol. 24(5), pp. 04019012, 2019.

[16] Nourani V, Molajou A, Tajbakhsh AD, Najafi H, **"A wavelet based data mining technique for suspended sediment load modeling,"** Water *Resources Management*. Vol. 33(5), pp. 1769-84, 2019.

[17] Nourani V, Molajou A, **"Application of a hybrid association rules/decision tree model for drought monitoring,"** *Global and Planetary Change*. Vol. 159, pp. 37-45,2017.

[18] Karimi D, Dou H, Warfield SK, Gholipour A, **"Deep**

**learning with noisy labels: Exploring techniques and remedies in medical image analysis,"** *Medical Image Analysis*. 2020 Oct 1;65:101759.

[19] Singh A, Sengupta S, Lakshminarayanan V, **"Explainable deep learning models in medical image analysis,"** *Journal of Imaging*. Vol. 6(6), pp. 52, 2020.

[20] Budd S, Robinson EC, Kainz B **"A survey on active learning and human-in-the-loop deep learning for medical image analysis,"** *Medical Image Analysis*. 2021 Jul 1;71:102062.

[21] Fourcade A, Khonsari RH, **"Deep learning in medical image analysis: A third eye for doctors,"** *Journal of stomatology, oral and maxillofacial surgery*. Vol. 120(4), pp. 279-88, 2019.

[22] Hibat-Allah M, Ganahl M, Hayward LE, Melko RG, Carrasquilla J, **"Recurrent neural network wave functions,"** *Physical Review Research*. Vol. 2(2), 023358, 2020.

[23] Li Z, Liu F, Yang W, Peng S, Zhou J, **"A survey of convolutional neural networks: analysis, applications, and prospects,"** *IEEE transactions on neural networks and learning systems*. 2021.

[24] Shaker AM, Tantawi M, Shedeed HA, Tolba M, **"Generalization of convolutional neural networks for ECG classification using generative adversarial networks,"** *IEEE Access*. 8:35592-605, 2020.

[25] Jiang J, Chen M, Fan JA, **"Deep neural networks for the evaluation and design of photonic devices**," *Nature Reviews Materials*. Vol. 6(8), pp. 679-700, 2021.

[26] Wasimuddin M, Elleithy K, Abuzneid AS, Faezipour M, Abuzaghleh O, **"Stages-based ECG signal analysis from traditional signal processing to machine learning approaches: A survey,"** *IEEE Access*. 8:177782-803, 2020.

[27] Jun, Tae Joon, Hoang Minh Nguyen, Daeyoun Kang, Dohyeun Kim, Daeyoung Kim, and Young-Hak Kim, **"ECG arrhythmia classification using a 2-D convolutional neural network,"** *arXiv preprint arXiv*:1804.06812, 2018.

[28] Acharya, U. Rajendra, Hamido Fujita, Muhammad Adam, Oh Shu Lih, Vidya K. Sudarshan, Tan Jen Hong, Joel EW Koh et al, **"Automated characterization and classification of coronary artery disease and myocardial infarction by decomposition of ECG signals: A comparative study,"** *Information Sciences* 377, pp. 17-29, 2017.

[29] Zhou, Lin, Yan Yan, Xingbin Qin, Chan Yuan, Dashun Que, and Lei Wang, **"Deep learning-based classification of massive electrocardiography data,"** *In 2016 IEEE Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC*), pp. 780-785. IEEE, 2016.

[30] Sannino G., and G. De Pietro, **"A Deep Learning Approach for ECG-based Heartbeat Classification for Arrhythmia Detection,"** Future *Generation Computer Systems*, pp. 1-31, 2018.

[31] Jo JM, **"Effectiveness of normalization pre-processing of big data to the machine learning performance,"** *The Journal of the Korea institute of electronic communication sciences*. Vol. 14(3), pp. 547-52, 2019.

[32] Singh D, Singh B, **"Investigating the impact of data normalization on classification performance,"** Applied Soft Computing. Vol. 97:105524, 2020.

[33] Koonce B, **"EfficientNet,"** *InConvolutional neural networks with swift for tensorflow*, pp. 109-123, Apress, Berkeley, CA, 2021.

[34] Tan M, Le Q, **"Efficientnet: Rethinking model scaling for convolutional neural networks,"** *InInternational conference on machine learning*, pp. 6105-6114, PMLR, 2019.

[35] Atila Ü, Uçar M, Akyol K, Uçar E, **"Plant leaf disease classification using EfficientNet deep learning model,"** *Ecological Informatics*. 2021 Mar 1;61:101182.

[36] Chow JK, Su Z, Wu J, Tan PS, Mao X, Wang YH, **"Anomaly detection of defects on concrete structures with the convolutional autoencoder,"** *Advanced Engineering Informatics*. 45:101105, 2020.

[37] Ahmed AS, El-Behaidy WH, Youssif AA, **"Medical image denoising system based on stacked convolutional autoencoder for enhancing 2-dimensional gel electrophoresis noise reduction,"** *Biomedical Signal Processing and Control*. 69:102842, 2021.

[38] Saravanan S, Sujitha J, **"Deep medical image reconstruction with autoencoders using deep Boltzmann machine training,"** EAI Endorsed *Transactions on Pervasive Health and Technology*. Vol. 6(24):e2, 2020.

[39] Öztürk Ş, **"Stacked auto-encoder based tagging with deep features for content-based medical image retrieval,"** *Expert Systems with Applications*. 161:113693, 2020.