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RESEARCH ARTICLE

A TRANSFER LEARNING APPROACH BY USING 2-D CONVOLUTIONAL NEURAL NETWORK FEATURES TO DETECT UNSEEN ARRHYTHMIA CLASSES

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ABSTRACT

Arrhythmia is an irregular heartbeat and can be diagnosed via electrocardiography (ECG). Since arrhythmia can be a fatal health problem, developing automatic detection and diagnosis systems is vital. Although there are accurate machine learning models in the literature to solve this problem, most models assume all arrhythmia types present in training. However, some arrhythmia types are not seen frequently, and there are not enough heartbeat samples from these rare arrhythmia classes to use them for training a classifier. In this study, the arrhythmia classification problem is defined as an anomaly detection problem. We use ECG signals as inputs of the model and represent them with 2-D images. Then, by using a transfer learning approach, we extract deep image features from a Convolutional Neural Network model (VGG16). In this way, it is aimed to get benefit from a pre-trained deep learning model. Then, we train a ν-Support Vector Machines model with only normal heartbeats and predict if a test sample is normal or arrhythmic. The test performance on rare arrhythmia classes is presented in comparison with binary SVM trained with normal and frequent arrhythmia classes. The proposed model outperforms the binary classification with 90.42 % accuracy.

Keywords: Convolutional neural networks, Transfer learning, One-class classification, Arrhythmia classification, Electrocardiography

1. INTRODUCTION

Heart diseases are the most serious and fatal causes of death. Irregular heartbeat, a.k.a arrhythmia, is a group of heart diseases. It occurs when there is a problem with the electrical signals that control the heartbeat. There are various causes and types of arrhythmia. They have different outcomes, e.g., skipping, fluttering, too hard, too slow, or too fast heartbeats. Electrocardiography (ECG) is the most common diagnostic method to detect arrhythmia because arrhythmia is an electrical impulse abnormality.

Automatic detection and diagnosis systems for arrhythmia are studied widely by the machine learning community. Because of the importance of the problem, this topic still keeps the interest of researchers. The problem is generally defined as a classification task and investigated from various points of view. The problem varies according to how arrhythmia data is represented, how many heartbeat classes are included, model assumptions and, how training and test data are split. Therefore although there are different reported accuracy results in the literature, it is hard to define which study superiors others. The main difference is because of problem definition: multi-class classification, outlier detection, binary classification, etc. The models can be applied in-person or off-person. Additionally, while some studies use ECG signals, some others use different data sources such as echocardiography. Even the data type is the same, accuracy results are sensitive to how data samples are selected. Data sets are not the same. Moreover, while some studies focus on feature extraction, some studies aim to develop novel classification methods. Detection accuracies can be found very high in the literature, and we provided

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more details about the literature in the Existing Work subsection. It is clear that due to arrhythmia classification is a life-threatening problem, developing more robust models are important.

For a classical classification approach, an adequate number of samples from each class should be collected to get a robust classification model. And, most of the studies in the literature assume a sufficient number of samples from all arrhythmia classes are collected in training. However, it is the fact that while some arrhythmia types are seen frequently, some of them are exceptional. Thus, in real life, it may not be possible to cover all arrhythmia types in training.

In the last decade, Convolutional Neural Networks (CNNs) have achieved the best results in image recognition task with AlexNet [1] in 2012 and then followed by VGGNet [2], GoogleNet [3], and ResNet [4]. Deep CNN models are trained with millions of images. One advantage of the CNN models is the possibility of extracting deep features from pre-trained models. Feature representation of the samples has a great effect on the classifier's accuracy, and thanks to this procedure, there is no need for millions of samples for a new image classification task.

In this study, the arrhythmia classification problem is dealt with from a novel perspective. The problem is defined as anomaly detection to classify rare arrhythmia types more accurately. Hence, heartbeats are labeled as normal or arrhythmic. We represent ECG signals obtained from the MIT-BIH data set with 2-D images. Using a transfer learning approach, we extracted input image features from a Convolutional Neural Network model (VGG16). These features are used as input to the ν-SVM classifier. Then, the model is tested with rare arrhythmia types that are not shown to the model.

The paper is organized as follows. In Section 2, data collection is provided in subsection 2.1, feature extraction is explained in subsection 2.2, and the novel method used in this study is given in subsection 2.3. Computational results are provided in Section 3 in comparison with binary classification. Finally, the paper is concluded in Section 4.

1.1. Existing Work

In this subsection, we present recent developments about arrhythmia classification. The literature about this topic is extensive. There are studies with different data types, and the studies have various aims such as preprocessing, P, Q, R S, or T wave detection, feature selection, feature extraction, and learning. We focused on ECG based learning algorithms and provided state of the art results in this subsection.

Cimen and Ozturk defined the arrhythmia detection problem as a multi-class classification and investigated five heartbeat groups. Their linear programming-based method achieved 98% accuracy [5]. Marinho et al. exhibit the impacts of how their model would behave in a real case scenario investigated six various feature extraction methods to classify five arrhythmia groups and achieved 94.3% accuracy [6]. The authors also claim their system is 1.3% more accurate than the best approach reported to 2019. Pan et al. aim to classify eight arrhythmia types [7]. The authors' discrete wavelet transform and random forest-based techniques achieved 99.77% accuracy.

Lannoy et al. focused on arrhythmia classification problems when the data is imbalanced [8]. They take into account class imbalance by using a weighted support vector machine classifier. Sharma et al. considered the arrhythmia classification problem from a different perspective [9]. They split arrhythmia into two groups as shockable and non-shockable. In this way, their study helps medical doctors at the first aid. They have obtained an overall accuracy of 98.9% using the SVM classifier in the best case.

Researchers use neural network-based algorithms to solve the arrhythmia classification problem frequently. Especially, convolutional models have an advantage because of automatic feature extraction capability. Yildirim et al. use one-dimensional CNNs to classify normal sinus rhythm, 15 cardiac arrhythmias, and pacemaker rhythm [10]. Their model achieves 91.33% overall accuracy. Singh et al. use Long Short Term Memory (LSTM) Networks and defined the problem as a binary classification problem [11]. Their method obtained 88.1% accuracy.

In recent studies, the transfer learning approach is used for arrhythmia classification by representing ECG signals as 2-D images [12, 13]. Jun et al. use 2-D CNNs on eight types of ECG beat and achieved 99.05% average accuracy. Salem et al. classify four ECG patterns from a transfer learning perspective, transferring knowledge from the image classification domain to the ECG signal classification domain [13]. They achieved 97.23% accuracy.

Ebrahimi et al. present a detailed survey about deep learning methods for ECG arrhythmia classification recently [14]. According to their study, CNN is dominantly observed as a suitable technique for feature extraction, seen in 52% of the studies. The authors report that deep learning methods have high accuracy in the classification of Atrial Fibrillation (100%), Supraventricular Ectopic Beats (99.8%), and Ventricular Ectopic Beats (99.7%).

From the existing studies, one can see that CNN-based models are accurate and keep the advantage of automatic feature extraction. When the ECG signal is represented as a 2-D image, it is possible to get the help of deep learning methods for image recognition tasks, and the studies obtain high accuracy via transfer learning. In this study, we set our problem definition to classify rare heartbeat types accurately. We train our model with common heartbeats that can be seen frequently, and our model does not see any data from rare classes. We represent heartbeats as 2-D images. Therefore we can apply transfer learning from deep image recognition models. To the best of our knowledge, this type of problem set is the first in the literature.

2. METHOD

2.1. Arrhythmia Data Collection

In this study, data are collected from the MIT-BIH Arrhythmia Database [15], and ECG signals of the heartbeats are represented as images. The MIT- BIH database contains 48 half-hour ECG recordings. ECG recordings are collected from 47 subjects between 1975 and 1979. Approximately 60 % of these recordings are obtained from inpatients. The digitization rate is 360 samples per second. Heartbeats are annotated by two or more cardiologists independently.

We downloaded data and converted them into 2-D images using Python scripts in a GitHub repository [16]. We created images by including 96 recordings to the right and left from the R peak of a heartbeat, so the ECG signal length is 193. The generated data set consists of a normal heartbeat class and eleven arrhythmia classes. Arrhythmia classes are atrial premature beat (A), premature ventricular contraction (V), aberrated atrial premature beat (a), atrial escape beat (e), nodal premature beat (J), supraventricular premature beat (S), ventricular escape beat (E), left bundle branch block (L), right bundle branch block (R), paced beat (/) and ventricular flutter wave (!). The symbols in the parentheses indicate the heartbeat symbol at the MIT- BIH database. We considered aberrated atrial premature beat, atrial escape beat, nodal premature beat, supraventricular premature beat, ventricular escape beat, and ventricular flutter wave types rare arrhythmic heartbeats. Frequently seen heartbeat classes (normal, atrial premature beat, premature ventricular contraction, left bundle branch block, right bundle branch block, paced beat) are sub-sampled randomly from the MIT-BIH data set. The number of samples in the validation set are balanced according to normal and arrhythmic heartbeats. Rare arrhythmia classes are kept for the testing set. Normal heartbeats are labeled 1 and arrhythmic heartbeats are labeled 0. Samples from the dataset can be found in Figure 1. Then, details about generated training, validation, and test sets are provided in Table 1.

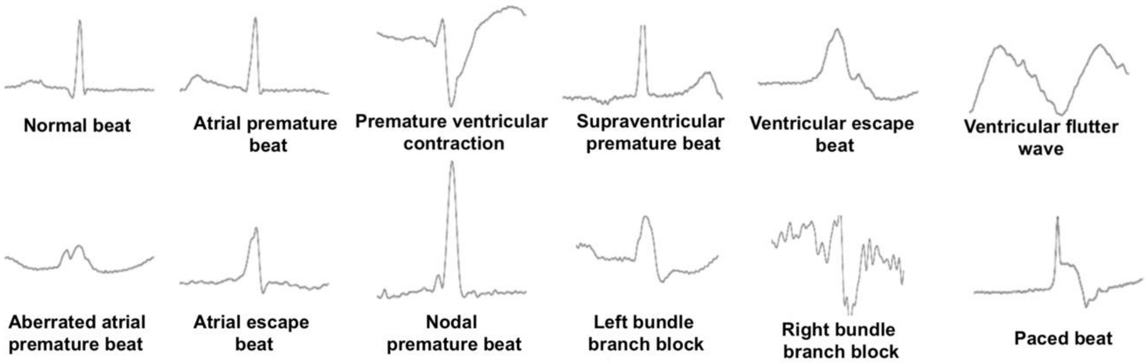

Figure 1. ECG figures of heartbeat groups.

Table 1. Generated datasets from MIT-BIH Arrhythmia Database

Set	Heartbeat Group	# of Samples	Label
Training	Normal	20000	1
Validation	Normal	12510	1
	Atrial premature beat	2500	0
	Premature ventricular contraction	2500	0
	Left bundle branch block	2500	0
	Right bundle branch block	2500	0
	Paced beat	2500	0
Testing	Normal	830	1
	Aberrated atrial premature beat	150	0
	Atrial escape beat	16	0
	Nodal premature beat	83	0
	Supraventricular premature beat	2	0
	Ventricular escape beat	106	0
	Ventricular flutter wave	472	0

2.2. Extracting Deep Features

Convolutional Neural Networks (CNN) based classifiers are the state of the art models for image recognition related problems. With AlexNet [1], researchers' attention focused on CNNs, and these models are applied to a wide variety of problems. Convolutional layers reduce the model decision variable size. Thus they make the model more robust to the over-fitting problem in comparison with fully connected layers. Moreover, through convolutional layers, the features are extracted automatically.

Additionally, when CNN has learned a kernel that can detect a particular feature, it can detect that feature anywhere on the image. Thus, a shift in the ECG signal will not cause a problem.

We represented heartbeats as images (as in Figure 1) in this study. The base part of the pre-trained VGG16 [2], which has 13 convolutional layers, is used to extract deep features. In VGG16 convolutional layers have 512 filters of size 3×3 and a stride of one. Input size is 224 x 224 x 3. Please see the architecture of the CNN model from Figure 2. The size of the last convolutional layer is 4096. Each heartbeat image is passed through convolutional layers, and each sample is represented with a vector, x, which has 4096 deep features.

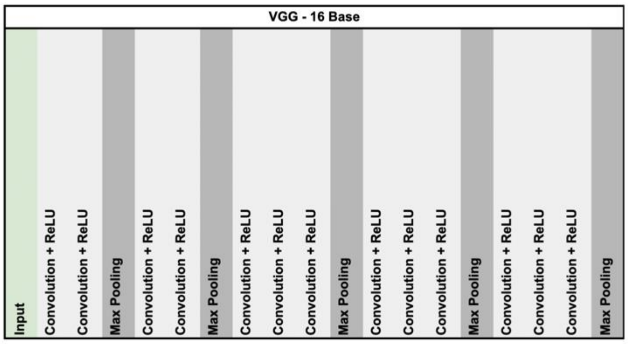

Figure 2. VGG16 base part is used for feature extraction.

2.3. Anomaly Detection with ν-SVM

In this study, a life-threatening problem, arrhythmia classification, is targeted to solve. There are a variety of machine learning solutions to this problem in the literature. In conventional classification approaches, it is assumed that training samples for each class are present. However, it is a fact that there are some unobserved classes in the training phase in real-life problems. Certainly, this case may arise in arrhythmia classification. While some arrhythmia types are seen frequently, some of them occur rarely. Thus, there may not be a sufficient number of samples from some arrhythmia types in training. With this problem set, we wanted to test the performance of a classifier on unobserved classes. The problem is defined as anomaly detection, and ν-SVM (anomaly detection) is used as the classifier.

The anomaly detection problem differs in one aspect from the multi-class classification problem. It is assumed that data from only one of the classes is available in training. Therefore only samples from the present class can be used in training. Data from the other class (outlier class) cannot be seen from the model, and outlier samples may arise only in the testing. Hence, the decision boundary between the two classes (normal and outlier) must be estimated from data corresponding to the normal class. This type of classification task has various names in the literature: one-class classification, concept learning, outlier/novelty detection, single-class classification.

ν-SVM is one of the first one class classifier model and presented by Schölkopf et al. [17]. In that study, the authors supposed there are some given datasets drawn from an underlying probability distribution P. Then, the task is defined to estimate a subset S of input space such that the probability that a test point drawn from P lies outside of S is bounded by some a priori specified ν between 0 and 1. In other words, ν is the upper bound on the fraction of outliers and controls the trade-off between outliers and normal samples. Coefficients of the classifier are found by solving a quadratic programming problem [17]. As in multi-class SVM, a kernel function can be used to get non-linear decision boundaries. In Equation 1 and Equation 2, the quadratic programming problem can be seen. In this model, l is the number of samples, and **x** is a sample vector. Φ maps the sample vector **x** into an inner product space *F*. Slack variables ξ_i penalize the objective function. **w** and ρ define the classifier. Once the classifier is obtained, a test sample label can be predicted with Equation 3. One can find theoretical details in [17].

$$\min_{\{w\in F,\xi\in R^l,\rho\in R\}} \frac{1}{2}\|w\|^2 + \frac{1}{\nu l}\sum_i \xi_i - \rho \tag{1}$$

$$s.t\ \big(w.\Phi(x_i)\big) \geq \rho - \xi_i\ ,\xi \geq 0 \tag{2}$$

$$f(x) = sgn(\big(w.\Phi(x_i)\big) - \rho) \tag{3}$$

3. COMPUTATIONAL RESULTS

In this section, we present the performance of this study in comparison with a binary SVM classifier. To train models, we used Python 3.6 and Sklearn package. To get the VGG16 model and to extract deep features, we used the Keras package. Tests are carried out on a computer with Intel(R) Core(TM) i7 CPU running at 2.5 GHz and 16 GB RAM.

In this study, we conducted two experiments. The first experiment is set to measure the accuracy of the proposed method. It is assumed that there are rare arrhythmia classes, and the task is to classify heartbeats belong to these rare arrhythmia classes as an arrhythmic beat. Therefore, any heartbeat seen rarely has not been included in the training or validation set. We train the ν-SVM model with only normal heartbeats, which are represented with deep features. We used the Radial basis function (RBF) as a kernel function for ν-SVM. RBF kernel function can be seen in Equation 4. To define the optimal ν and γ parameters, we used the grid search approach. γ is selected among $\{2^{-5}, 2^{-4}, \ldots, 2^4, 2^5, \text{auto}\}$ and ν is selected among {0.1, 0.2, . . . , 0.8, 0.9} based on validation set accuracy score.

$$K(x_i, x_j) = exp(-\gamma\|x_i - x_j\|^2) \tag{4}$$

In the second experiment, we set a binary classification model to benchmark the proposed method's performance. Although we assume there are no rare arrhythmic classes present in the training phase; there are some available arrhythmia classes that can be seen frequently. Thus, one can train a binary classifier with normal and frequent arrhythmic classes and then can use this classification model on rare arrhythmia samples. To get the performance of this case, we trained a binary SVM model. Similarly, RBF is selected as the kernel function. We used training and 90 % of the validation set to train the binary classifier. The remaining 10 % of the validation set is kept for grid search evaluation. γ parameter is selected among $\{2^{-5}, 2^{-4}, \ldots, 2^4, 2^5, \text{auto}\}$ and C is selected among {0.1, 1, 10, 100, 1000}. Then, we tested the binary model on the test set. Training, validation, and test set details are provided in Table 1. As a summary, ν-SVM use only normal data shown in Table 1 – training set and use Table 1 validation set for hyper-parameter selection. On the other hand, binary SVM uses Table 1 – training set data and 90% of the validation set data for training. Binary SVM selects hyper-parameters according to the rest of the 10% of validation set accuracy.

The performances of the models are compared in Table 2. While calculating recall and precision scores, the normal heartbeat class is considered as the positive class. Precision is the fraction of positive instances among the positive labeled instances, while recall is the fraction of the total amount of positive instances that were positively labeled. F_1 score is the harmonic mean of recall and precision scores. Formulations are given in Equations 5, 6 and, 7. tp, fp and, fn respectively correspond to true positive, false positive and, false negative in Equations 5 and 6.

Table 2. Performance comparison of classification models.

Method	Accuracy	F_1 Score	Recall	Precision
ν-SVM	0.904	0.900	0.870	0.930
binary SVM	0.863	0.880	1.00	0.790

$$Precision = \frac{tp}{tp + fp} \tag{5}$$

$$Recall = \frac{tp}{tp + fn} \tag{6}$$

$$F_1 \text{ score} = 2 \times \frac{precision \times recall}{precision + recall} \tag{7}$$

Computational results lead us to conclude that the proposed anomaly detection model outperforms the binary SVM model. Although the binary classification model can catch all normal heartbeat samples, its ability to correctly classify arrhythmic samples is worse than the anomaly detection method. Moreover, the proposed model's ability to classify normal heartbeats is 87 %, and the ability to classify arrhythmic heartbeats is 93 %. The accuracy score of the ν-SVM model is 4.1 % better than binary SVM. Receiver Operating Characteristic (ROC) curves are provided in Figure 3 and, the anomaly detection area under the curve is better than binary classification.

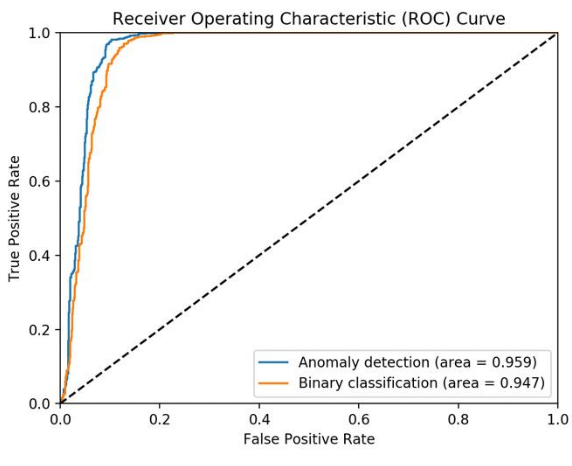

Figure 3. Receiver Operating Characteristic (ROC) curve comparison.

We also computed the test time required by the proposed method. Our model requires 0.519 seconds for feature extraction and 0.015 seconds for classification. According to these results, we can say that the proposed method can be used in real-time systems.

4. CONCLUSIONS

Heart diseases are fatal health problems and, arrhythmia is one of the most important among them. Due to the importance of the disease, it has been investigated widely by researchers. The machine learning community have built automatic diagnostic methods to classify normal and arrhythmic heartbeats correctly. Although there are various accurate classification models in the literature, most of the studies assume there are a sufficient number of samples from all classes. However, some arrhythmia classes are seen rarely and, it is not possible to train a model with rare arrhythmia classes.

In this study, we built an anomaly detection model to classify rare arrhythmia classes. Data are collected from the MIT-BIH database and, heartbeats are represented as images. To get the help of a pre-trained deep CNN model, VGG16, images are passed through the CNN model and, deep features are extracted. Then, the ν-SVM model is trained with only normal heartbeats. The performance of the proposed method is evaluated on rare arrhythmic classes. Results are compared with the performance of binary classification. The results of this study outperform the binary classification. One can benchmark the performance of the proposed study with the literature. We provided the state of the art performances at the Existing Work subsection. The accuracy we obtain in this study is compatible with the literature. However, each study has a different problem set, different assumptions and, different number of classes. Therefore, the advantages and disadvantages of these studies should be evaluated separately.

The topic keeps the interest of the researchers and, it is important to improve the accuracy even marginally. Since these models' one application area is wearable devices, test speed should be fast and testing should not require high computation. This study will serve the community with these aspects.

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CONFLICT OF INTEREST

The author stated that there are no conflicts of interest regarding the publication of this article.

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